

Labor Supply, Taxation and Unemployment

by

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Submitted to the Department of Economics
in partial fulfillment of the requirements for the degree of

Doctor of Philosophy

at the

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Abstract

Chapter Two: The standard public finance analysis of the dead weight loss of labour income taxation is based on the estimation of labour supply functions that treat unemployed individuals as non-participants. The innovation in this paper is to apply econometric models of multinomial discrete choice to the labour market, explicitly allowing individuals to be in any of three possible states (employment, unemployment and non-participation). I also control for individual unobserved (random) effects. Based on these estimates, I present calculations of the dead-weight loss of taxes, which turn out to be much larger than those suggested by the standard literature.

Chapter three: Macroeconomic models predict that taxes can affect the level of unemployment. Empirical investigation of this hypothesis to date has consisted of estimation of small scale structural macroeconomic models using aggregate data. This endeavor has produced weak evidence in favor of the hypothesis. By contrast, in this paper I estimate reduced form specifications on aggregate data. I find that taxes have a small but significant effect on the level of unemployment. In contrast with most of the rest of the literature, I find that this effect can persist in the long run.

Chapter Four: Most theories of involuntary unemployment predict that the equilibrium wage in the labor market will be greater than the reservation wage of the unemployed. These theories concentrate on explaining why the labor market does not clear with the market wage falling to the level of the reservation wage as predicted by the classical paradigm. Relatively little, however, has been said about the behavior of reservation wages. This paper seeks to fill the gap in the literature. We look at the empirical determinants of the reservation wage and suggest what this implies for the evolution of the natural rate of unemployment.

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To
Maureen

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Chapter 1

Introduction

This collection of essays consists of three separate papers empirically analyzing the impact of taxation on unemployment. In this introductory chapter I attempt to tie together the three research papers, indicating the themes common to all and explaining the reasons behind the different approaches taken by each paper.

I first became interested in the possible connection between taxation and unemployment while I was an undergraduate in Ireland in the late 1980s. At that time, Ireland, in common with other European countries, was just emerging from a sustained period of high unemployment. Also at that time tax systems throughout Europe had tended to place a high burden of taxation on labor income. Many commentators had come to believe that these two facts were connected, that high unemployment was the result of the high taxation.¹ The experiences of Europe were often contrasted with the experience of the United States, which had low tax and low unemployment. This was often cited as *prima facie* evidence that taxes cause unemployment. Professional economists have tended to be a little less sanguine. They recognize that the multiplicity of interacting effects in general equilibrium means that the identification of any causal relationship is very difficult (see Bean, 1994). Nevertheless taxation was often cited in the literature as one of a number of possible causes of unemployment (see Layard, Nickell & Jackman, 1991).

I decided to investigate the issue in the course of my thesis. I approach the issue from the

¹For Example, in a leading article in 1995 reviewing the performance of the French economy, the *Economist* commented that “[The French tax system] still relies far too much on employment-killing payroll taxes”.

viewpoint of the two separate fields of economic research that have investigated the problem up to now, namely public finance and macroeconomics. The first paper is entitled “Estimating the Dead Weight Loss of Taxes in a Labor Market with Unemployment and Non-Participation”. It adopts the traditional approach of public finance. The second paper, “Do Taxes Cause Unemployment?”, adopts a macro-empirical approach. The third paper, “The Determinants of the Reservation Wage” also adopts a micro approach.

The impact of tax on labor markets has been one of the dominant issue in public economics at least since the early 1970s when Mirlees published his seminal papers. Somewhat surprisingly, the empirical work on this question tended to ignore the specific issue of unemployment. Most of the empirical papers tended to assume, at least implicitly, that the labor market was competitive.²

The first paper in this dissertation corrects this omission. The purpose of this paper is to calculate the dead-weight loss of labor market taxes in a framework that explicitly allows for unemployment and non-participation. I apply multinomial discrete choice econometric models to individual level labor market data from the UK. These models explicitly allow an individual to occupy any of three labor market states (employment, unemployment, non-participation).

I use two broad classes of models. The first class assumes that the individual can choose to be unemployed. In this sense these are models of voluntary unemployment. The second class of models that I estimate treat unemployment as completely involuntary. Individuals can choose whether or not to participate. Then, conditional on participation, they get a job with some probability. When making the participation decision individuals are aware that participation does not guarantee employment. This setup leads to a NMNL estimator and also, to what may be described as, a “nested probit” estimator.

It is possible to calculate the dead weight loss (DWL) of taxes from these estimates using the method reported in Small & Rosen (1981) and McFadden (1986). The resulting values for the DWL are considerably higher than those found in much of the public finance literature.

The models estimated in this paper represent an improvement over the traditional literature in so far as they allow for both non-participation and unemployment. They are still lacking in one significant aspect, however. In common with much of the literature, they are partial

²There were some exceptions, notably Ham (1982).

equilibrium. I do not model the aggregate constraint that generates unemployment. I assume that there is some inefficiency operating behind the scenes that prevents the labor market from clearing. I do not investigate how this inefficiency interacts with the tax system. This interaction could have important implications for social welfare. It is possible to envisage a multiplicity of interacting effects. The dead-weight loss calculations that I present do not account for these effects. Correcting this omission is an obvious topic for future research.

The second paper in this dissertation approaches the issue of the impact of taxation on unemployment from a macroeconomic perspective. It takes its inspiration from an empirical macro literature that developed during the 1980s. This literature sought to measure the impact of taxation on unemployment by estimating small scale models of the macro economy using aggregate data. These models usually consist of a wage equation that models the behavior of the supply side of the labor market and an employment equation that models the demand for labor. Various parameters of the tax system enter the equation as regressors. The results of this literature are ambiguous. The size and significance of the estimated effects of the tax system varies across countries. For example, Layard, Nickell & Jackman (1991) estimate this kind of model for all the OECD countries. They find that the tax wedge is statistically insignificant in eight countries (Belgium, Germany, Italy, Canada, USA, Japan, Austria, Switzerland) and positive and significant in five (France, Ireland, Finland, UK).

The specification of these models is problematic. Taxation, unemployment and most other macro variables are likely to move together for a variety of reasons. How we identify the causal relationship between tax and unemployment is of crucial importance. The appropriate exclusion restrictions are not always obvious. The variation in results between different papers looking at the same country suggests that the estimated models are not robust to small changes in specification.

In contrast with most of the existing literature, I estimate parsimonious reduced form models rather than specifying simple structural models. The basic estimation strategy is to see whether unemployment and wages respond to exogenous changes in tax policy in a way consistent with theory. By estimating reduced forms I avoid the problem of having to specify exclusion restrictions necessary to identify a structural model. This is an advantage over the existing literature. It has to be admitted, however, that the reduced form approach has its price. The

model is vulnerable to the Lucas Critique. The coefficients of the reduced form may themselves change in response to changes in the tax system.

The methodology of this paper owes a lot to Poterba, Rotemberg & Summers (1986). They treat a change in tax policy as an exogenous shock to the price structure and used this to identify the effect of money on output. I effect I treat the tax changes as shocks to the structure of real wages and use this to test for the presence of real wage rigidities. The results of this analysis show that an increase in taxation increases unemployment. The effect is statistically significant, but numerically small.

The macro approach has an advantage over the micro approach of the first paper. By default it takes into account any interaction between taxation and unemployment. Thus, it does not suffer from the omission of the general equilibrium interactions as does the first paper. The disadvantage of the approach is, however, that it is not grounded in a specific model of individual utility maximizing behavior. It is difficult therefore to infer the implications of taxation for welfare from these estimates, as in the first paper.

The first and second chapters of this thesis are attempts to measure the same phenomenon, namely the impact of taxation on unemployment. The first paper, using individual level data, found that taxation had a large effect on the probability that an individual becomes unemployed. The second paper, using aggregate data, found that taxation had a relatively small impact on the aggregate level of unemployment. The difference in results could be due to the general equilibrium interactions between tax and unemployment that are not accounted for in the first essay. This possibility only serves to emphasize the need to address this issue in future research.

The third paper is written jointly with Professor Olivier Blanchard. The purpose of the paper is to discover the determinants of the reservation wage. This is the wage that makes workers indifferent between taking a job or remaining unemployed. This topic is interesting in its own right, but it also has important implications for the central topic of this thesis, the impact of taxation on unemployment. How this adjustment takes will be an important determinant of the long run response of unemployment to real shocks such as tax changes. Bean (1994) and Blanchard & Katz (1997) point out that we might expect that the workers bear the entire burden of the tax in the long run. Their intuition is as follows. A permanent increase in taxation will reduce permanent income and consumption. This will increase the

marginal utility of consumption relative to the marginal utility of leisure. This in turn implies that the reservation wage will fall. It is not hard to design a specific set up where the net result is no change in the mark-up and therefore the wage. Thus the incidence of the tax falls completely on workers. This would imply that even a permanent increase in taxes would have only a temporary effect on unemployment.

We specify the reservation wage as a function not only of the relevant distribution of wages, of labor market conditions, and of unemployment benefits, but also of the wage received in the previous job. We estimate this relation using the British household Panel Survey over four years (1991-95). That data set contains explicit information about reservation wages, labor market status, lagged wages, and can be used to construct a mean wage based on observable characteristics of each worker. The main econometric challenge is to disentangle whether the coefficient on the lagged wage reflects causality, or the fact that the lagged wage contains information about the unobservable characteristics of workers. We do so in a variety of ways, through instrumental variables, or through use of the panel data dimension of our data and the use of individual fixed effects.

We find a large and significant effect of the mean of the distribution of wages on the reservation wage. We find a significant, but—to our surprise—a relatively small effect of the lagged wage on the reservation wage. We also find a significant but small effect of benefits. One other surprising result is our inability to find a significant effect of labor market conditions, proxied either by a worker specific unemployment rate, or by local unemployment and vacancy rates, on the reservation wage.

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Chapter 2

Estimating the Dead-Weight Loss of Taxation in a Labour Market with Unemployment and Non-Participation

2.1 Introduction

The purpose of this paper is to calculate the dead-weight loss of labor market taxes in a framework that explicitly allows for unemployment and non-participation. In doing so, this paper is part of a long tradition in the public economics literature. The calculation of the dead-weight loss of labor market taxes has been a focus of research for at least two decades. This level of interest is not surprising. Modern governments raise such a high proportion of their revenue from income and social security taxes that the welfare costs of these taxes are of crucial interest for policy makers. What is surprising, however, is that most of the empirical analysis has tended to avoid the issue of unemployment. The focus has been on the estimation of hours equation over samples consisting of the employed workers only. Some authors, especially when analyzing women's labor supply, did allow for non-participation¹. In general, however, little attempt has

¹See Mroz (1987) for an example.

been made to account for the unemployed.

Within the frame work of the traditional literature there are two possible ways of dealing with those individuals observed to be unemployed. One can either include them in the estimation sample and treat them as having supplied zero hours or, alternatively, one can exclude them from the sample, using only the employed to estimate labor supply elasticities. Ham (1982) showed that both these approaches resulted in biased estimates of the labor supply function. If the unemployed are included in the estimation sub-sample, and if they are truly constrained, then the difference between observed and desired hours will be incorporated into the residual. Thus the residual will be correlated with the independent variables rendering least squares estimates of the labor supply function inconsistent. Alternatively, if the unemployed are dropped, sample selection bias is introduced. Unless one is prepared to believe that unemployment is a random event whose occurrence is uncorrelated with any variables that may influence tastes for work, estimation over a sample consisting of only the employed, will lead to biased results. For example, if the unemployed tend to be those with less education, their exclusion from the sample will bias estimates of the influence of education on tastes for work.

Ham (1982) dealt with this problem by excluding the unemployed from the sample and correcting for the resulting selection bias using Heckman (1979) procedure. However, he did not offer a consistent treatment of non-participants, those who reported zero hours but who were not unemployed. Non-participants may have tastes for work that are systematically different from either those of the employed or the unemployed. Thus treating them as being like the employed (with zero hours "supplied") or like the unemployed, would lead to biased estimates. Similarly, excluding them from the sample would lead to another selection bias.

In this paper, I apply multinomial discrete choice econometric models to labor market data from the UK. These models explicitly allow an individual to occupy any of three labor market states (employment, unemployment, non-participation). Issues of sample selection do not arise because these models can be estimated over the entire sample. The econometric innovation of this paper is to control for individual unobservable (random) effects in each of the non-linear models on panel data.

I use two broad classes of models. The first class assumes that the individual can choose to be unemployed. In this sense these are models of voluntary unemployment. However,

unemployment is still distinct from non-participation. Suppose, for example, that an individual turns down an offer of a job at a low wage and opts instead to remain searching. He is constrained having not received a “reasonable” offer. His unemployment is voluntary however, in the sense that he could have accepted the low wage job or have dropped out of the labor market. This setup leads to Multinomial Logit (MNL), Multinomial Probit (MNP) and Nested Multinomial Logit (NMNL) estimators.

These estimates confirm some reasonable hypotheses regarding the labor market. Most particularly, it seems that employment, unemployment and non-participation are all qualitatively different states. Formal tests of the hypothesis that the unemployed have the same preferences as either the employed or the nonparticipants are overwhelmingly rejected. Thus the results confirm those of Flinn & Heckman (1983). Any analysis of labor supply that fails to take this into account could be misleading.

It is possible to calculate the dead weight loss (DWL) of taxes from these estimates using the method reported in Small & Rosen (1981) and McFadden (1986). The resulting values for the DWL are considerably higher than those found in much of the literature.

The second class of models that I estimate treat unemployment as completely involuntary. Individuals can choose whether or not to participate. Then, conditional on participation, they get a job with some probability. When making the participation decision individuals are aware that participation does not guarantee employment. This setup leads to a NMNL estimator and also to what may be described as a “nested probit” estimator. Again it is possible to calculate the DWL of taxes in these models using the method reported in Small & Rosen (1981) and McFadden (1986). The resulting values for the DWL are similar to those calculated from the first set of models and considerably higher than those found in much of the literature.

A possible explanation for these higher dead weight loss results is that the estimates presented here capture the effect of wages (and taxes) on participation. The estimates in the traditional literature report the effects of wages on hours supplied conditional on participation. If there are fixed costs of entry to the labor market, then we might expect the participation elasticity to be higher than the hours elasticity.

Interestingly my results are similar in magnitude to those calculated using the Non-Linear Budget Set (NLBS) method and reported in Hausman (1985b). This is despite of the fact that I

treat the budget constraint as being linear. This result helps shed some light on the controversy regarding the alleged bias of the NLBS model. Some authors² have suggested that the NLBS results are due to the estimation method imposing high compensating elasticities on the data. It may be, however, that the difference in the results is due to the different treatment of the non-participants. The linearized method is typically estimated over the employed, so it returns the low compensated elasticity of hours conditional on participation. The NLBS method, being a generalized version of the Tobit procedure, easily accommodates the non-participants (but not the unemployed). Therefore the difference in measured elasticities could be entirely due to a high elasticity of participation. This issue requires further research.

The models estimated in this paper represent an improvement over the traditional literature in so far as they allow for both non-participation and unemployment. They are still lacking in one significant aspect, however. In common with much of the literature, they are partial equilibrium. I do not model the aggregate constraint that generates unemployment. I assume that there is some inefficiency operating behind the scenes that prevents the labor market from clearing. I do not investigate how this inefficiency interacts with the tax system. This interaction could have important implications for social welfare. The imposition of even a small tax on an already distorted economy could have first order welfare effects increasing even more the welfare cost of taxation. Suppose, for example, that unemployment is the result of inefficient matching of job seekers and vacancies. The imposition of a tax on labor income could reduce an individual's search effort. Apart from the direct effect on the individual's welfare, this would also reduce other individuals' and firms' welfare via the search externality: one person's reduced search effort reduces the effectiveness of all other individuals' job search and firms' efforts to fill vacancies. Thus, the search externality magnifies the welfare cost of taxation.

Alternatively, the two sources of inefficiency may actually counteract each other. Continuing the search example. Suppose that workers face a cost of participation in the labor market and/or a search cost. In this case, anything that forces workers to leave the labor market, will save them the search cost. Thus the cost of taxation would be less than estimated here.

Alternatively, one could view unemployment as a job queue in a ranking model i.e. where firms have multiple applications for their vacancies. In this economy, anything that causes an

²See MaCurdy (1992) for example.

individual to leave the queue, raises the welfare of those remaining on it, without hurting the firms who receive multiple applications. Also in this case the search externality reduces the welfare cost of taxation.

The point being made here is that it is possible to envisage a multiplicity of interacting effects. The dead-weight loss calculations that I present do not account for these effects (if they exist). It is not possible to sign the bias that results from this omission. As the examples given above indicate, it could go either way. The standard models of competitive general equilibrium used in public finance to examine the issue of tax incidence are obviously unable to resolve this issue. Its resolution requires further research into the incidence of tax in non-competitive models. Correcting this omission is an obvious topic for future research.

The paper is arranged as follows. Section 2 discusses in detail the previous approaches. Section 3 discusses the data set used and some specification issues. Section 4 presents estimates of the first class of model. Section 5 presents estimates of the second class of models. Section 7 calculates the dead-weight loss of taxes. Section 8 concludes.

2.2 Previous Approaches to Labor Supply

Consider a standard labor supply function such as equation (2.1). Suppose that equation (2.1) is the true labor supply function i.e. H_{it}^* is the hours of work desired by the individual, where X is a vector of independent variables and ε is a normally distributed error.

$$H_{it}^* = X_{it}\beta + \varepsilon_{it} \tag{2.1}$$

We wish to estimate (2.1) in order to get consistent estimates of the underlying tastes for work of all individuals. We can then use these estimates to calculate the social cost of taxation. It turns out that the nature of the estimation sample we choose is crucial. As noted by Ham (1982) least squares applied to (2.1) will almost certainly be biased no matter how we construct the sample. Suppose that we try to estimate (2.1) using a sample consisting of both the employed and the unemployed. In effect, we would be estimating equation (2.2) where $u(X)$ is the probability that an individual is unemployed and H_{it} is the actual observed hours, with $H_{it} = 0$ for the unemployed. We have incorporated into the residual any difference between

observed and desired hours, such as that caused by unemployment.³

$$H_{it} = X_{it}\beta + \eta_{it} \quad (2.2)$$

$$\eta_{it} = \left\{ \begin{array}{ll} \varepsilon_{it} & w.p \quad 1 - u(X_{it}) \\ \varepsilon_{it} - H_{it}^* + H_{it} & w.p \quad u(X_{it}) \end{array} \right\}$$

If the unemployed are not truly constrained, so that $E(H_{it}^* - H_{it}) = 0$, then there is no problem. They could be treated as censored observations and equation (2.1) estimated using the Tobit procedure. If they are constrained, however, it is clear from the definition of η that $E(\eta|X) = -H^*u(X) = -X\beta u(X)$. The residual is correlated with the independent variables and least squares on (2.2) will be biased. There are two sources of bias. Firstly, even if unemployment is random i.e. $u(X)$ is a constant, any change in X will change the size of the constraint faced by the unemployed. This biases the least squares estimate of β towards zero. Secondly, if unemployment is not random and changes in X change the probability that an individual is unemployed, then the extent to which the constraint is binding in the population also changes. Least squares estimation of equation (2.2) incorporates both these effects into the estimate of β . Consider, for example, a variable measuring an individual's educational achievement. It is plausible that this variable affects an individual's taste for work. It is equally plausible that education also affects an individual's chances of becoming unemployed. In this case, if we try to estimate (2.1) over all individuals, employed and unemployed, the residual will be correlated with one of independent variables rendering the estimates inconsistent.

Ham (1982) also notes that the alternative procedure, excluding the unemployed from the estimation sample is also likely to be biased. This is standard the issue of sample selection. Least squares estimation of (2.1), over the sub-sample of the employed, will be consistent only if $E(\varepsilon|employed) \neq f(X)$. If unemployment is a random event, so that the unemployed are not systematically different from the employed, then this condition is satisfied. We expect, however, that the probability of being unemployed is a function of the same sort of variables that enter a labor supply equation (education, for example). Intuitively, if the unemployed tend to be

³ Actually any difference between the actual and desired hours will be incorporated into the residual, whether it is due to unemployment over-employment or under-employment. I ignore the issues of over- and under-employment. Ham (1982) did estimate his model also allowing for underemployment.

those with less education, their exclusion from the sample will bias estimates of the influence of education on tastes for work. Ham (1982) corrected for this bias using the selection model of Heckman (1979) to estimate a labor supply equation over the sample consisting of employed individuals only.

The Heckman procedure can deal successfully with the problem of unemployment, but does not account for the possible distinction between the unemployed and non-participants. In fact we face a similar set of issues regarding non-participants as we did regarding the unemployed. As in the case of the unemployed, we can either include or exclude non-participants from the sample used to estimate the model. In either case the estimates are likely to be biased.

If we believed that non-participants were randomly selected, then we could safely exclude them from the estimation sample. If we believed that they were not significantly different from the employed, then we could treat them as censored observations and estimate a Tobit type model.⁴ If we believed that they were not significantly different from the unemployed we could simply re-estimate the Ham model treating them as such. If we believe that the non-participants are, potentially, systematically different from both the employed and the unemployed, then we must account for them separately. This is most clearly done by estimating multinomial models of discrete choice.

2.3 Data & Specification

From Table 2.1, we can see that unemployment in Europe tends to be higher and more persistent than unemployment in the United States. This suggests that estimates of labor supply are more likely to be affected by unemployment in the case of Europe. Therefore, I conduct the analysis using a British dataset, the British Household Panel Survey (BHPS). This panel covers 4 years from 1991-95. This data has two particular advantages. Firstly, it contains a wealth of information on the labor market status of respondents, enabling the difference between unemployment and non-participation to be clearly defined. Secondly, as the data is a panel, we will be able to control for individual specific (unobserved) effects.

I exclude women from the sample following the tradition in the labor supply literature which

⁴See Blundell, Ham & Meighir (1987)

views the labor supply decision processes of the two sexes as being qualitatively different. I also exclude from the analysis all those men who were employed but for whom no wage was reported⁵. In all, after dropping observation with missing values, approximately 3,900 men are observed at each of the four waves of the panel.

The precise definitions of employment status are obviously crucial to a study like this. Unfortunately, the exact definition of involuntary unemployment is problematic as both Solow (1990) and Ashenfelter (1978) have pointed out. An economically sensible definition, proposed by Ashenfelter (1978) would hold that an individual, *A*, is involuntarily unemployed if, and only if, two conditions are met. Firstly, there must exist another individual, *B*, identical to *A* in preferences and skills, who is employed. Secondly, *A* must be willing to take *B*'s job under the same terms as *B* if it were to be offered. Obviously in practice it is impossible to implement this definition because it is impossible to match people so closely.

Most statistically implemented definitions of unemployment rely on individuals reporting their own employment status and then apply some consistency check to ensure that the constraint they claim to face is reasonable and that the unemployed individual is close to satisfying Ashenfelter's definition. The standard OECD definition requires that the unemployed individual has actively searched for work during the previous 4 weeks. If he has not done so, then he is judged to be a non-participant. In practice there is quite a lot of variation across countries in the precise definition of the "standardized" unemployment rate.⁶

The OECD definition seems too restrictive. Search effort is as much determined by the perceived probability of success as it is by the tastes of workers. The OECD would tend to systematically exclude, for example, discouraged workers. These individuals may have as much a desire to work as other unemployed but are disillusioned with the efficacy of job search and therefore, no longer actively search.

For this reason I define as unemployed any individual who does not have a job but reported that he would work if he were offered a job. As a consistency check, to ensure that the unem-

⁵Most of these excluded observations were for individuals interviewed by proxy. Their exclusion will bias the results if they are systematically different from those interviewed directly. We might expect this to be the case if individuals interviewed by proxy tended to be young men living in their parents' home, whereas those interviewed directly were older men living independently. The former group may be expected to have a greater propensity to be unemployed than the later. There is some evidence for this bias in the data.

⁶See OECD (1986)

employed individual is truly constrained and that his aspirations are truly reasonable, I require that he can indicate the minimum wage at which he would work and/or the type of occupation which he would accept. both of these variables are available in the dataset. Furthermore if these criteria are out of line with the individuals previous job and wage (if any) or his level of education, age, region of residence etc., he is coded as a non-participant.⁷

The precise definition of employment status is as follows:

- A person is defined as employed (E) if he was working the week before the interview. For these individuals I observe hours worked strictly greater than zero and the usual net hourly wage (**hwage**).
- A person is defined as unemployed (U), if he did not have a job the week before the interview but reported that he would take one if offered. Both the employed and the unemployed constitute the labor force.
- A person is considered to be “not in the labor force” (N) if he does not belong to either of the other two categories.

Table 2.3 shows the percentage of individuals in each labor market state during each wave of the sample. The sample unemployment rate is about 18% over the four years⁸. This makes it significantly higher than the official unemployment rate for the U.K. over the same period, which was 10% or so.⁹ This reflects the difference in the definition of unemployment. Some individuals, who are classified as non-participants under the official scheme, are classified as unemployed here. This probably results from my re-classification of discouraged workers as being unemployed rather than as non-participants. The problem is that we are trying to approximate a continuous variable (degree of attachment to the labor force or search effort) by a discrete division. There will always be a degree of ambiguity in the choice of where exactly we should draw the dividing line between unemployment and non-participation.

⁷More precisely I regress wage on education age and region dummies for the employed. I use this regression to generate a predicted market wage for the unemployed. If the individuals reported reservation wage is more than two standard deviations greater than his predicted market wage, then he is recoded as a non-participant. Only a very small number of individuals (93) were recoded.

⁸Unemployment rate is defined as $\frac{U}{U + E}$

⁹See Table 2.1

Another issue is how to deal with the likely joint endogeneity of a number of regressors. The presence of progressive taxes implies that employment status, net wages and unearned income are all jointly endogenous. Any change in employment status will tend to lead to higher income, placing the worker in a higher tax band, which in turn reduces the net wage and after tax unearned income. For this reason and because of the suspicion of error in both wage and unearned income, I first regress **hwage** and **dsave** on the set of exogenous variables and use the fitted values as regressors.

The exogenous variables used here are similar to those used throughout the literature. They fall into three broad categories: Human Capital, Household Composition, Aggregate Demand Side Variables, and time and region fixed effects. The human capital variables are all related to education and occupation (**educ**, **soc**, **pasoc**, **tae**, **voced**). The household composition variables include marital status (**marstat**), the number of dependent children of various ages (**k02y-k1618y**) and a dummy for being head of household (**hoh**). The aggregate demand side variables are long term interest rate (**longi**), national and regional unemployment rates (**uktot** and **regu**), retail price index (**rpi**) and a regional index of the change in house prices (**dval**).

The fitted values were estimated by regressing **hwage** and **dsave** on dummies created from the above exogenous variables together with interactions between time and region dummies. This procedure is not without controversy. Only the exogeneity of fathers occupation (**pasoc**), age and the time dummies are absolutely assured. One could argue that the human capital variables, the household composition variables and even the regional dummies are all the result of choices that are made jointly with the choice of labor market status and are therefore not exogenous.

There are two defences against this criticism. Firstly, it can be argued that, while these variables are formally the result of choices, those choices are sufficiently independent of the choice of employment status to enable the resulting variables to be treated as being exogenous in practice. For example, education may be thought to be endogenous because we choose a higher level of education in anticipation that this will enable us to earn higher wages, avoid unemployment etc. But it is also plausible to suggest that the choice of education is as much a result of available opportunities, parental encouragement, personal abilities etc. To the extent that this is so, the level of education can be considered to be exogenous. Similar arguments

can be made in relation to the household composition variables. In the case of the aggregate variables we can invoke a Nash type argument. Individuals are assumed to act on the basis that they cannot affect the aggregate variables such as the interest rate and the unemployment rate, even if they know that all individuals acting together collectively determine these variables.

The second defence is that the contribution of this paper to the literature, is not intended to be the improvement on the identification of previous models. Instead the focus of the paper is on the implications of unemployment for estimation of labor supply. It seems reasonable, therefore, to adopt standard practice in all other respects.

Another issue that arises is the nature of the identifying variation. The wage variable used throughout (**hwage**) is the individual's reported hourly wage after tax. This implies that the identifying variation is a combination of variation in the gross wage and variation in the tax paid by individuals. There was very little change in the tax structure through time (at least during the period covered by the BHPS data). Thus most of the tax variation will be cross-sectional. The progressive nature of the tax structure implies that those with higher earnings tend to have higher average tax rates.

2.4 A Model With “Voluntary” Unemployment

It is clear from section 2 that we need an econometric procedure that is flexible enough to allow for three labor market states. Of crucial importance to this estimation scheme is how I choose to model unemployment. I adopt two polar assumptions. In this section I propose estimators based on the assumption that unemployment is voluntary (in a sense to be made precise shortly). In the next section I propose estimators based on the opposite assumption that unemployment is completely involuntary. In either case the Random Utility Model (RUM)¹⁰ is a convenient framework within which to consider the alternative econometric methods.

The RUM model of labor market choice is given by equation (2.3). An individual, i , assigns (indirect) utility (U_{it}^j) to each of the three labor market states in each time period. Utility consists of a deterministic component (V_{it}^j) and an stochastic component (ϵ_{it}^j) where j and $k \in \{e, u, n\}$ are indices of employment status. The deterministic component is a “linear in

¹⁰See McFadden (1986)

parameters" function of X_{it}^j , a matrix of independent variables at time t , and α^j a vector of individual specific effects. The stochastic components have a joint distribution $F(\epsilon^e, \epsilon^u, \epsilon^n)$ with a covariance matrix Σ . For convenience, I assume that the covariance matrix is the same for all individuals (homoscedastic) and for all time periods. The stochastic component of utility can be interpreted as either true randomness in preferences across time and individuals, or as being that component of utility that is not observed by the econometrician.¹¹ Specification of the functional form of F will generate particular econometric model.

$$U_{it}^j = V_{it}^j + \epsilon_{it}^j$$

$$V_{it}^j \equiv \alpha_i^j + X_{it}^j \beta^j \quad (2.3)$$

$$Cov(\epsilon_{it}^j, \epsilon_{is}^k) = \Sigma \equiv [\sigma_{jk}]$$

Equation (2.3) is relatively unrestrictive. It implies that each of the three labor market states may induce different levels of utility. In particular, being unemployed is not necessarily the same as being a non-participant. In this manner the model already departs from much of the traditional analysis.

In the standard RUM the individual chooses whichever state provides the highest utility. So, for example, the probability that an individual chooses employment at time t , conditional on individual effects (α_i), is given by equation (2.4). The other probabilities are defined symmetrically.

$$\begin{aligned} \Pr(E_{it}|\alpha_i) &= \Pr\{U_{it}^e > U_{it}^j \text{ where } j = (u, n)\} \\ &= \Pr\{\epsilon_{it}^j < V_{it}^e - V_{it}^j + \epsilon_{it}^e \text{ where } j = (u, n)\} \end{aligned} \quad (2.4)$$

Equation (2.4) is not innocent. It implies that individuals may choose to be unemployed. In fact they will do so if $U_{it}^u > U_{it}^j$. In this sense unemployment is voluntary. This does not mean, however, that unemployment is the same as non-participation. Suppose, for example, that an individual turns down an offer of a job at a low wage and opts instead to remain searching. Such a person meets the definition of unemployment given in the last section. He is constrained having not received a "reasonable" offer. His unemployment is voluntary however, in the sense

¹¹We could specify a random coefficient model by allowing ϵ_{it}^j to be a function of X_{it}^j . See Hausman & Wise (1978) for an example.

that he could have accepted the low wage job or have dropped out of the labor market. This interpretation may strike some as being unreasonable, or at least restrictive, which is why it is relaxed in the next section.

Following Ben-Akiva & Lerman (1985) a specific multinomial model can be derived from equation (2.4) by specifying the form of F , the joint distribution of the errors. Let $f(\epsilon^e, \epsilon^u, \epsilon^n)$ be the joint density of the error terms, where time and person subscripts have been dropped in the interest of notational simplicity. Equation (2.4) can be evaluated by integration, as in equation (2.5).

$$\Pr(E_{it}|\alpha_i) = \int_{\epsilon^e=-\infty}^{+\infty} \int_{\epsilon^u=-\infty}^{\epsilon^e+V^e-V^u} \int_{\epsilon^n=-\infty}^{\epsilon^e+V^e-V^n} f(\epsilon^e, \epsilon^u, \epsilon^n) d\epsilon^n d\epsilon^u d\epsilon^e \quad (2.5)$$

In many cases it is more convenient to work with the distribution function F . If we denote the partial derivative of F with respect to ϵ^e by F_e , then (2.5) can be re-written as

$$\Pr(E_{it}|\alpha_i) = \int_{\epsilon^e=-\infty}^{+\infty} F_e(\epsilon_{it}^e, \epsilon_{it}^e + V_{it}^e - V_{it}^u, \epsilon_{it}^e + V_{it}^e - V_{it}^n) d\epsilon_{it}^e \quad (2.6)$$

The integrand in (2.6) is the probability that ϵ^e equals a particular value *and* that the other disturbances are such that E will be chosen. By integrating over the support of ϵ^e we get the probability that E is chosen (conditional on α_i).

Given these probabilities, we can calculate equation (2.7), the log likelihood of the sample of N individuals over T periods, conditional on individual effects, where d_{it}^j is a dummy variable equal to one if individual i is observed in state j at time t .

$$\ln L = \ln \prod_{i=1}^N \prod_{t=1}^T \left\{ \sum_{j=e,u,n} d_{it}^j \Pr(J_{it}|\alpha_i) \right\} \quad (2.7)$$

In general the first, and second, order conditions of (2.7) do not have convenient analytical forms. Maximization of the likelihood may have to be done numerically.

With only cross-section data we would be unable to control for the individual specific effects. We would be forced to maximize the conditional likelihood (2.7) which treats the panel as a set of T pooled cross-sections. But because the data is a panel we can control for the

individual (random) effects. In principle this is relatively straight forward. We integrate them out of equation (2.6), and maximize the resulting unconditional likelihood (2.8), where ϕ is the p.d.f. of the random effects.¹² In practice, however, maximization of (2.8) is computationally burdensome. It requires an extra numerical integration each time the likelihood function is evaluated and the use of numerical procedures to evaluate the gradient and the hessian.

$$\ln L = \ln \prod_{i=1}^N \int_{-\infty}^{\infty} \left\{ \prod_{t=1}^T \sum_{j=e,u,n} [d_{it}^j \Pr(J_{it}|\alpha_i)] \right\} \phi(\alpha) d\alpha \quad (2.8)$$

Before proceeding, it is worth making clear why I do not attempt to implement fixed effects estimators. These are not generally available for non-linear models. Because of the nonlinearities, the fixed effect cannot be differenced out as with the least squares “within-groups” estimator. Therefore, it must be estimated as an incidental parameter. This yields consistent estimates only if $T \rightarrow \infty$, which is clearly not true in this dataset. Furthermore, because the MLE of the coefficients on the independent variables and the incidental parameter are jointly determined, this inconsistency will be passed on to the estimates of the other coefficients also.

An important special case where the above is not true is described by Chamberlin (1980). He suggested controlling for fixed individual effects using a conditional likelihood estimator of the MNL model. Unfortunately this procedure effectively drops from the sample all those whose status has not changed over the period of the sample. This would tend to bias the estimates if, for example, those who were employed for the entire duration are systematically different from those who were not. Therefore, when I estimate a MNL model I adopt the alternative to the Chamberlin method and treat the individual effects as being random, assume a distribution (here normal) and integrate them out as in equation (2.8). This allows the MNL to be estimated over the entire sample without the loss of any class of observations.

Estimation of a RUM amounts to estimation of the parameters of the utility function. But because we observe only the demand functions and not the utility functions directly, we cannot identify all the parameters of the model. In effect we only observe the difference in utility

¹²I assume that the individual specific unobservables are distributed across individuals according to a normal distribution. Originally I had intended to estimate a model with different individual effects attached to each utility index i.e. $\alpha^e \neq \alpha^u \neq \alpha^n$, with α^n normalised to zero and with α^e and α^u jointly normally distributed. It proved impossible, however, to separately identify α^e and α^u in any model, so α^e is assumed to equal α^u

functions. Define $\Delta U^{jk} = U^j - U^k$. Then, dropping subscripts, the two equations below are sufficient to characterize the individual's decisions.

$$\Delta U^{eu} = (\alpha^e - \alpha^u) + (\beta^e - \beta^u)X + (\epsilon^e - \epsilon^u)$$

$$\Delta U^{en} = (\alpha^e - \alpha^n) + (\beta^e - \beta^n)X + (\epsilon^e - \epsilon^n)$$

Clearly we can only identify the differences in parameters when the variable in question does not vary across alternatives. Normalizations are necessary. In what follows I normalize U^n to be zero and $\sigma_\epsilon^2 = 1$.

2.4.1 Multinomial Logit (MNL)

Following McFadden (1974), assume that the ϵ in (2.3) are i.i.d. extreme value, then F takes the form

$$F(\epsilon^e, \epsilon^u, \epsilon^n) = \exp(-[\exp(-\epsilon^e) + \exp(-\epsilon^u) + \exp(-\epsilon^n)]) \quad (2.9)$$

Performing the integration in (2.6) will generate equation (2.10), giving the MNL model.

$$P(E_{it}|\alpha_i) = \frac{\exp(V_{it}^e)}{\exp(V_{it}^e) + \exp(V_{it}^u) + \exp(V_{it}^n)} \quad (2.10)$$

More generally the probability of observing state j conditional on the individual effects, is given by equation (2.11).

$$P(J_{it}|\alpha_i) = \frac{\exp(\alpha_i^j + X_{it}^j \beta^j)}{\sum_{m=e,u,n} \exp(\alpha_i^m + X_{it}^m \beta^m)} \quad (2.11)$$

By maximizing the log-likelihood in (2.7) or in (2.8) with $P(J_{it}|\alpha_i)$ given by (2.11) we can estimate the MNL model ignoring and controlling for individual effects respectively.

Table 2.4 provide estimates of the MNL model. The actual model estimated included as regressors, polynomials in age and dummies reflecting the age groups of dependent children (k02-k1618). The coefficients on these variables are not shown in the tables for reason of clarity. The first column reports estimates for the unrestricted case without controlling for individual effects. The second column reports estimates when wages are constrained to

have no direct impact on unemployment and benefits are constrained to have no direct impact on employment, and again not controlling for individual effects. In the context of the RUM interpretation of the MNL model, this restriction implies that the conditional utility of each state is dependent only on the “price” associated with that state. The third and fourth columns report estimates of the unrestricted and restricted model respectively, controlling for individual random effects.

The coefficients take on plausible values in most cases. A higher wage tends to increase the relative probability that an individual is employed and reduces the relative probability that he is unemployed.¹³ The discrete model does not pick up the negative effect that higher wages have on the hours supplied, conditional on participation. This accords with the standard labor supply literature which has tended to report participation elasticities much larger than the hours elasticity conditional on participation.

The negative coefficient on the wage variable in the unemployment equation, while plausible, is not a logical necessity. If we think of a model where unemployment and employment are very similar states e.g. a simple search model where unemployment is a temporary state inhabited relatively painlessly while waiting to take up a job. In this case a rise in the wage may encourage non-participants to seek employment even if that means a short period of frictional unemployment while they wait to be matched. Thus we might expect to see an increase in the wage lead to an increase in the relative probability of being unemployed. The fact that we do not observe this suggests that unemployment and employment are very different states. A more formal test of this hypothesis can be conducted by re-estimating the model subject to the constraint $\beta^u = \beta^e$. The likelihood ratio test of this restriction produces the χ^2 statistics shown in the second last row of Table 2.4. The models reject this restriction.

The other hypothesis that we may wish to test is that the unemployed are the same as non-participants i.e. $\beta^u = \beta^n = 0$. If this hypothesis were true then we could explain the labor market behavior by estimating a (binomial) logit model of participation. Again likelihood ratio tests of this hypothesis lead to its rejection.

The coefficient on benefit income in the first column suggests that larger benefits increase

¹³Some care should be taken when interpreting the coefficients in any multinomial model. They do not necessarily have the same sign as the marginal probabilities. In the case of MNL they represent the marginal effect of the covariates on the log of the odds ratio i.e. $\beta^e = \frac{\delta \ln(P^e/P^n)}{\delta X}$

the probability of being unemployed but also have a small positive (but insignificant) effect on employment. This could be because the benefit system makes participation in general more likely than non-participation. Imposing the restriction that benefits do not directly affect employment and that wages do not directly affect unemployment improves the precision.

The positive coefficient on unearned income in the employment equation in the first two columns is curious. I would have expected that unearned income should be negatively correlated with the probability of employment as it tends to be with the quantity of hours supplied. One explanation of this is that leisure is an inferior good! A more plausible explanation is that this positive coefficient is the result of a spurious correlation. Those who were employed in the past are more likely to be employed today. Also as a result of their previous employment, they are more likely to have accumulated more assets giving them a higher unearned income today. Hence we could observe a spurious positive correlation between employment today and unearned income today. A possible way to control for this employment history effect is to implement the random effects estimator of equation (2.8). Intuitively, if the long-term *employed* are somehow different, then we can control for this by tracking them over time. Controlling for random effects does change the sign of the coefficient on unearned income, making it negative. Note, however, that, since the data has been re-scaled the coefficient is very small. This suggests that income effects are low.

2.4.2 Multinomial Probit (MNP)

The assumption inherent in the MNL model, that the errors are i.i.d. is not reasonable in many situations. This assumption has the undesirable consequence known as “Independence of Irrelevant Alternatives” (IIA). The model assumes that all the alternatives are equally similar, once we have controlled for observables. This is often unrealistic. In the context of the labor market, for example, we might expect that employment and unemployment are similar in unobservables, because both imply attachment to the labor force. The Multinomial Probit (MNP) model can help overcome this problem.

The MNP has been used widely in the transport literature but less so in the labor economics or public finance literatures (see Burtless & Hausman (1982) for an example). The main advantage of the MNP model is that we are free, principle, to parameterize the covariance

matrix as we like. Most particularly we are not obliged to impose IIA by restricting Σ to be diagonal. The main disadvantage is that the model can be computationally burdensome to estimate especially as the number of alternatives increases. In the context of the labor market, however, this is not such a problem as there are only three alternatives. The model can be estimated in reasonable time by brute force numerical integration.

If the errors (ϵ^j) in equation (2.3) are assumed to have a joint normal distribution with covariance matrix Σ , then F is the trivariate normal joint distribution function and the MNP model results. Allowing for the necessary normalizations there are two free parameters to be estimated in Σ , one variance parameter and one covariance parameter. As noted previously, I choose to normalize U^n to zero, so that the covariance matrix is given by equation (2.12).

$$\Sigma = \begin{bmatrix} 1 & & \\ \rho_{eu}\sigma_u & \sigma_u^2 & \\ 0 & 0 & 0 \end{bmatrix} \quad (2.12)$$

For estimation of the MNP model it is inconvenient to work with equation (2.6) directly. It is more convenient to follow Hausman & Wise (1978) and re-parameterize the model in terms of differences in utility. Define $\eta^{ij} = \epsilon^i - \epsilon^j$, $\Delta V^{ij} = V^i - V^j$ and $\Omega = [\omega]$ to be the correlation matrix of the η^{14} . In this way equation (2.6), the probability of observing an employed individual, reduces to a single evaluation of the bivariate normal distribution, as in equation (2.13). The other probabilities are defined symmetrically.

$$\Pr(E_t|\alpha) = \Pr(\eta^{eu} < \Delta V^{eu} \ \& \ \eta^{en} < \Delta V^{en}) \quad (2.13)$$

$$\Pr(E_t|\alpha) = \int_{-\infty}^{\Delta V^{eu}} \int_{-\infty}^{\Delta V^{en}} f(\eta^{eu}, \eta^{en} | \rho_{eu}, \sigma_u) d\eta^{eu} d\eta^{en}$$

¹⁴ $\omega_{11} = \text{Var}(\eta^{eu}) = 1 + \sigma_u^2 - 2\rho_{eu}\sigma_u$
 $\omega_{22} = \text{Var}(\eta^{en}) = 1$
 $\omega_{12} = \text{Covar}(\eta^{eu}, \eta^{en}) = 1 - \rho_{eu}\sigma_u$
 $\theta = \text{Corr}(\eta^{eu}, \eta^{en}) = \frac{\omega_{12}}{\sqrt{\omega_{11}\omega_{22}}}$

$$f(\eta^{eu}, \eta^{en} | \rho_{eu}, \sigma_u) = -\frac{1}{2\pi\omega_{11}\sqrt{1-\theta^2}} \exp \left\{ \frac{-\left[\left(\frac{\eta^{eu}}{\omega_{11}}\right)^2 - 2\theta \left(\frac{\eta^{eu}\eta^{en}}{\omega_{11}}\right) + (\eta^{en})^2 \right]}{2(1-\theta^2)} \right\}$$

By substituting (2.13) into the conditional likelihood function, equation (2.7) we can estimate the MNP model over the pooled cross section. Alternatively we can substitute (2.13) into the unconditional likelihood function, equation (2.8) and estimate the MNP controlling for random effects.

Unfortunately, it proved impossible to estimate the MNP model with the covariance parameter free. Attempts to do so always resulted in a singular Hessian matrix. The estimates reported are when Σ is constrained to be diagonal i.e. IIA imposed. This result, however, is not entirely unexpected. Keane (1992) conducted Monte Carlo simulations of the MNP model. He found that unless the data was very well conditioned, it may be impossible to identify the covariance parameters. He suggested that, while the covariance parameters are formally identified, they can easily be mimicked by the coefficients on the independent variables. Thus, in practice the MLE algorithms will generate very large standard errors on estimates of all parameters or even fail completely due to the Hessian being singular. He suggested that a solution to this problem may lie in exclusion restrictions, which may help separate movement in the independent variables from movements in the covariance parameters. I have failed, however, to estimate the model successfully with any economically sensible exclusion restrictions. I also estimated the model with the covariance parameter constrained to equal values other than zero.¹⁵ The resulting estimates were almost indistinguishable from those reported here. This confirms that the covariance parameter is not well identified.

The first two columns of Table 2.5 show estimates of the independent MNP applied to the pooled dataset. The third and fourth columns of Table 2.5 gives the estimates of the independent MNP model controlling for random individual effects. As can be seen, the coefficients are very similar (up to a scale factor) to those estimated in the corresponding MNL model. This suggests that the specification is robust to different distributional assumptions. Thus the basic results of the previous sub-section are confirmed. A higher wage tends to increase the relative probability of being employed and reduce the relative probability of being unemployed. The coefficient on

¹⁵The correlation coefficient, ρ_{eu} , was constrained to be 0, 0.5, 0.75 and 0.9.

benefit income has a small positive effect on the relative probability of being employed and a larger positive effect on the relative probability of being unemployed. Restricting wages to have zero effect in the unemployment equation and benefits to have zero coefficient in the employment equation, improves precision but does not change the direction of any effect. As with the MNL model, the sign of the coefficient on **dsave** changes when we control for individual random effects.

2.4.3 Nested Multinomial Logit (NMNL)

The assumption of “Independence of Irrelevant Alternatives” (IIA) inherent in the MNL and independent MNP models is not reasonable in the context of the labor market. The NMNL model, McFadden (1978) was designed to overcome this kind of problem. In terms of the RUM of (2.3) the distribution of the ϵ^j is given by the function F below

$$F(\epsilon^e, \epsilon^u, \epsilon^n) = \exp\{-[\exp(-\epsilon^e) + \exp(-\epsilon^u)]\mu - \exp(-\epsilon^n)\}$$

Performing the integration in equation (2.6) will generate (2.14) the NMNL

$$P(E|\alpha) = \frac{\exp(V^e)\{\exp(V^e) + \exp(V^u)\}\mu}{\{\exp(V^e) + \exp(V^u)\}\mu + \exp(V^n)} \quad (2.14)$$

The parameter μ represents the degree of dissimilarity between the unobserved components of the utility of employment and unemployment.¹⁶ When μ is one, all the unobservables are equally dissimilar, F reduces to (2.9), equation (2.14) reduces to equation (2.10) and the NMNL reduces to the MNL model.

The model could be estimated directly by substituting (2.14) into the likelihood function (2.8). The model is more easily understood, however, if it is expressed in terms of tree structure of sequential decisions conditional probabilities, as explained in McFadden (1984).

We can think of estimating the model in two stages. Suppose that labor market decisions are structured as follows. Individuals choose between participating in, or dropping out of, the labor force. This is the standard labor supply, or participation, decision. Then, conditional on

¹⁶More precisely numerical simulation reported by Maddala (1983) has indicated that if ρ is the correlation between ϵ^e and ϵ^u and μ is the coefficient on the inclusive value then $\rho < 1 - \mu < \rho + 0.045$.

participation, individuals choose either to become employed or unemployed.

$$P(L_{it}|\alpha_i) = \frac{\exp(\mu\lambda_{it})}{\exp(V_{it}^n) + \exp(\mu\lambda_{it})} \quad (2.15)$$

$$P(E_{it}|L_{it}, \alpha_i) = \frac{\exp(V_{it}^e)}{\exp(V_{it}^e) + \exp(V_{it}^u)} \quad (2.16)$$

$$\lambda_{it} \equiv \ln(\exp(V_{it}^e) + \exp(V_{it}^u)) \quad (2.17)$$

Each decision can be modelled as a standard binomial logit. The first stage “participation” logit (2.15) has an extra regressor λ_i , known as the “inclusive value”, which summarizes the outcome of the second stage “employment” logit (2.16). The coefficient on this parameter is a measure of the similarity of **U** and **E**. If the coefficient is unity the NMNL reduces to the MNL with all three states being equally dissimilar.

McFadden (1984) shows that the model can be estimated consistently in two stages. First the employment logit (2.16) is estimated using a standard logit algorithm. Then the inclusive value, λ_{it} is calculated from (2.17), and is included as a regressor in the participation logit (2.15). The participation logit is then estimated by the usual method. Note that λ_{it} is calculated for all individuals even the non-participants, otherwise λ_{it} would trivially determine the participation logit.

Alternatively, the system can be estimated by Maximum Likelihood. Equations (2.15) to (2.17) can be used to calculate, the probability of observing an individual in each state as in (2.18) below. We can then substitute $P(J_{it}|\alpha_i)$ into the conditional likelihood function (2.7) in order to estimate the model over the pooled dataset. In order to control for random effects we use the unconditional likelihood function in equation (2.8).

$$\begin{aligned} P(E_{it}|\alpha_i) &\equiv P(E_{it}|\alpha_i, L_{it}) * P(L_{it}|\alpha_i) \\ P(U_{it}|\alpha_i) &\equiv (1 - P(E_{it}|\alpha_i, L_{it})) * P(L_{it}|\alpha_i) \\ P(N_{it}|\alpha_i) &\equiv 1 - P(L_{it}|\alpha_i) \end{aligned} \quad (2.18)$$

The MLE of the participation logit of the NMNL model are given in Table 2.6. The model was estimated in three steps. Firstly, the two stage logit estimates were obtained. These estimates were used as starting values for the maximization of the conditional likelihood (2.7)

i.e. without random effects. The results of the conditional model are shown in the first column of table 2.6. These estimates were used, in turn, as starting values for the maximization of the unconditional likelihood (2.8), with random effects. The results of the unconditional model are shown in the second column of table 2.6.

The first two columns of Table 2.6 show estimates of the independent NMNL applied to the pooled dataset. The third and fourth columns of Table 2.6 gives the estimates of the independent NMNL model controlling for random individual effects. As can be seen, the coefficients are very similar to those estimated in the corresponding MNL model. Thus the basic results of the MNL model are confirmed by the NMNL model. A higher wage tends to increase the relative probability of being employed and reduce the relative probability of being unemployed. The coefficient on benefit income has a small positive effect on the relative probability of being employed and a larger positive effect on the relative probability of being unemployed. Restricting wages to have zero effect in the unemployment equation and benefits to have zero coefficient in the employment equation, improves precision but does not change the direction of any effect. As with the MNL model, the sign of the coefficient on *dsave* changes when we control for individual random effects.

The coefficient on the inclusive value term deserves special attention. The fact that it is significantly different from zero indicates that the second stage logit is relevant. We cannot model the labor market with a standard binomial participation logit. McFadden (1984) notes that if the coefficient on the inclusive value is significantly different from unity, then the data rejects the hypothesis of independent errors necessary to estimate the model as a standard multinomial logit. As can be seen from Table 2.6, this data rejects the hypothesis. In fact the estimates suggest that the correlation between ϵ^e and ϵ^u is approximately 0.3. While the coefficient on the inclusive value is significantly different from unity, numerically it is quite close. This helps explain why the NMNL estimates of the other coefficients are so close to those produced by the MNP and MNL models. Independence of Irrelevant Alternatives (IIA) is not a bad approximation to the "true" model. Therefore the coefficients estimated by the MNL and MNP models i.e. with IIA imposed, are not that different from the "true" NMML.

2.5 Involuntary Unemployment

The estimates of the previous section were based on the idea that unemployment was voluntarily chosen but still different from non-participation. In this section I adopt the polar opposite assumption that unemployment is completely involuntary. Suppose that the labor market decisions are structured as follows. Individuals choose between participating in, or dropping out of, the labor force. This is the standard supply decision. Then, conditional on participation, individuals either get a job or become unemployed. The second stage is the result of the imposition of an outside constraint. This is the sense in which unemployment is involuntary. Individuals make their participation decision knowing that participation does not guarantee employment. The probability that an individual gets a job if he participates is modeled as a function of exogenous variables that are outside the control of the individual.¹⁷ So for example, a youth with a low level of education, living in a high unemployment area has a low probability of being employed. Knowing this, he would tend to be less willing to and seek work at any given wage level. This interpretation of unemployment is different from that given in the last section. Unemployment is the result of a constraint. The individual can do nothing to alter the probability of being employed once he decides to participate. The only choice that exists is between participation and non-participation. Unemployment is involuntary in this sense.

This structure can be modeled formally as follows. Individuals choose between participation, which yields indirect utility U_{it}^l , and non-participation which yields U_{it}^n . The utility of non-participation is as defined previously. The utility of participation is modeled as a function of the payoff if the individual secures employment, the payoff if he becomes unemployed and the probability that participation will yield employment. A convenient specification is to model the utility of participation as the expected utility of the gamble that participation will yield employment with probability p_{it} , as in (2.19). The random variables, U_{it}^e , U_{it}^u and U_{it}^n are as

¹⁷I have assumed that the probability of employment conditional on participation is a function of variables that are assumed to be exogenous. Thus the analysis does not allow for any attempt by participants to improve their chances of finding employment by, for example, migrating to a different region or improving their educational qualifications.

defined in (2.3) and $\eta_{it} \equiv p_{it}(\epsilon_{it}^e - \epsilon_{it}^u) + \epsilon_{it}^u$

$$\begin{aligned} U_{it}^l &= p_{it} * U_{it}^e + (1 - p_{it}) * U_{it}^u \\ &= p_{it}(V_{it}^e - V_{it}^u) + V_{it}^u + \eta_{it} \end{aligned} \quad (2.19)$$

The individual will choose participation if $U_{it}^l > U_{it}^n$. Conditional on participation he will get a job with probability p_{it} . We can estimate the model in two stages. First we estimate the probability of employment conditional on participation, p_{it} as a function of all the exogenous variables. This is a standard binomial discrete dependent variable model such as probit or logit. Then the fitted values from this regression can be used for p_{it} in estimating the binomial choice between participation and non-participation. Alternatively, we could jointly estimate both models using the two stage estimates as starting values. The probability of observing the individual in each of the three states is given by (2.20). Substituting (2.20) into (2.8) will enable FIML estimation of the model controlling for random effects.

$$\begin{aligned} P(L_{it}|\alpha_i) &= P(U_{it}^l > U_{it}^n) \\ P(E_{it}|\alpha_i) &= p_{it} * P(L_{it}|\alpha_i) \\ P(U_{it}|\alpha_i) &= (1 - p_{it}) * P(L_{it}|\alpha_i) \\ P(N_{it}|\alpha_i) &= 1 - P(L_{it}|\alpha_i) \end{aligned} \quad (2.20)$$

2.5.1 Nested Logit

The conditional probability story described above leads naturally to consideration of the NMNL model. The NMNL was originally derived in order to overcome the restrictive assumption of independence of irrelevant alternatives inherent in the MNL model. This was why it was used in section 3. However, McFadden (1984) shows that it also has a conditional probability interpretation that is particularly convenient in this context. It is important to note that the NMNL in this section should not be confused with that of section 3. The estimation method is the same but the regressors and the underlying economic model are different.

Suppose that the utility of participation takes the form of equation (2.21). This equation states that the utility of participation rises with the wage and falls with the increasing probability of unemployment

$$U_{it}^l = \alpha_i + \beta \ln W_{it} + \delta X_{it} + \mu \ln P(U_{it}|L_{it}, \alpha_i) \quad (2.21)$$

Each decision in the two stage process can be modelled as a standard binomial logit. The first stage “participation” logit (2.22) has an extra regressor λ_i , known as the “inclusive value”, which summarizes the outcome of the second stage “employment” logit (2.23). The participation logit (2.22) is the same as that estimated by MNL in the previous section, with the exception that it has an extra regressor, λ_i the inclusive value term. Equation (2.24) shows that, in this model, the inclusive value term is equal to the negative of the log of the probability of being unemployed conditional on participation. Thus, the NMNL effectively includes the probability of being unemployed in an otherwise standard participation equation. The employment logit (2.23) includes the aggregate and individual level variables that may be hypothesized to influence an individuals chance of becoming unemployed.

$$P(L_{it}|\alpha_i) = \frac{\exp(\beta X_{it} + \mu \lambda_{it})}{1 + \exp(\beta X_{it} + \mu \lambda_{it})} \quad (2.22)$$

$$P(E_{it}|L_{it}, \alpha_i) = \frac{\exp(\theta Z_{it})}{1 + \exp(\theta Z_{it})} \quad (2.23)$$

$$\begin{aligned} \lambda_{it} &\equiv \ln(1 + \exp(\alpha_i + \theta Z_{it})) \\ &= -P(U_{it}|L_{it}, \alpha_i) \end{aligned} \quad (2.24)$$

The system can be estimated consistently in two stages. First the employment logit (2.23) is estimated using a standard logit algorithm. Then the inclusive value, λ_i is calculated from (2.24), and is included as a regressor in the participation logit (2.22). The participation logit is then estimated by the usual method. Note that λ_i is calculated for all individuals even the non-participants, otherwise λ_i would trivially determine the participation logit.

Alternatively, the system can be estimated by Maximum Likelihood. Equations (2.22) to (2.24) can be used to calculate, the probability of observing an individual in each state as in (2.25) below. We can then substitute $P(J_{it}|\alpha_i)$ into the conditional likelihood function (2.7) in order to estimate the model over the pooled dataset. In order to control for random effects we

use the unconditional likelihood function in equation (2.8).

$$\begin{aligned}
 P(E_{it}|\alpha_i) &\equiv P(E_{it}|\alpha_i, L_{it}) * P(L_{it}|\alpha_i) \\
 P(U_{it}|\alpha_i) &\equiv (1 - P(E_{it}|\alpha_i, L_{it})) * P(L_{it}|\alpha_i) \\
 P(N_{it}|\alpha_i) &\equiv 1 - P(L_{it}|\alpha_i)
 \end{aligned}
 \tag{2.25}$$

The MLE of the participation logit of the NMNL model are given in Table 2.8. The model was estimated in three steps. Firstly, the two stage logit estimates were obtained. These estimates were used as starting values for the maximization of the conditional likelihood (2.7) i.e. without random effects. The results of the conditional model are shown in the first column of table 2.8. These estimates were used, in turn, as starting values for the maximization of the unconditional likelihood (2.8), with random effects. The results of the unconditional model are shown in the second column of table 2.8.

The coefficients on the participation logit have plausible values. A higher wage increases the probability that an individual will participate. Higher unearned income (*dsave*) decreases the probability of participation as does higher benefit income. Note that, in contrast to the models of the previous section, the inclusion of random effects does not affect the sign of the coefficient on *dsave*. In both cases it is positive, as we would expect it to be. However, when we do not allow for random effects, we cannot reject the hypothesis that the coefficient is positive.

The fact that coefficient on the inclusive value term is significantly different from zero indicates that the second stage employment logit is relevant. The labor market cannot be modeled with a standard binomial participation logit. The probability of being unemployed at the second stage influences an individual's decision to participate. The positive coefficient implies that the higher is the probability that an individual will be unemployed, the lower the probability that he will participate. The estimates of the reduced form employment logit (not reported here) are jointly significant. This implies that occurrence of unemployment is not a random event but is correlated with variables that typically enter labor supply equations either directly or indirectly via the wage equation. This is what the traditional labor supply models miss

2.5.2 Nested Probit

While the model of (2.22)-(2.24) is intuitive, it is not an expected utility formulation. The expected utility model of equation (2.19) can be estimated directly. The probability of participation is given by $P(L_{it}) = P(U_{it}^l > U_{it}^n)$.

$$P(L_{it}|\alpha_i) = \Phi\left(\frac{p_{it}(V_{it}^e - V_{it}^u) + V_{it}^u}{\sqrt{Var(\eta_{it})}}\right) \quad (2.26)$$

$$\eta_{it} = p_{it}(\epsilon_{it}^e - \epsilon_{it}^u) + \epsilon_{it}^u$$

As in previous sections I normalize $\alpha^n = \beta^n = \epsilon^n = 0$ and I assume for simplicity that $\alpha^e = \alpha^u$.

If we assume that the errors, ϵ have a joint normal distribution, then so will η . A problem arises with the error term. The variance of η_{it} is a function of p_{it} which varies across individuals. Thus even if the ϵ are homoscedastic, the errors in the estimated model will be heteroscedastic except in the special case where $\epsilon^e = \epsilon^u$. Heteroscedasticity in non-linear models leads to inconsistency as well as inefficiency (see Greene, 1993). Fortunately, the nature of the heteroscedasticity is clear in this case, thus we can model it directly. Assuming that ϵ are homoscedastic, the variance of η is given by

$$Var(\eta_{it}) = 2 + 2 * p_{it}^2 - 2 * p_{it}$$

Thus $P(L_{it}|\alpha_i)$ is given by (2.26). The model can be estimated in two stages. First we estimate the probability of being employed conditional on participation. The fitted values from this probit are used for p_{it} in (2.26), the participation equation, which is estimated as a standard binomial probit. The two stage estimates are used as starting values for FIML estimation of the model. From (2.20) we can derive the probability of individual being in each state, then using (2.8) we can derive the likelihood of the sample controlling for random effects.

The estimates of the reduced form employment equation are not reported in Table 2.7, for reasons of space. The coefficients are jointly significant. This implies that occurrence of unemployment is not a random event but is correlated with variables that typically enter labor

supply equations either directly or indirectly via the wage equation. This is what the traditional labor supply models miss. Table 2.7 shows results for the joint (FIML) estimation of (2.26). The coefficients show are the estimated parameters of U^e and U^u that comprise U^L as in equation (2.19). As expected, a higher wage increases the utility of employment and hence the probability of participation. Higher unearned income (*dsave*) decreases utility of both employment and unemployment and hence the probability of participation.

2.6 Supply Response & Welfare Effects

We can use the estimates from the previous two sections to calculate how an individual's response to changes in taxation and hence calculate the deadweight loss of taxes. Before doing so, however, it is useful to present estimates of a standard labor supply model. Table 2.9 shows the results of 2SLS estimates of equation (2.27) over a sample consisting of the employed workers only.¹⁸

$$H_{it} = \alpha_i + \beta \ln W_{it} + \gamma \frac{Y_{it}}{W_{it}} + \delta X_{it} + \varepsilon_{it} \quad (2.27)$$

The results are consistent with theory in so far as the estimated Hicksian wage elasticity is positive. The size of the elasticity is within the range reported by other authors for the UK, although it is at the lower end of the range.¹⁹

In contrast with the results in Table 2.9, the estimates of the previous two sections all show large wage elasticities. In order to see this more clearly, we can calculate the supply response of the representative agent. Table 2.10 shows how the probability of observing the average individual in each state varies with the tax rate using the estimates of the MNL model of section four. The table are calculated using the estimates of the restricted MNL model controlling for random effects (the fourth column of Table 2.4). I assume that the UK tax system over the period of the panel can be thought of as imposing a single proportional tax rate of 23% on an average worker²⁰ who earns the sample mean of £6.44 per hour. All other variables are evaluated at their sample means. Table 2.10 shows that the imposition of 23% tax rate is sufficient to lead to the probability of being *employed* falling by 16 percentage points, from 76%

¹⁸Equation (2.27) has been used by Blundell et. al. (1994).

¹⁹See Blundell (1993) and Pencaval (1986).

²⁰This is approximately true. See OECD (1993)

to 60%. The size of this effect suggests that the DWL of taxes will be correspondingly large. In fact the elasticity of the probability of being *employed* with respect to the wage, evaluated at point of imposition of the 23% tax is 1.02.

Performing the same calculation as above for the nested logit model of section four generates Table 2.11. The nested logit model generates a wage elasticity of *participation* of 1.2. and the nested probit generates an elasticity of 0.98, both evaluated at the point of imposition of the 23% tax.

These effects are obviously a much larger effect than that measured by the standard labor supply model of Table 2.9. The labor supply model and the models of section three and section four are all measuring different but related responses. The labor supply model measures the response to wages of hours worked *conditional on participation and employment*. This elasticity is small. Once they have made the decision to participate in the labor force and once they have a job, men are relatively insensitive to the wage. The discrete models, however, estimate participation elasticities. These elasticities are much higher. This is not surprising. If there are fixed costs of participation and job search then individuals' participation decisions will be very sensitive to the wage level, but once those fixed costs have been incurred, individuals behavior (hours supplied) is relatively insensitive to the wage level.

The results for the wage response suggests that the calculated DWL of the same taxes will differ greatly depending on whether we focus on discrete choice or the hours model. The DWL of taxes based only on the hours model will be quite low, since workers are relatively insensitive to wage, the government can tax hours with relative impunity. On the other hand if we use the discrete models, we will get large dead weight losses, because the participation decision is very sensitive to the wage level.

In order to see this more formally, we need a method of calculating the dead-weight loss in the context of discrete choice models. Small & Rosen (1981) and McFadden (1986) show that in the context of a RUM such as (2.3) or (2.19), the probability function can be treated as the demand function for a discrete good. Define \tilde{h} to be the hours supplied conditional on employment and h to be the unconditional hours. Small & Rosen (1981) show that for the representative agent equation (2.28) holds, where P^e is the estimated probability of being

employed.

$$h = P^e * h \quad (2.28)$$

They also show that the standard results of consumer theory for continuous goods carry over to case of discrete choice. Specifically we can apply Roy's Identity to the conditional hours supply function ($\tilde{h} = -\frac{\delta V^e / \delta w}{\delta V^e / \delta Y}$) and Shephard's Lemma to the unconditional hours supply function ($h = \frac{\delta C}{\delta W}$) where C is the consumers cost function. By substitution into (2.28) we get (2.29) where θ is the marginal utility of income ($\theta = \delta V^e / \delta Y$).

$$\frac{\delta C}{\delta W} = -\frac{1}{\theta} \frac{\delta V^e}{\delta W} P^e \quad (2.29)$$

The compensating variation is calculated by changing variables and integrating the area under the compensated demand curve, given by (2.29), to get equation (2.30). The DWL of a tax is given by the CV less the tax revenue.

$$CV = \int_{W_0}^{W_1} \frac{\delta C}{\delta W} dW = -\frac{1}{\theta} \int_{V_0^e}^{V_1^e} P^e(V^e) dV^e \quad (2.30)$$

In order to take the θ outside the integral we must assume that the marginal utility of income is independent of wages. Thus strictly speaking, (2.30) is the Marshallian consumer surplus. In the models estimated here, utility is linear in the income term, so the marginal utility of income is independent of the wage. In this case the Marshallian concept of consumer surplus coincides with the compensating variation.

The expression in (2.30) has a convenient closed form in the case of the MNL and NMNL models. In the case of the MNL model (2.30) reduces to equation (2.31) and in the case of the NMNL it reduces to equation (2.32). In the case of the MNP model (2.30) must be evaluated by numerical integration.

$$CV = \left[-\frac{1}{\theta} \ln \left\{ \sum_{j \in \{e, u, n\}} \exp(V^j) \right\} \right]_{V_0^j}^{V_1^j} \quad (2.31)$$

$$CV = \left[-\frac{1}{\theta} \ln \{1 + \exp(V^l + \mu\lambda)\} \right]_{V_0^j}^{V_1^j} \quad (2.32)$$

Table 2.12 and Table 2.13 show the dead-weight loss caused by various different tax rates, as calculated from the estimates of sections three and four respectively. In the case of the MNL and MNP, the estimates used are for the restricted model with random effects. Calculations are for the case of the average worker in the sample. I assume that he earned £6.44 per hour, paid tax at 23% (£1.48 per hour) and worked 43 hours a week.

Consider, for example, the calculation of the DWL of tax at 23% using the estimates of the MNL model. Evaluating equation (2.31) at the sample means generates a compensating variation of £0.99 per hour. This amount is sufficient to restore the average worker to his pre-tax utility given that he is now less likely to be employed. The revenue raised by this tax is £1.48 per hour but this must be adjusted for the fact that the imposition of the tax reduces the number of individuals working. From Table 2.10, the imposition of the 23% tax reduces the probability of an individual being employed by 16 percentage points, from 76% to 60%. This gives a tax revenue of £0.88 per hour for each average individual (as distinct from each average worker). Thus the DWL of the tax is £0.11 per hour or £20.48 per month for the average worker. This is equal to 13% of revenue. The rest of Table 2.12 and Table 2.13 are calculated in a similar manner.

Table 2.12 must be interpreted with care. Equation (2.30) applied to the models of section three effectively views unemployment as just another discrete choice individuals can make. The models of section four *view* unemployment as completely involuntary. Individuals can decide to participate or not, but they cannot affect their probability of getting a job once they participate. In this case the DWL formula measures the distortionary effect of taxes on *participation*, when there is a possibility that participation may not lead to employment.

The DWL figures calculated from both models are much larger than those typically estimated by labor supply models that adopt the linear approach to the budget constraint. For example, using the estimates of the labor supply model reported in Table 2.9, I calculated the DWL of the 23% tax rate to be equal to 1.7% of revenue.²¹ The difference in size can be

²¹This calculation was done using the Harberger Triangle formula. This is a second order approximation to the true dead-weight loss. It is unlikely, however, that this approximation can account for the difference.

explained, to some extent, by the fact that the traditional estimators do not account for participation effects, whereas the multinomial models used in this paper account for participation and employment effects at the expense of ignoring the hours margin. Typically when compensated hours elasticities are estimated, on the assumption of a linear budget constraint, they turn out to be low (often less than 0.2).²² Thus, conditional on participation workers are relatively insensitive to tax changes. The discrete choice models, effectively estimate participation elasticities, which are generally regarded as being larger than the standard hours elasticity.

It is interesting to note that the DWL figures shown in Table 2.12 are very close to those reported by Hausman (1985a) using the NLBS method. This fact helps shed some light on controversy over whether the NLBS method is biased. The existing literature on the estimation of labor supply models suggests that the treatment of the budget constraint matters. Pencavel (1986) reports that estimates of the compensated elasticity of supply given by the linearization method are smaller, by a factor of five, than the estimates using the alternative, Non-Linear Budget Set (NLBS), procedure of Hausman (1985b). McCurdy (1992) has argued that this difference is due to the fact that the Hausman method effectively imposes large compensated elasticities on the data. The results presented here suggest that the crucial issue may be the treatment of non-participants. The linearized method is typically estimated over the employed, so it returns the low compensated elasticity of hours conditional on participation. The NLBS method, being a generalized version of the Tobit procedure, easily accommodates the non-participants (but not the unemployed) generating an average of the participation and hours elasticities. Therefore the difference in measured elasticities could be entirely due to a high elasticity of participation.

2.7 Conclusions & Extensions

The goal of this paper was to calculate the dead-weight loss of taxes in a framework that explicitly allowed for both unemployment and non-participation. Two different classes of econometric models were applied to British panel data. Each model allowed individuals to be employed, unemployed or a non-participant. The paper's technical innovation was to apply these non-linear

²²See Pencavel (1986) or Blundell (1993) for surveys of the literature.

models to panel data controlling for individual specific random effects.

The estimates confirmed some reasonable hypotheses regarding the labor market. Most particularly, it seems that employment, unemployment and non-participation are all qualitatively different states. Any analysis of labor supply that fails to take this into account could be misleading.

The estimates were used to calculate the DWL of labor market taxes. These figures turned out to be much higher than those estimated by the traditional labor supply literature. This appears to be because the estimates presented are of participation elasticities. These might be expected to be higher than the hours elasticity conditional on participation measured by the traditional literature. Interestingly my results are close to those estimated using the NLBS method of Hausman (1985). This fact helps shed some light on the controversy regarding the alleged bias of the NLBS model. The higher elasticity estimated by the NLBS model could be due to fact that NLBS accounts for participation (if not unemployment) whereas the linearized method typically does not.

This paper is a step towards the ultimate goal of a complete characterization of the impact of taxation on the labor market. Much remains to be done. In particular two important statistical extensions to this paper and one important theoretical extension suggest themselves.

Firstly, we must develop an estimation strategy that can incorporate variation in hours, without dropping the distinction between the three labor market states. Not accounting for the variation in hours means that we are throwing away information which could be used to identify individuals' preferences more accurately.

Another important extension to the statistical model is to allow for dynamics. It is quite likely that employment status is more persistent than the independent variables would suggest. This would occur, for example, if there are large costs to both the employer and employee of breaking the match. This would tend to generate autocorrelated errors. In non-linear models autocorrelation leads to inconsistency as well as inefficiency. If the persistence is due to the presence of some unobserved factor specific to each individual, then the problem could be dealt with through the use of the random effects estimators. More, generally, however, we might want to model the autoregressive nature of the errors directly i.e. the equivalent of including lags of the dependent variable as regressors in the estimated models.

Lastly, and more importantly, we must try to improve on the partial equilibrium nature of the analysis in this paper. Specifically we must explicitly model the interaction between the inefficiency generated by taxation and the inefficiency responsible for unemployment in the first place. This is important because the interaction could have very substantial implications for welfare. The imposition of even a small tax on an already distorted economy could have first order welfare effects. Alternatively, the two sources of inefficiency could counteract each other, leading to a lower welfare costs of taxation than that reported here. Clearly the usual competitive general equilibrium models of tax incidence are unable to resolve this issue. Its resolution requires research into the theory of taxation in the labor market.

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Table 2.1: OECD Standardised Unemployment Rates

	1975	1980	1985	1990	1991	1992	1993	1994
US	8.3	7.0	7.1	5.4	6.6	7.3	6.7	6.0
Japan	1.9	2.0	2.6	2.1	2.1	2.2	2.5	2.9
FRG	3.6	2.9	7.1	4.8	4.2	4.6	7.9	8.4
France	4.0	6.2	10.2	8.9	9.4	10.4	11.6	12.3
Italy	5.8	7.5	9.6	10.3	9.9	10.5	10.2	11.1
UK	4.3	6.4	11.2	6.9	8.8	10.1	10.4	9.5
Spain	3.6	11.1	21.1	15.9	16.0	18.1	22.4	23.8
Ireland	-	-	17.0	13.3	14.7	15.5	15.6	14.3

1. Source: OECD Main Economic Indicators, Various issues

Table 2.2: BHPS Data

Variable	Definition	Mean
age	age at interview	43.33
tae	terminal age of education	17.42
month	month of interview	9.69
year	year of interview	92.49
mastat	=1 if married	0.57
region	region	8.44
hwage	usual net hourly wage	4.96 2
hours	usual hours per week	43.62
pasoc	Father's occupation code	3.52
soc	interviewee's occupation code	5.46
educ	level of education	1.8
race	ethnic background	0.94
k02y	no. of children aged 0 to 2 in household	0.06
k34y	no. of children aged 3 to 4 in household	0.07
k511y	no. of children age. 5 to 11 in household	0.15
k1215y	no. of children aged 12 to 15 in household	0.12
k1618y	no. of children aged 16 to 18 in household	0.036
Regu	Regional Unemployment	7.15
uktot	Total Unemployment	9.7
dval	change in house prices	155.3
rpi	Consumer prices	1.07
nli	reported non-labor income	308.91
longi	rate on long term govt. bonds	8.64
dsave	dissaving	-580.95

1. Summary Statistics are calculated for the pooled cross section

Table 2.3: Percentage of Sample in Each State

Wave	%E	%U	%N
1	63	14	24
2	60	15	25
3	63	13	24
4	60	14	26

Table 2.4: Voluntary Unemployment (MNL)

Empl. Eqn. (V^e)				
ln(hwage)	1.65 (0.39)	2.55 (0.27)	2.65 (1.67)	3.12 (0.43)
dsave/100	0.0387 (0.03)	0.091 (0.03)	-0.036 (0.01)	0.02 (0.01)
Benefit/100	0.007 (0.07)	- -	-0.041 (0.01)	- -
Unempl. Eqn. (V^u)				
ln(hwage)	-1.486 (0.43)	- -	-3.8 (1.80)	- -
dsave/100	0.008 (0.04)	0.095 (0.02)	-0.037 (0.03)	-0.116 (0.03)
Benefit/100	0.12 (0.08)	0.157 (0.06)	-0.008 (0.01)	-0.19 (0.05)
Random Effect	-	-	2.75 (1.28)	3.75 (1.85)
Test				
$H_0 : E = U$	901.66	-	1036.32	-
$H_0 : U = N$	1074.76	750.59	1301.75	1175.02

1. Standard Errors are in parentheses
2. (V^e) and (V^u) also include polynomials in age and dummies for the number of dependent children of various ages

Table 2.5: Voluntary Unemployment (MNP)

Empl. Eqn. (V^e)				
ln(hwage)	2.28 (1.13)	3.05 (0.86)	1.8 (0.88)	2.75 (0.70)
dsave/100	0.08 (0.02)	0.10 (0.03)	-0.049 (0.12)	-0.018 (0.01)
Benefit/100	0.04 (0.03)	- -	-0.005 (0.06)	- -
Unempl. Eqn. (V^u)				
ln(hwage)	-2.412 (0.48)	- -	-1.34 (0.07)	- -
dsave/100	0.163 (0.11)	0.23 (0.03)	-0.6532 (0.29)	-0.84 (0.13)
Benefit/100	0.238 (0.11)	0.28 (0.08)	-0.845 (0.16)	-0.12 (0.08)
Random Effect				
	..	-	1.702 (1.08)	2.87 (1.59)
Test: χ^2				
$H_0 : E = U$	856.4	-	1152.37	-
$H_0 : N = U$	927.48	758.26	1479.25	1051.76

1. Standard Errors are in parentheses

2. (V^e) and (V^u) also include polynomials in age and dummies for the number of dependent children of various ages

Table 2.6: Voluntary Unemployment (NMNL)

Empl. Eqn. (V^e)				
ln(hwage)	1.95 (0.8)	3.14 (0.6)	2.43 (1.48)	3.09 (1.02)
dsave/100	0.042 (0.07)	0.104 (0.09)	-0.045 (0.02)	-0.03 (0.01)
Benefit/100	0.01 (0.03)	- -	-0.02 (0.04)	- -
Unempl. Eqn. (V^u)				
ln(hwage)	-1.62 (0.04)	- -	-2.7 (1.6)	- -
dsave/100	0.01 (0.06)	0.903 (0.01)	-0.04 (0.03)	-0.16 (0.04)
Benefit/100	0.08 (0.1)	0.112 (0.08)	-0.01 (0.008)	-0.09 (0.02)
Random Effect	- -	- -	1.83 (0.65)	2.45 (2.04)
Inclusive Value	0.8 (0.23)	0.67 (0.15)	0.73 (0.31)	0.62 (0.24)

1. Standard Errors are in parentheses
2. (V^e) and (V^u) also include polynomials in age and dummies for the number of dependent children of various ages

Table 2.7: Involuntary Unemployment (Nested Probit)

Empl. Eqn. (V^e)		
ln(hwage)	3.27 (0.24)	3.792 (0.13)
dsave/100	-0.241 (0.026)	-0.325 (0.026)
Benefit/100	- -	- -
Unempl. Eqn. (V^u)		
ln(hwage)	- -	- -
dsave/100	-0.051 (0.06)	0.109 (0.04)
Benefit/100	-0.083 (0.04)	0.114 (0.02)
Random Effect	- -	2.3 (0.4)

1. Standard Errors are in parentheses

2. (V^e) and (V^u) also include polynomials in age and dummies for the number of dependent children of various ages

Table 2.8: Involuntary Unemployment (NMNL)

Part. Eqn.		
ln(hwage)	3.45 (0.557)	2.369 (0.406)
dsave/100	-0.101 (0.08)	-0.263 (0.011)
benefits/1000	-0.127 (0.06)	-0.104 (0.04)
inclusive value	0.65 (0.12)	0.776 (0.087)
Random Effect	-	4.2 (1.2)

1. Standard Errors are in parentheses
2. Also include polynomials
in age and dummies for the number of
dependent children of various ages

Table 2.9: 2SLS Estimates of Hours Eqn.

$\ln(\text{hwage})$	-0.33 (0.21)
$\text{dsave}/(\text{hwage} \cdot 100)$	-3.59 (0.44)
Marshallian Elasticity	0.07
Hicksian Elasticity	0.1

1. Standard Errors are in parentheses
2. Also include polynomials
in age and dummies for the number of
dependent children of various ages

Table 2.10: Voluntary Unemployment Model (MNL)

Tax Rate	0%	10%	20%	23%	30%	40%	50%
%E	76	69	62	60	54	45	34
%U	8	10	12	13	15	18	22
%N	17	21	25	27	31	37	44

Table 2.11: Involuntary Unemployment Model (NMNL)

Tax Rate	0%	10%	20%	23%	30%	40%	50%
%L	97	88	77	73	64	50	33
%N	3	12	23	27	36	50	67

Table 2.12: DWL of Voluntary Unemployment Models

Tax Rate	0%	10%	20%	23%	30%	40%
MNL	-	5%	13%	13%	31%	52%
NMNL	-	4%	11%	12%	27%	45%
MNP	-	6%	14%	15%	34%	57%

Table 2.13: DWL of Involuntary Unemployment Models

Tax Rate	0%	10%	20%	23%	30%	40%
Logit	-	8%	23%	24%	51%	92%
Probit	-	12%	32%	33%	75%	110%

Chapter 3

Do Taxes Cause Unemployment?

3.1 Introduction

Are high taxes responsible for high unemployment in Europe? Many commentators take it for granted that they are. In a recent leading article reviewing the performance of the French economy, the *Economist* commented that “[The French tax system] still relies far too much on employment-killing payroll taxes”. Professional economists have tended to be a little less sanguine. They recognize that the multiplicity of interacting effects in general equilibrium means that the identification of any causal relationship is very difficult (see Bean, 1994). Nevertheless taxation has often been cited in the literature as one of a number of possible causes of unemployment (see Layard, Nickell & Jackman, 1991).

The interest of both pundits and economists in the possibility of a causal link between taxation and the level and persistence of unemployment, has been stimulated by recent OECD experience. There appears to be a correlation between high taxation and high unemployment. This correlation can be observed both across countries at any given time and within countries, through time.

Table 3.1 shows OECD standardized unemployment rates for selected countries since 1965. The basic facts illustrated by table 3.1 are well known. There was an inexorable rise in unemployment from the early seventies until the mid eighties in all countries. After 1985 unemployment tended to fall but not to the level of the 1960s, and it remained very high in some countries.

Table 3.2 shows total tax revenue as a percentage of GDP. It appears that taxes have risen in those countries that have experienced high unemployment (e.g. Ireland, Denmark, Italy). This is the correlation that sparked the interest of economists and pundits alike. It is especially obvious in the case of the United States versus Europe. As Blanchard & Katz (1997) have commented, the low tax and low unemployment US economy is often cited as *prima facie* evidence that taxes cause unemployment. Taxes, however, have also risen in a number of countries that have not experienced high unemployment. Indeed the share of taxation is highest in those countries (Sweden Austria, Finland) with traditionally the lowest unemployment! Thus even with this crude analysis, the evidence is far from clear.

The observed correlation could be explained by many things other than the hypothesis that taxes cause unemployment. An empirical macro literature on this topic developed in the 1980s. It sought to disentangle all the effects, and to identify and measure the causal link between taxes and unemployment. This activity was most common in Europe where a plethora of papers have been produced since the late eighties.¹

This literature has focused on the estimation of small scale models of the macro economy using aggregate data. These models usually consist of a wage equation that models the behavior of the supply side of the labor market and an employment equation that models the demand for labor. Various parameters of the tax system enter the equation as regressors. The results of this literature are ambiguous. The size and significance of the estimated effects of the tax system varies across countries. For example, Layard, Nickell & Jackman (1991) estimate this kind of model for the OECD countries. They find that the tax wedge is statistically insignificant in eight countries (Belgium, Germany, Italy, Canada, USA, Japan, Austria, Switzerland) and positive and significant in five (France, Ireland, Finland, UK).

These results appear to suggest that taxation is not the primary cause of unemployment in Europe, but provides some evidence that taxes are a contributory factor. There are, however, three different grounds on which to criticize the existing literature. Model specification is problematic. Taxation, unemployment and most other macro variables are likely to move together for a variety of reasons. How we identify the causal relationship between tax and

¹See for example Bean & Dreze (1990), Bean, Layard & Nickell (1986), Layard & Nickell (1986), Layard, Nickell & Jackman (1991), and Whelan (1995). The various papers co-authored by Layard, Nickell, Jackman and Bean are typical and much imitated.

unemployment is of crucial importance. The appropriate exclusion restrictions are not always obvious. The variation in results between different papers looking at the same country suggests that the estimated models are not robust to small changes in specification.

The insignificance of the results could also be attributed to the data. Many of these models are estimated using annual macro data, as are the models estimated in this paper. This means that there are relatively few observations with which to identify the model. This problem is compounded if we try to identify a structural model, as most existing studies do. This problem is even more serious if we try to identify the dynamic effect of tax on unemployment. The inclusion of lagged variables reduces the degrees of freedom even further. In this context, a lack of precision is not surprising. This is unfortunate because the issue of whether taxes have permanent or transitory effect on the level of employment is particularly interesting. In fact many of the existing studies impose the long run neutrality of taxes as an identifying restriction. This is a restriction that we might want to test rather than imposing on the data.

There is another reason for being suspicious of results that imply that taxes have no significant effect. Insignificance has an important policy implication. If taxation has relatively little impact on output and employment, then a country could solve severe budgetary problems by increasing labor taxes dramatically, without fear of adverse consequences. Few economists would ever recommend this policy, and indeed, where it has been tried, it has failed (see Alesina & Perotti, 1995).

In contrast with most of the existing literature, I propose to estimate parsimonious reduced form models rather than to specify simple structural models. The basic estimation strategy is to see whether unemployment and wages respond to exogenous changes in tax policy in a way consistent with theory. By estimating reduced forms I avoid the problem of having to specify exclusion restrictions necessary to identify a structural model. This is an advantage over the existing literature. It has to be admitted, however, that the reduced form approach has its price. The model is vulnerable to the Lucas Critique. The coefficients of the reduced form may themselves change in response to changes in the tax system.

A similar procedure was used by Poterba, Rotemberg & Summers (1986) to test for the presence of nominal rigidities. They treated change in tax policy as exogenous shocks to the price structure and used this to identify the effect of money on output. In effect I treat the tax

changes as shocks to the structure of real wages and use this to test for the presence of real wage rigidities.

The results of this analysis show that the effect of an increase in taxation is to increase unemployment. The effect is statistically significant, long lasting, but numerically small.

The paper is organized as follows: Section two outlines a simple model of the interaction of taxes and unemployment. Section three discusses some data and specification issues. Section four discusses econometric methodology. Section five presents the results. Section six concludes.

3.2 A Review of the Theory

The question of whether labor market taxes cause unemployment is essentially a question of the incidence of those taxes. If it is the case that the burden of the taxes falls entirely on the workers, then the cost of labor does not rise and the tax has no implications for unemployment. Of course, individuals whose after tax wage has fallen may withdraw from the labor force, leading to a fall in *employment*. These individuals, however, not unemployed; they are nonparticipants. Thus the quote from the *Economist*, and the conventional wisdom it represents, are wrong unless it can be shown that the burden of taxes is shifted, to some extent, onto employers.

In order to test this hypothesis, we need a simple model of unemployment. When there is involuntary unemployment the competitive model is not suitable for analyzing the labor market. Almost by definition, it precludes the existence of involuntary unemployment. For this reason most of the macro literature treats the labor market as non-competitive. There is some inefficiency in the labor market that prevents it from clearing in a classical fashion. For example in Shapiro & Stiglitz (1984) model of efficiency wages employers have imperfect information regarding workers level of effort. This causes them to pay a wage above the market clearing level in order to induce workers to exert effort. This leads to unemployment. Another example is the search model due to Diamond (1982) and Pissarides (1990). In this case the inefficiency is the inability of firms and prospective workers to form matches instantaneously. This results in a stock of unemployment even while some jobs remain unfilled.²

While these models differ in structure, many can be expressed in terms of equations such as

²Discussion of other examples can be found in Bean(1994), Blanchard & Katz (1997) and Layard et. al. (1991).

(3.1). The presence of some inefficiency prevents the market from clearing to the point where workers reservation wage equals the value of the marginal productivity of their labor to firms. Firms are willing to offer a wage that workers would be willing to accept, but hiring is prevented by the inefficiency in the labor market. In the case of the search model, unemployed workers and firms do not meet sufficiently quickly, whereas in the case of the efficiency wage model, workers cannot credibly commit not to shirk if they are hired. This implies that in equilibrium unexploited rents to employment. Therefore, at the margin, if firms and workers somehow overcome the inefficiency, there will exist a surplus which must be divided between the firm and worker. It is usually assumed that the wage is set according to Nash bargain between firms and workers over this surplus. Firms then set employment given the negotiated wage.³ If we think of a simple model where firms and workers split equally the rents generated by employment, then the wage will be given by the maximization of (3.1), where W is the real wage, W^R is the reservation wage (the worker's outside option), $\Pi(W)$ is the profit function and τ is the tax rate. Models such as Diamond (1982) and Pissarides (1990) as well as the model estimated by Layard et. al. (1991) all include an equation of the form (3.1).

$$[W(1 - \tau) - W^R]\Pi(W) \quad (3.1)$$

Typically the first order condition of (3.1) takes the form of (3.2), where the market wage is some multiple of the reservation wage. If the wage that maximizes (3.1) is greater than W^R , then there will be involuntary unemployment. Workers will not be on their supply curves. Some workers, who are prepared to accept to work at the going wage ($W > W^R$), will not be offered a job in equilibrium. Even those models that do not explicitly contain as bargaining equation such as (3.1) will generate an equation like (3.2). An example is the efficiency wage model of Shapiro & Stiglitz (1984). Workers are paid a markup on their reservation wage in order to discourage them from shirking.

$$W = \frac{W^R}{(1 - \tau)} B(u, v, X) \quad (3.2)$$

³McDonald & Solow(1981) look at what happens when firms and workers negotiate over employment as well as the wage. Layard et. al. (1991) show that two structures give the same results if unemployed are excluded from the negotiating process after some time.

The size of the markup of the market wage over the reservation wage depends on the relative bargaining strength of workers and firms, which in turn depends on unemployment among other factors. For example, in the search model of Pissarides (1990), higher unemployment and lower vacancies strengthens the hand of firms allowing them to take a larger share of the surplus, resulting in a lower wage rate. In the case of efficiency wages, the efficiency wage premium declines as unemployment rises, because higher levels of unemployment act a deterrent against shirking.

The imposition of a tax on wage income will alter the Nash maximand and result in higher unemployment. Workers, seeking to preserve the markup of net wage on the reservation wage, shift some of the burden of taxes onto employers in the form of a higher gross wage. Firms respond to an increase in the cost of labor by cutting back on hires.

In this framework, if a more general income tax could be levied on the workers' outside option also, it would lead to less of an effect on unemployment. In fact if the tax rates on inside and outside options were the same then the tax would have no effect on the markup over the reservation wage. The incidence of the tax would fall entirely on the workers. Thus, there would be no effect on employment. An important example of this is the case of a general sales tax. This would, in effect, be a tax on income both in and out of unemployment. Thus we would expect a sales tax to have no effect on bargained wage. This is the rationale for suggesting that income and social security taxes have an effect on employment, but that sales taxes do not.

The determination of the reservation wage is crucial. For example, if the reservation wage is equal to unemployment benefits and if unemployment benefits are taxable at the same rate as wage income, then $W^R = (1 - \tau)b$. Clearly τ cancels out of (3.2) and thus taxes will have no effect on unemployment. In this simplistic case the reservation wage adjusts immediately and completely to the change in taxes. In a more realistic case, we might expect any adjustment in the reservation wage to take time. How the reservation wage adjusts to tax changes will be an important determinant of the long run response of unemployment to taxes. Bean(1994) points out that we might expect that the workers bear the entire burden of the tax in the long run. A permanent increase in taxation will reduce permanent income and consumption. This will increase the marginal utility of consumption relative to the marginal utility of leisure. This implies that the reservation wage will fall. It is not hard to design a specific set up where the

net result is no change in the mark-up and therefore the wage. Thus the incidence of the tax falls completely on workers. This would imply that even a permanent increase in taxes would have only a temporary effect on unemployment.

Consider the following illustrative example. Suppose that an individual derives utility from consumption (c) and leisure (l) according to the function (3.3).

$$u(c_t, l_t) = \ln c_t + \ln l_t \quad (3.3)$$

Suppose also that credit markets are such that the individual can consume the annuity value of permanent income, so that c_t is given by (3.4), where Y is permanent income, r is the discount rate and τ is the tax rate on permanent income.

$$c_t = rY(1 - \tau) \quad (3.4)$$

In this context the reservation wage can be defined as the marginal rate of substitution of consumption for leisure⁴ and is given by (3.5)

$$W^R = \frac{rY(1 - \tau)}{l} \quad (3.5)$$

Substituting W^R from (3.5) into (3.2) results in an expression for the gross wage that is independent of the tax rate. Thus, real wages are not rigid, any change in taxation will fall entirely on the workers. Therefore, even a permanent increase in taxation will have no effect on unemployment. This sort of reasoning has led the macro literature to search for temporary (although possibly long lasting) effects of taxation on unemployment.

Of course this story only works to the extent that the Permanent Income Hypothesis is true. There is still scope for taxes to have a long run impact on unemployment if we allow for a departure from the utility maximizing framework of equations (3.3)-(3.5). Consider a more general definition of the reservation wage. Assume it reflects, not just the value of leisure, but workers aspirations also. As a simple, if extreme, example of this aspirations scenario, suppose

⁴I am being sloppy here. Presumably the possibility of being unemployed would effect the individual's permanent income as well as the definition of the reservation wage. I ignore these complications in order to illustrate the basic point.

that pride ensures that an unemployed individual will never accept a job at a wage lower than the wage he received during a previous period of employment. In this case the reservation wage would be given by $W_t^R = W_{t-1}$. Substituting into equation (3.2) will generate

$$\ln W_t = \ln B(u, v, X) + \ln W_{t-1} - \ln(1 - \tau)$$

This shows that the burden of the tax shifts entirely to firms. Also the wage equation now has a unit root. Both these properties imply that increases in taxation will have a permanent effect on wages and employment. The scenario modeled here is one where a worker fails to adjust his aspirations to changes in reality. Following a tax increase (from zero to τ), he still seeks the same after tax wage as he had before, despite the fact that this wage is now economically infeasible for the (marginal) employer. Unemployment results and will last as long as aspirations fail to adjust to the new reality.

Obviously, this aspirations story is extreme and simplistic, but then so is the utility maximization scenario. The truth probably lies somewhere in between. But, to the extent that the aspirations are an issue, there is clearly scope for taxes to have persistent, even permanent effects on employment.⁵ Therefore, I do not impose long-run neutrality on the estimated models.

3.3 Specification & Data

In essence we want to estimate a system of equations with unemployment and the wage rate as dependent variables and various parameters of the tax system as regressors. If the coefficients on tax parameters are positive in both equations, this would be evidence that real wages are rigid and that taxes cause unemployment. Furthermore if we added distributed lag and autoregressive terms to each equation we model the dynamic effect of taxation on unemployment and wages. We could then test the hypothesis that taxes are neutral in the long run.

Ideally we would like to estimate the model using the true legislated tax rates. These are the rates that actually influence economic behavior. The tax system, however, is much

⁵Blanchard & Hogan (1997), the third paper in this dissertation, attempt to ascertain the importance of previous wages for the reservation wage. We find that there is a significant, but small effect.

too complicated for us to think in terms of a single tax rate observable in aggregate data.⁶ Therefore following tradition in the literature I define τ to be the share of direct taxes in *GDP* and θ to be the share of indirect taxes in *GDP*. Direct taxes includes all income and social security taxes levied on the household. Indirect taxes includes the VAT, excise taxes and other duties levied on goods and services. The definition, source and summary statistics of the data used in this paper are given in table 3.3.

There are several problems with estimating regressions of unemployment on taxation. The difficulty lies in trying to identify the nature of any observed correlation between tax rates and unemployment. There are several possible explanations for any such correlations, only one of which we are actually interested in. The effect of interest is a substitution effect. Real wage rigidities, caused by search, efficiency wages etc., enable workers to shift the burden of taxation to firms who respond by substituting away from labor. The econometric problem is to separate this effect from the many others that could be responsible for any observed correlation between taxes and unemployment.

The most obvious source of correlation between tax and unemployment, other than the substitution effect, is a cyclical income effect. An increase in taxation will reduce disposable income, reducing the demand for labor via lower private consumption. This would be true even if taxes were lump sum (and therefore not distortionary). Typically this is controlled for using the total tax revenue as a regressor.

Another source of spurious correlation is the automatic stabilizer. A regression of unemployment on taxation will pick up the unwanted effects of unemployment on measured tax rates. For example, in a recession we expect unemployment to rise and tax revenue to fall automatically. Because the true tax rates are not proportional and are not levied on all of *GDP*, and because recessions do not effect all the income distribution uniformly, it is probable that the measured tax/*GDP* ratios, τ and θ , will vary over the business cycle as a result of compositional effects. For example, if a recession reduces the incomes of lower paid workers more than higher paid workers, and if the true tax system is progressive, we could observe tax share to rise while unemployment is also rising. Similarly, if sales taxes are levied more on luxury goods i.e. on

⁶For an estimation of the impact of taxation on unemployment and individual labor market behavior, using micro data see Hogan (1997)

goods with high income elasticities, we would observe a fall in sales taxes coincident with a rise in unemployment.

Poterba, Rotemberg & Summers (1986), developed a simple way of lessening the impact of this reverse causality. They calculate a variable, *tmix*, which is equal to the difference between the aggregate income tax rate, τ , and the aggregate sales tax rate, θ . The idea is that *tmix* is more likely to capture true exogenous changes in policy than are the aggregate tax rates. These aggregate tax rates vary over time as the result of both policy shocks and in response to (endogenous) cyclical variation in *GDP* such as the automatic stabilizer identified above. If the elasticity of τ with regard to *GDP* has the same sign as the elasticity of θ , *tmix* will offset the two sources of bias. While there is no guarantee that they will offset exactly, it is reasonable to suggest that there will be less systematic reverse causality between *tmix* and economic activity. Therefore we can treat *tmix* as being exogenous with respect to unemployment. It must be admitted, however, that some reverse causality will still exist. To the extent that it does the results will suffer from simultaneous equation bias. Nevertheless, such a bias will be smaller than that which would result from using the aggregate tax rates as separate regressors.

The focus of this paper is on the measurement of the effect of taxes on unemployment. Unlike much of the rest of the literature I do not attempt to account for the other causes of unemployment. Therefore I do not specify a model of the entire macro economy. I estimate several parsimonious reduced form systems. Specifying a full macro model, as Layard, Nickell & Jackman (1991) do, is the alternative strategy. I choose the reduced form approach for three reasons. Firstly, specifying a structural model would involve specifying identifying exclusion restrictions which may not be reasonable. Secondly, modeling the entire structure of the economy distracts attention from the central question of interest, namely the real effects of taxation. Thirdly, it is difficult to keep structural models parsimonious. Once we start building a macro model it is tempting to include almost any macro variable. I resist the temptation to include the kitchen sink and specify parsimonious models. This is an important issue here, because I am working with annual data, degrees of freedom are a precious commodity. Nevertheless I need to include other macro variables in order to control for the potential sources of spurious correlation identified earlier.

It has to be admitted, however, that this reduced form procedure comes at a price. Firstly,

the parsimonious specification may suffer from omitted variable bias. It may leave out an important effect, perhaps inducing a spurious correlation between the tax and unemployment variables. Secondly, because I do not model the structure of the economy, I lose the ability to say how taxes affect unemployment and wages. Thirdly, and most importantly, the reduced form models are open to the Lucas critique. The reduced form parameters may not be independent of the tax parameters, because they do not come from estimation of behavioral equations.

The defence against the Lucas critique is to note that the theories of unemployment reviewed in section two generate clear predictions of the effect of tax on unemployment and wages. If we observe the predicted correlation in data, while controlling for other possible causes, we can be reasonably sure what we have identified.

Most studies included the change in the tax rate as a regressor rather than the tax rate itself. This specification implicitly accepts the idea that taxes have only short run effects on unemployment and wages. Eventually the level of wages will adjust to completely offset the level of taxes, with only further changes in the level of taxes having any impact on wages and employment. While the hypothesis of long run tax neutrality is plausible, it was shown in section two that it results from a special case. Therefore, we might want to test this hypothesis, rather than assuming it. For this reason, I include the level and several lags of the tax variables in each regression and explicitly examine the dynamic relationship implied by each set of estimates.

3.4 Econometric Methodology

3.4.1 A Vector Auto Regression (VAR) Model

The most obvious specification to employ when looking at aggregate data is Sims' Vector AutoRegression (VAR) technique. The advantage of using this technique is that as VARs are reduced forms, they are easy to estimate. They enable us to track the correlations in aggregate data through time. Of course, in order to infer causation from the observed correlation, we must impose some structure on the estimated specification. The VAR provides a convenient framework within which to test the sensitivity of the results to different structural assumptions.

The estimated VARs are of the form (3.6), where $\alpha(L)$ and $\beta(L)$ are matrices of lag poly-

nomials.

$$Y_t = \alpha(L)Y_{t-1} + \beta(L)A_t + \varepsilon_t$$

$$Y_t = \begin{bmatrix} U_t \\ W_t \\ Ttot_t \\ Tmix_t \end{bmatrix} \quad (3.6)$$

The variables U and A are the natural logarithms of the unemployment rate and total factor productivity series described in table 3.3. The variable W is the logarithm of the real consumption wage, as in (3.7) where WRM is the wage rate in manufacturing and P is the consumer price index as defined in table 3.3. Finally $Ttot$ is the aggregate tax share of GDP and $Tmix$ is the tax policy variable.

$$\begin{aligned} W &= \frac{WRM(1 - \tau)}{P} \\ Ttot &= \tau + \theta \\ Tmix &= \tau - \theta \end{aligned} \quad (3.7)$$

The productivity term is included as it is likely to be the major determinant of real wages in the long run. Treating A as being exogenous in the short run, may be problematic. If firms hoard high productivity workers, and/or layoff low productivity workers during a recession, then measured productivity would be a function of unemployment. Equation (3.6) would suffer from simultaneous equation bias. In practice, however, this turned out not to matter. Results were virtually identical when contemporaneous A was left out of (3.6) or when it was replaced with a deterministic trend.

Estimation of (3.6) will account for the observed correlation in the aggregate data series. In order to infer the causation of interest, we must put some structure on the model. This is usually accomplished in the context of a VAR by specifying a Cholski decomposition of the variance-covariance matrix of ε . This is equivalent to specifying a just-identified triangular structure form which has (3.6) as its reduced form. We can then track how the endogenous variables respond to structural shocks. There are many different structures that may have (3.6) as their reduced form. Obviously the results can be highly sensitive to the choice of the particular structural form. Given the discussion in section three, it is reasonably clear that

tmix is exogenous. Thus contemporaneous causation runs from *tmix* to the other variables, in the jargon of VARs, *tmix* is ordered first. It is less clear, but not unreasonable to say that *Ttot* is ordered before unemployment and wages. In other words, the automatic stabilizer notwithstanding, contemporaneous causation runs from the tax share to unemployment and wages and not the other way round. It is, however, completely unreasonable to attempt to order *U* and *W*. It is not possible to say, a priori, whether prices or quantities are determined first in the labor market. The best that can be done is to present estimates of the impulse response functions for both cases and see if they are significantly different.

As discussed earlier, one of the interesting hypothesis we might want to test is the supposed long run neutrality of taxes. Estimation of (3.6) will probably imply in a structural form in which *tmix* does not have a unit root exactly. Therefore, any shock to *tmix* will represent a temporary, if long-lasting, policy change. This would be true even if the coefficients were such that we could not reject the hypothesis that there is a unit root. In order to test the hypothesis that taxes are neutral in the long run, we need to have a permanent change in *tmix*. The concept of long run neutrality has no meaning otherwise. Thus I re-estimate a restricted version of (3.6) with a unit root imposed on *tmix*.

3.4.2 An Alternative Specification

There is an alternative way of identifying the dynamic responses of unemployment and wages that places less of a burden on the econometrics and more on the underlying economic theory. This procedure is very close to that adopted by Poterba, Rotemberg & Summers (1986) and is discussed in detail in Rigobon (1997). The idea is to make greater use of the exogeneity of *tmix*.

Modeling the system as a standard VAR, in the last section, *tmix* was treated in the same manner as the other variables. We regressed it on lags of itself and the other variables. This reduced form did not distinguish *tmix* from the other variable in any way. We only made use of the exogeneity of *tmix* by ordering last in the structural decomposition of the VAR i.e. we assumed that *tmix* contemporaneously caused the other variables, but that they did not contemporaneously cause it.

On reflection this procedure both imposes unnecessary restrictions on the other variables

and fails to make full use of the exogeneity of *tmix*. For example, in order to calculate figure 1, it was assumed that unemployment caused wages and not the other way round. As it turned out the results were not sensitive to this assumption, but nonetheless it not very satisfying assumption to have to make. It turns out that we can avoid making any assumption regarding causation between unemployment and wages. The question of interest is the effect of tax on unemployment and wages. As long as we are not trying to distinguish between different mechanisms through which that effect occurs, we do not care whether unemployment causes wages or wages cause unemployment. In other words assumptions regarding the contemporary causation between wages an unemployment are unnecessary. Conceptually, all that we want to do is to track the response of unemployment and wages to an exogenous shock to the level of taxation. Therefore all that is needed is to estimate reduced form regressions of unemployment and wages on the exogenous parameters of the tax system. Provided that we are sure that the tax variables are truly exogenous, no further identifying assumptions are needed. Thus I need to be able to assume the contemporaneous causation runs from *tmix* to the other variables. But I do not need to make any assumption regarding causation among those other variables.

The actual model estimated is given in equation (3.8), where all the variables have the same meaning as in the previous section. The first three equations, for U , W and $Ttot$ are almost the same as in the VAR model of equation (3.6) with the crucial exception that both the current value and lags of *tmix* are included as regressors. Thus *tmix* is treated explicitly as an exogenous variable.

$$Y_t = \alpha(L)Y_{t-1} + \beta(L)A_t + \gamma(L)Tmix_t + \varepsilon_t$$

$$Y_t = \begin{bmatrix} U_t \\ W_t \\ Ttot_t \end{bmatrix} \quad (3.8)$$

The estimated coefficients from (3.8) can be used to calculate the impulse response of Y to permanent and temporary shocks to *tmix*. In order to model the shock to *tmix*, I think of it as following an $AR(1)$ process. To model a temporary shock to *tmix*, the autoregressive coefficient can be set equal to zero. Thus the shock disappears from *tmix* after one period. Its effect on

the other variables may persist, depending on the rigidities in the labor market. It is precisely these rigidities that we are interested in. For the case of a permanent shock, the autoregressive coefficient is set equal to unity. Thus the shock lasts forever in *tmix*, but may not persist in *Y* if, for example, the reservation wage adjusts in the manner hypothesized in section two. Clearly any intermediate case can be examined by setting the autoregressive coefficient to a value between zero and one.

It could be argued that the above experiments are not clean, because *ttot* is allowed to move in response to *tmix*. Thus the observed effect of unemployment and wages could be the result of changes in *ttot* and not just *tmix*. Therefore, I re-estimate the system dropping the equation for *ttot* and with lags of *ttot* (but not its contemporaneous value) included as regressors in the equations for *U* and *W*.

The impulse response functions exhibit a curious initial effect on unemployment. When contemporaneous *tmix* is included in the equations for *U* and *W*, a rise in *tmix* leads to an initial *fall* in *U* in that period. This fall turns into a large rise in the next period. This is clearly an anomalous result. The size of the decline and the fact that it is immediately reversed casts doubt on the assumption that *tmix* is exogenous with regard to unemployment. The impulse response function seems to be picking up a positive effect of activity on measured aggregate tax rates. The possibility of this spurious correlation was discussed in section three. The initial decline in *tmix* can be eliminated if contemporaneous *tmix* is excluded from the unemployment equation. This suggests that the anomaly does indeed result from some sort of cyclical dependence of *tmix*. Similarly, if *tmix* is first regressed on lagged real GDP and the residual used in place of *tmix* in (3.8) the anomaly also disappears. This lends credence to the idea that the anomaly is the result of some spurious reverse causation from activity to *tmix*. This procedure could be regarded as dangerous, however. It may be the case that instead of removing some spurious cyclical effect we are removing a genuine effect of *tmix* on unemployment. Nevertheless, the fact that the only qualitative difference between the two methods is the presence of the anomalous initial decline in unemployment suggests that the procedure is valid.

3.5 Empirical Results

3.5.1 VAR

The basic VAR specification (3.6) was estimated using UK annual data (1960-96), where w is the log of the real consumption wage after tax. The coefficients and their standard errors are shown in Table 3.4. The VAR was estimated with two lags of the endogenous variables. I experimented with the inclusion of extra lags of the endogenous variables but these turned out to be insignificant, even in their own autoregressions.

The estimated coefficients in Table 3.4 suggest that tax changes have real effects on unemployment and wages. The *tmix* coefficients are jointly significant at the 5% level in only the wage equation. (This is the F-test reported in the last row of Table 3.4). Although *tmix* does not appear to have any effect directly on unemployment, it will affect unemployment indirectly via the wage. This test rejects the hypothesis that taxes do not have an effect on wages and unemployment.

The null hypothesis that taxes are neutral in the long run can also be rejected. A Likelihood Ratio test that the coefficients on *tmix* sum to zero in each equation produces a test statistic of 8.923, which is distributed under the null as χ^2 with four degrees of freedom. Thus the hypothesis is rejected at the 5% significance level.

In order to illustrate the dynamic effects of a change in *tmix*, I compute the impulse response functions of the variables to changes in *tmix*. Figure 1 plots the response of the variables to a one standard deviation increase in *tmix* (i.e. an increase in income tax relative to the sales tax) in period zero. As expected the log of the real after tax wage falls and the log of the unemployment rate rises. Wages reach their lowest point roughly four years after the shock, around the same time as unemployment reaches its highest point. Thereafter, they both return to their initial positions within another five years. Even at its maximum point, unemployment rose only by one quarter of a standard deviation. The tax mix appears to have an effect, but it is not very large.

The impulse response functions suggest the following story. After a tax increase, or more precisely a shift from sales to income taxes, workers real take home pay falls. It does not fall by enough however, some of the burden of the taxes is shifted to the firms. This causes the

real cost of labor to firms to rise. This in turn causes the unemployment rate to rise. In order to verify this, I re-estimated (3.6) with the wage variable given by the log of the real labor cost (*RLC*). The resulting impulse response functions are shown in figure two. They confirm that the shift to income taxes results in an increase in the real cost of labor to employers. This cost falls back to its initial level quite quickly, however. Unemployment rises in response to the cost of labor, but it remains higher for longer than does the real cost of labor. This may indicate the presence of persistence in unemployment. Further evidence for this persistence can be found in Table 3.6, where I report the results of Augmented Dickey-Fuller (ADF) tests for the presence of a unit root in unemployment. As can be seen the null hypothesis that unemployment has a unit root cannot be rejected. This result is robust to the inclusion of extra lags, a constant and/or a deterministic trend in the testing autoregression.

In order to calculate the impulse response functions in figures one and two, a triangular structural form had to be assumed. The particular "ordering" used was that *tmix* caused *ttot* which, in turn, caused *U* which caused *W*. The results turn out not to be very sensitive to the particular ordering assumption used as long as *tmix* is ordered first. I tried all combinations of ordering *U*, *W* and *ttot*. In no case were the results qualitatively different from those depicted in figures 1 and 2. This is not surprising given that the estimated covariance matrix of the two VARs were almost diagonal.

A problem with the impulse responses illustrated in figures one and two is that they represent the response to a temporary change in tax policy. This can be seen from the graph of the response of *tmix* to itself. Clearly the shock to *tmix* is temporary as it returns to its initial level within ten years. Therefore it is not really that surprising that wage and unemployment also return to their initial levels. In order to illustrate the neutrality of the tax policy mix in the long run we need to look at the response of the variables to a permanent change in taxes. The concept of long run neutrality has very little meaning otherwise. The problem arises in the standard VAR because the estimated autoregressive coefficients on *tmix* do not sum to unity. Therefore, I re-calculated the impulse response functions with the *tmix* equation containing only autoregressive terms and with the coefficients constrained to sum to unity. Repeated ADF tests on *tmix* (shown in table 3.6) failed to reject the hypothesis that *tmix* had a unit root. This result was robust to the inclusion of an intercept, deterministic trend and several lags in

the testing autoregression. Indeed the best fit to *tmix* seemed to be a simple random walk with no drift.

Figures three and four show the impulse response functions generated by the new system. Figure three is for the case when the wage is the real after tax wage received by workers and figure four is for the case when the wage is the real cost of labor to the firms. As can be seen from the impulse response of *tmix* to itself, the shock is permanent. Together the two figures indicate that the wage received by workers falls permanently and the unemployment rate rises permanently, but that the rise in the cost of labor to firms is only temporary. This is curious. One explanation for it could be hysteresis. Initially the burden of taxes is split between workers and firms. This causes workers take-home pay to fall and the cost of labor to rise. As a result of the rise in the cost of labor, the unemployment rate rises. Eventually, the cost of labor falls back to its original level, while workers take home wage remains low, indicating that the burden of taxes is shifted completely to the workers in the very long run. The question is therefore, why does unemployment not fall back also. One explanation could be hysteresis type effect like those discussed by Blanchard & Summers (1986). Those who become unemployed initially as a result of the tax policy, remain unemployed for so long a period that they drop out of the labor market. Either they become discouraged workers, so that they no longer actively search for a job or they become de-skilled and therefore unemployable. Either way, when the labor market reaches its new long run equilibrium, it does so in their absence leaving the measured unemployment rate high.

While this story is plausible, there is little direct evidence to support it. One piece of evidence of course, is the apparent unit root in unemployment discussed previously

3.5.2 Alternative Specification

The alternative specification (3.8) was estimated using UK annual data (1960-96), where w is the log of the real consumption wage after tax. The coefficients and their standard errors are shown in Table 3.5. The model was estimated with two lags of the endogenous variables. As in the case of the VAR, extra lags of the endogenous variables but turned out to be insignificant, even in their own autoregressions.

The estimated coefficients given in Table 3.5 suggest similar results to those of the VAR.

Taxes appear to have real effects on unemployment and wages. The hypothesis that they are jointly insignificant in each equation can be rejected at the 5% level, only in the case of the wage equation. (This is the F-test reported in the last row of Table 3.5). These tests support the hypothesis that taxes do have an effect on wages and unemployment.

The null hypothesis that taxes are neutral in the long run can also be rejected. A Likelihood Ratio test that the coefficients on *tmix* sum to zero in each equation produces a test statistic of 7.321, which is distributed under the null as χ^2 with three degrees of freedom. Thus the hypothesis is rejected at the 10% significance level, but cannot be rejected at the 5% significance level.

In order to illustrate the dynamic effects of a change in *tmix*, I compute the impulse response functions of the endogenous variables to changes in *tmix*. As discussed in section four, the inclusion of contemporaneous *tmix* in the unemployment equation, leads to the anomalous result that unemployment declines in the initial period. This anomaly disappears if contemporaneous *tmix* is excluded from the unemployment equation or if *tmix* is first regressed on lagged real GDP. The impulse response function shown in figures five to eight are for this latter case. I suspect that this anomaly results from the fact that I use annual data calculated on the basis of the calendar year. The UK tax year begins in April. Therefore changes in tax policy would not be felt until the middle of the period covered by *tmix*. We could get around this problem if we had access to quarterly or even six monthly data.

Figure 5 plots the response of the variables to an increase in *tmix* (i.e. an increase in income tax relative to the sales tax) in period zero. This increase is temporary, it disappears after one period. As expected the log of the real after tax wage falls and the log of the unemployment rate rises. Wages reach their lowest point roughly two years after the shock, around the same time as unemployment reaches its highest point. Thereafter, they both return to their initial positions within another five years, with unemployment returning slightly slower than wages. Figure six shows the responses when the wage is given by the real cost of labor. The real cost of labor rises in response to the initial increase in *tmix* in period zero. The cost of labor then falls back to its initial level quite quickly. Unemployment rises also and returns to its initial level slightly slower than the real cost of labor.

Both sets of impulse responses confirm the results of the VAR analysis reported previously.

The shift to income taxes (rise in *tmix*) results in a fall in the net pay of workers and an increase in the real cost of labor to employers. This cost falls back to its initial level quite quickly, however. Unemployment rises in response to the cost of labor, but it remains higher for longer than does the real cost of labor, suggesting the presence of some sort of hysteresis effect.

The impulse responses illustrated in figures five and six represent the response to a temporary change in tax policy. This can be seen from the graph of the response of *tmix* to itself. Clearly the shock to *tmix* is temporary as it returns to its initial level within a year. Therefore it is not really that surprising that wage and unemployment also return to their initial levels. In order to illustrate the neutrality of the tax policy mix in the long run we need to look at the response of the variables to a permanent change in taxes.

Figures seven and eight show the impulse response functions generated by a permanent increase in *tmix*. Figure seven is for the case when the wage is the real after tax wage received by workers and figure eight is when the wage is the real cost of labor to the firms. As can be seen from the impulse response of *tmix* to itself, the shock is permanent. These figures again confirm the result of the VAR analysis. Together the two figures indicate that the wage received by workers falls permanently and the unemployment rate rises permanently, but that the rise in the cost of labor to firms is only temporary. A potential explanation for this is the presence of hysteresis effects in the labor market.

3.6 Conclusions

There do appear to be some striking results. A shift in tax policy away from indirect to direct taxes seems to have the effects predicted by theory. The burden of the tax is shared by the workers and employers and as a result unemployment rises. Even a temporary tax change, which itself disappears after 5 years, has real effects which persist for up to 10 years. The size of these effects is relatively small. The shock results in increase in unemployment of less than one standard deviation.

The persistence of the real effects of taxes is even more starkly illustrated by the reaction to a permanent shock to taxes. It appears that a permanent shock has permanent effect on

unemployment and the consumption wage, but a temporary effect on the real product wage. This result is consistent with theory, but is nevertheless unusual. It is certainly not the result that I expected to get. In common with most of the literature I expected that in the long run a change in tax policy would have no effect on the level of unemployment. Most of the empirical literature (see Layard, Nickell & Jackman, 1991) use specifications that actually impose neutrality on the estimates. This approach would appear to be invalid.

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Table 3.1: OECD Standardised Unemployment Rates

	1975	1980	1985	1990	1991	1992
US	8.3	7.0	7.1	5.4	6.6	7.3
Japan	1.9	2.0	2.6	2.1	2.1	2.2
FRG	3.6	2.9	7.1	4.8	4.2	4.6
France	4.0	6.2	10.2	8.9	9.4	10.4
Italy	5.8	7.5	9.6	10.3	9.9	10.5
UK	4.3	6.4	11.2	6.9	8.8	10.1
Spain	3.6	11.1	21.1	15.9	16.0	18.1
Ireland	-	-	17.0	13.3	14.7	15.5
Denmark	5.3	7.0	9.0	9.5	10.4	11.1
Sweden	1.6	2.0	2.8	1.5	2.7	4.8
Austria	1.5	1.6	3.6	3.2	3.5	3.6

1. Source: OECD Main Economic Indicators, various issues

Table 3.2: Tax Share of GDP

	1975	1980	1985	1990	1991
US	28	29	28	29	30
FRG	36	38	38	37	42
France	37	42	44	44	44
Italy	26	30	35	39	40
UK	36	35	38	37	36
Spain	20	24	29	34	35
Ireland	32	34	38	37	37
Denmark	41	45	49	48	48
Sweden	43	49	50	56	53
Austria	39	41	43	41	42

1. Source: OECD Main Economic Indicators, various issues

Table 3.3: Data

Variable	Definition	Series No.	Mean	Stn. Dev.
<i>U</i>	Unemployment Rate (%)	26UR	5.66	3.738
<i>WRM</i>	Wage rate Manfact. Sector (Index 1984=1)	26WRMA	0.74	0.666
<i>RLC</i>	Real labor Cost (Index 1991=1)	26RLC	0.76	0.207
τ	Income & Social Security Taxes as share of GDP	26THY	0.106	0.014
θ	Indirect taxes/GDP	26IND	0.147	0.012
<i>TFP</i>	Total Factor Productivity (Index 1991=1)	26PTY	0.803	0.170
<i>P</i>	Retail Price Index (1990=1)	IFS	0.472	0.361

1. Series No. refers to the reference no. for the series on the OECD CD-ROM database

Table 3.4: Basic VAR

Regressor	Dependent Variable			
	W_t	U_t	$Ttot_t$	$tmix_t$
W_{t-1}	0.244 (0.229)	-3.778 (2.265)	-0.105 (0.094)	0.068 (0.117)
W_{t-2}	-0.044 (0.149)	0.924 (1.478)	-0.109 (0.061)	0.034 (0.076)
U_{t-1}	-0.036 (0.025)	1.260 (0.245)	-0.008 (0.010)	-0.021 (0.013)
U_{t-2}	-0.022 (0.031)	-0.591 (0.311)	-0.009 (0.013)	0.016 (0.016)
$Ttot_{t-1}$	-1.017 (0.476)	5.092 (4.716)	1.231 (0.195)	0.181 (0.243)
$Ttot_{t-2}$	0.405 (0.455)	-6.517 (4.513)	-0.709 (0.187)	0.041 (0.233)
$Tmix_{t-1}$	-0.560 (0.404)	2.354 (4.009)	0.095 (0.166)	1.001 (0.207)
$Tmix_{t-2}$	-0.209 (0.381)	-4.130 (3.773)	-0.137 (0.156)	-0.195 (0.194)
Constant	0.567 (0.178)	2.268 (1.765)	0.241 (0.073)	-0.092 (0.091)
A_t	0.960 (0.303)	-3.434 (3.002)	-0.044 (0.124)	-0.011 (0.155)
A_{t-1}	-0.350 (0.421)	3.621 (4.178)	0.392 (0.173)	-0.160 (0.215)
A_{t-2}	0.342 (0.231)	3.464 (2.291)	-0.073 (0.095)	0.079 (0.118)
$F - Test\ of\ Tmix = 0$	4.402	0.693	0.4011	21.78

1. Standard errors are in Parentheses

Table 3.5: Exogenous System

Regressor	Dependent Variable		
	W_t	U_t	$Ttot_t$
U_{t-1}	-0.026 (0.026)	1.190 (0.252)	-0.009 (0.011)
U_{t-2}	-0.020 (0.030)	-0.561 (0.292)	-0.009 (0.013)
W_{t-1}	0.149 (0.223)	-3.283 (2.170)	-0.092 (0.098)
W_{t-2}	-0.138 (0.172)	-0.999 (1.674)	-0.150 (0.076)
$Ttot - 1$	-0.873 (0.445)	5.888 (4.329)	1.237 (0.195)
$Ttot - 2$	0.189 (0.417)	-7.979 (4.057)	-0.730 (0.183)
Constant	0.667 (0.189)	3.118 (1.837)	0.258 (0.083)
A_t	0.931 (0.300)	-2.269 (2.924)	-0.025 (0.132)
A_{t-1}	-0.271 (0.417)	3.243 (4.062)	0.388 (0.183)
A_{t-2}	0.477 (0.232)	4.329 (2.257)	-0.056 (0.102)
$Tmix_t$	-0.411 (0.383)	0.433 (3.732)	0.049 (0.168)
$Tmix_{t-1}$	-0.122 (0.556)	4.251 (5.412)	0.055 (0.244)
$Tmix_{t-2}$	-0.403 (0.384)	-6.160 (3.741)	-0.141 (0.169)
$F - Test of Tmix = 0$	4.402	0.693	0.4011

1. Standard errors are in Parentheses

Table 3.6: Augmented Dickey-Fuller Tests

	$\ln U_t$		$\ln A_t$		$tmix_t$				
1 st Lag	0.041 (0.834)	-0.084 (1.038)	-2.169 (2.226)	0.002 (0.045)	-0.086 (1.51)	-0.955 (1.563)	-0.001 (0.836)	-0.047 (2.311)	-0.048 (2.35)
constant	-	0.246 (1.855)	-1.06 (1.712)	-	0.074 (2.05)	-0.489 (1.235)	-	-1e-12 (2.153)	-1e-12 (1.559)
Trend	-	-	0.179 (2.146)	-	-	0.017 (1.428)	-	-	-4e-15 (0.547)
Critical Values									
1%	2.67	3.75	4.417	2.67	3.75	4.417	2.582	3.483	4.034
5%	1.957	2.997	3.622	1.957	2.997	3.622	1.943	2.885	3.446
10%	1.624	2.638	3.57	1.624	2.638	3.57	1.617	2.579	3.208

1. Absolute value of t -statistics are in parentheses
2. The t -statistic is the ADF test statistic of $H_0 : X_t \sim I(1)$
3. All regressions included 12 lags of the first difference
4. The Critical values are due to MacKinnon

Figure 1: VAR Model
Response to a Temporary Tax Shock

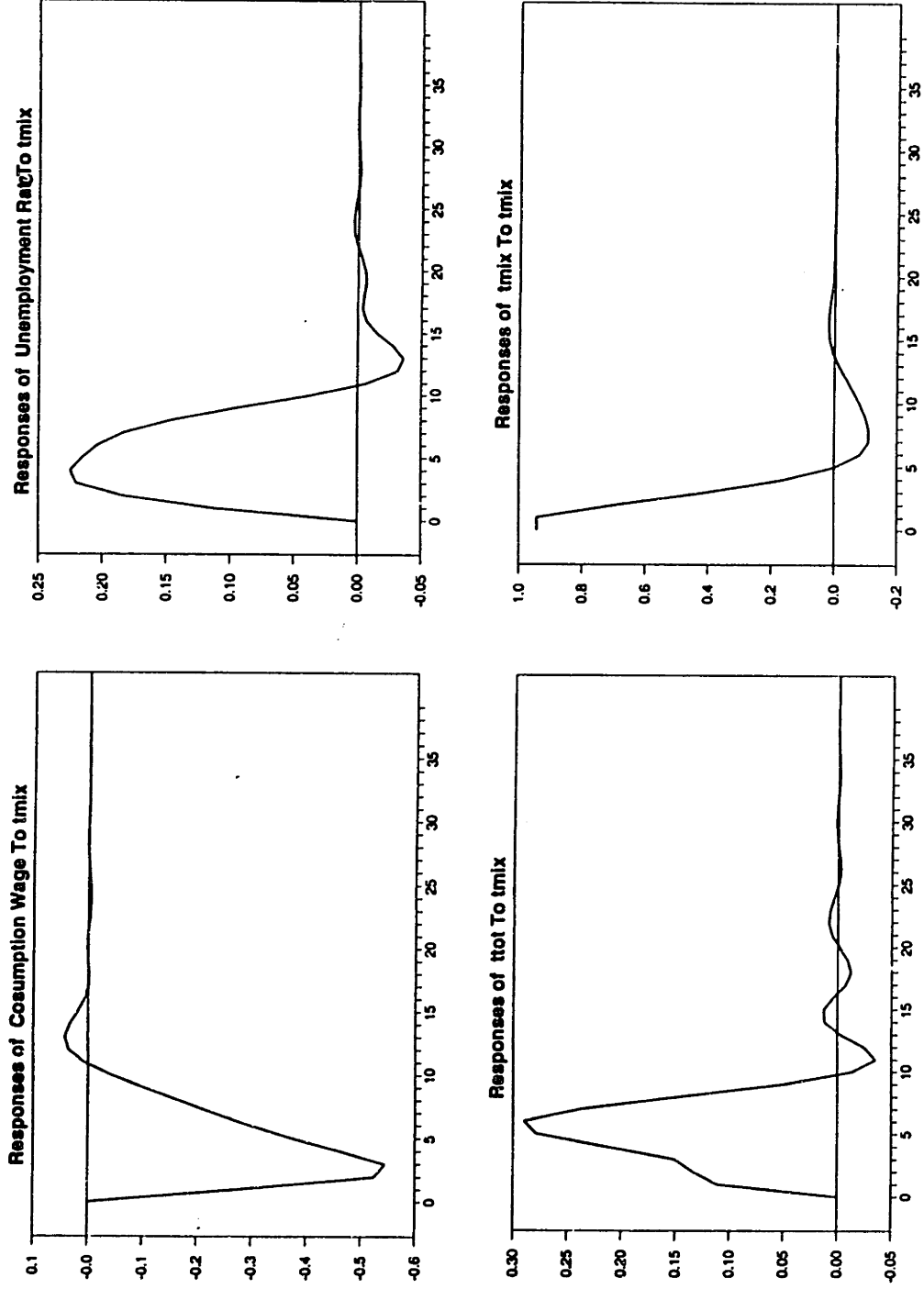


Figure 2: VAR Model
Response to a Temporary Tax Shock

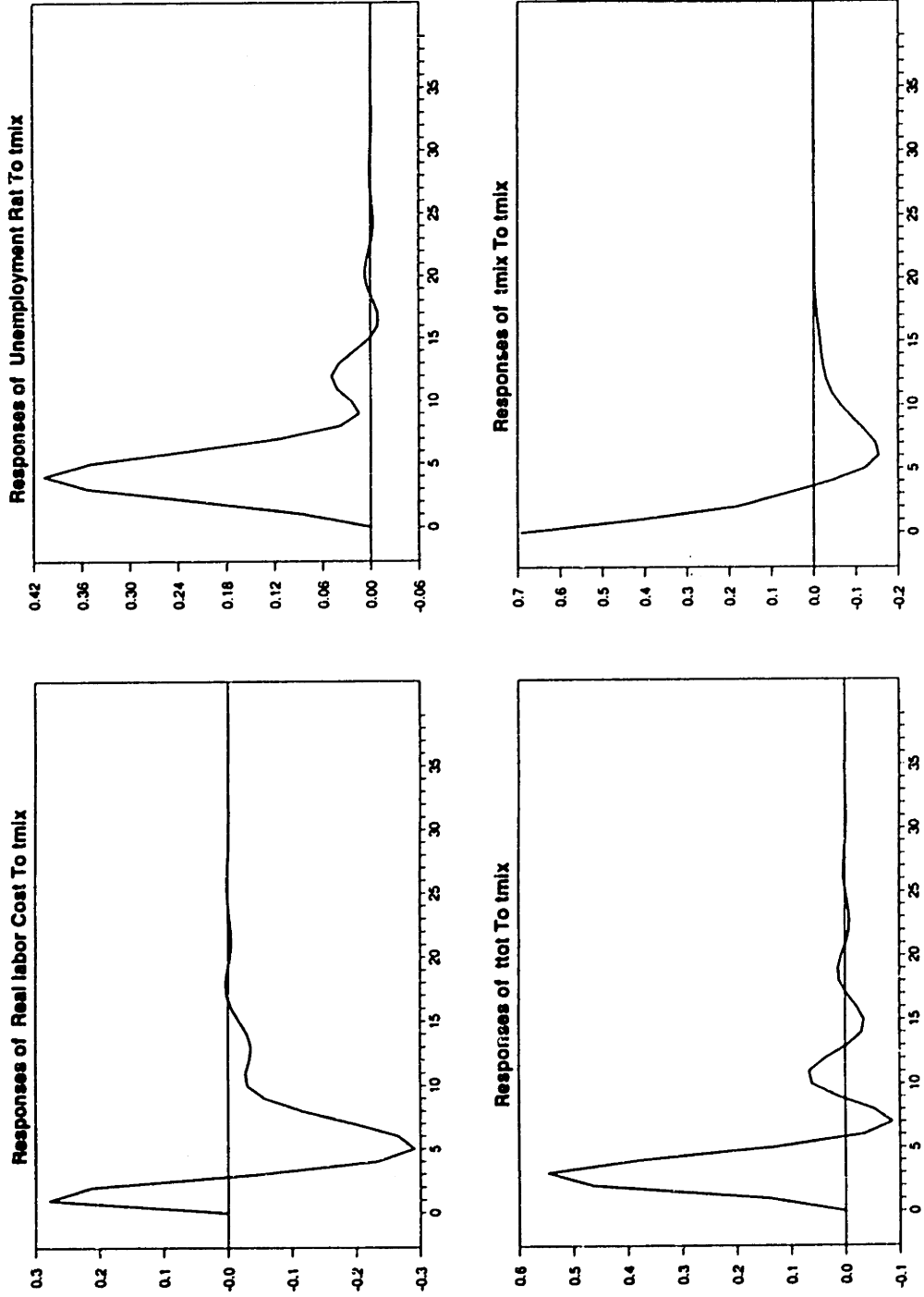


Figure 3: VAR Model
Response to a Permanent Tax Shock

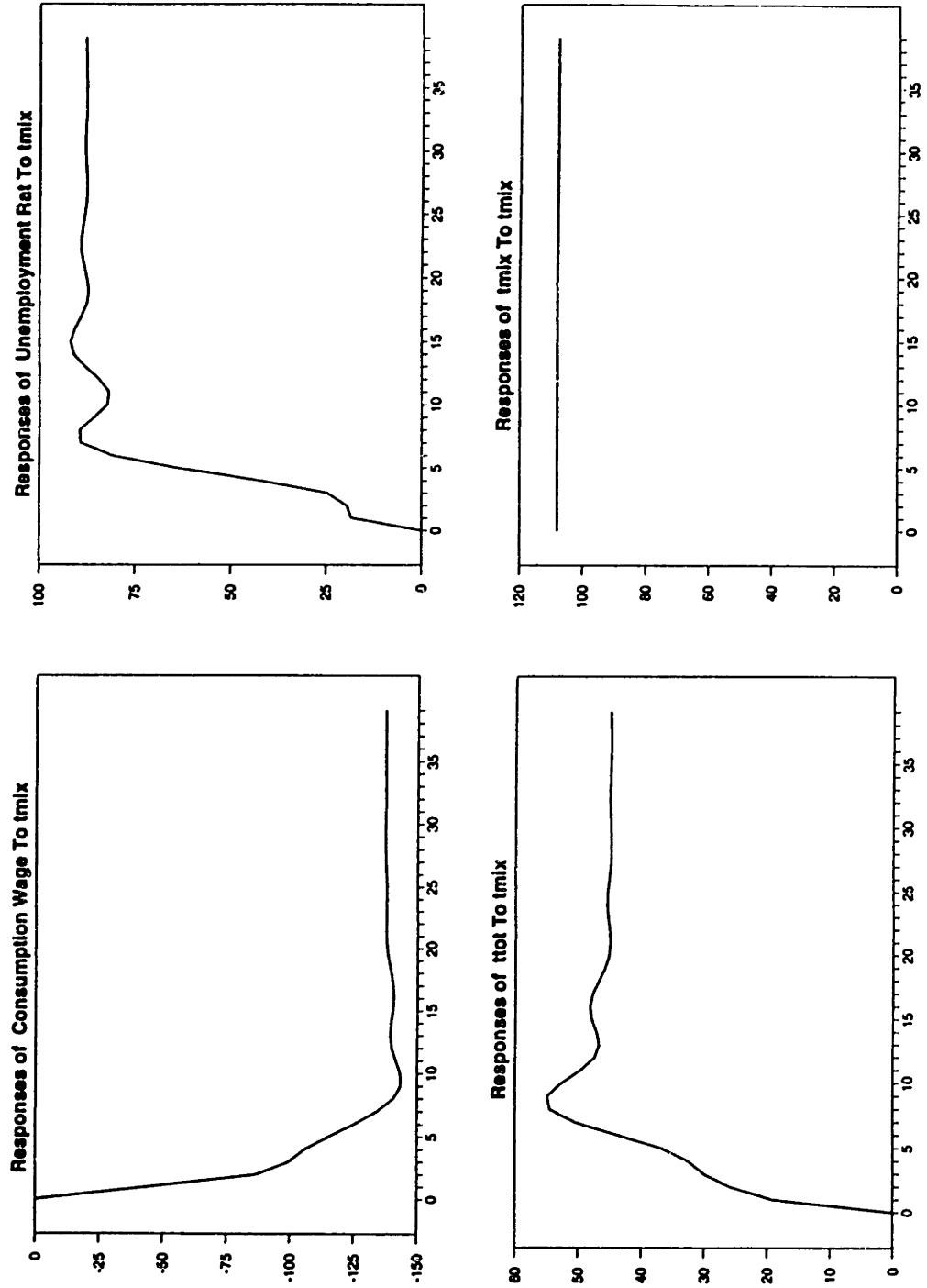


Figure 4: VAR Model
Response to a Permanent Tax Shock

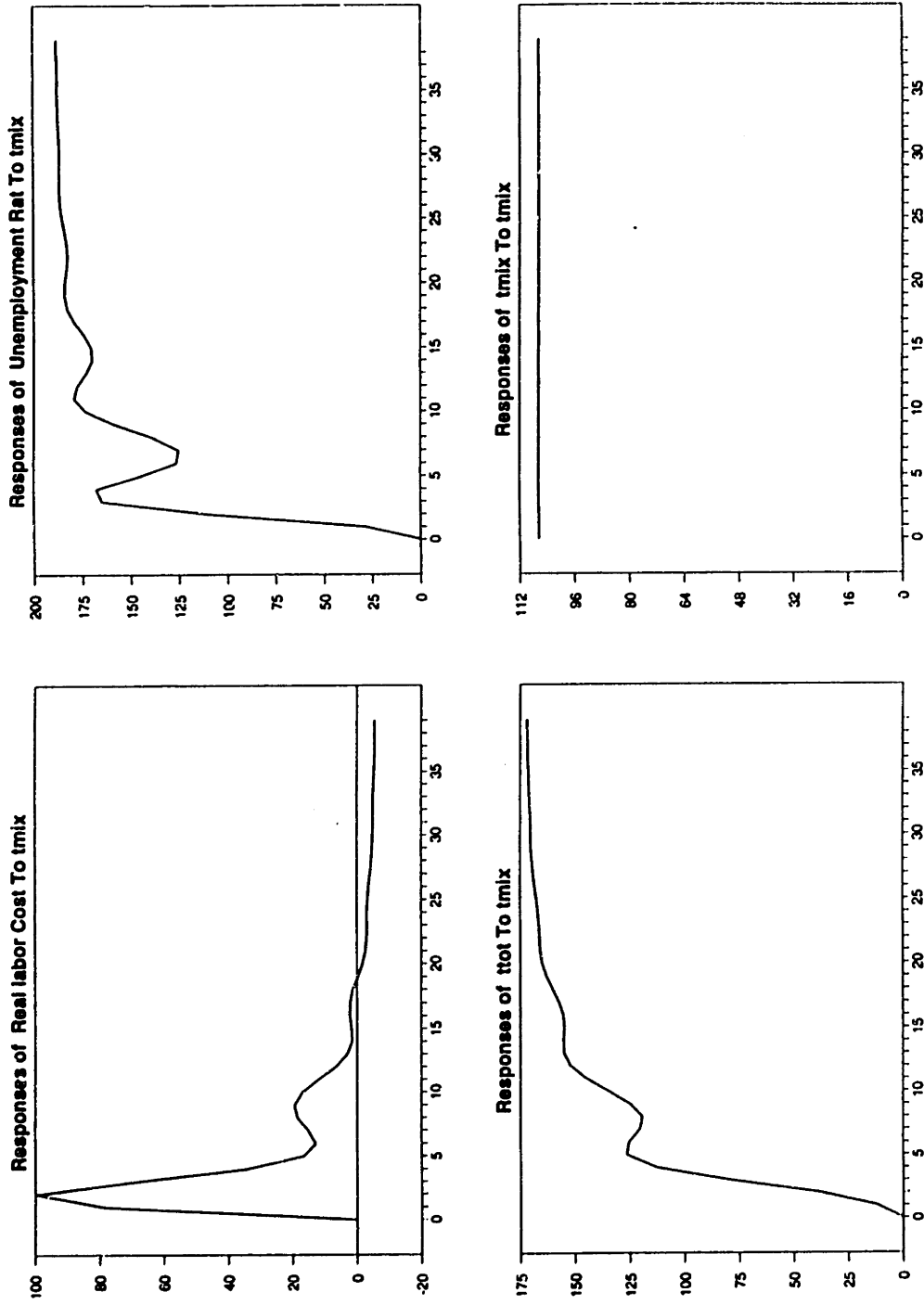


Figure 5: Alternative Model
Response to a Temporary Tax Shock

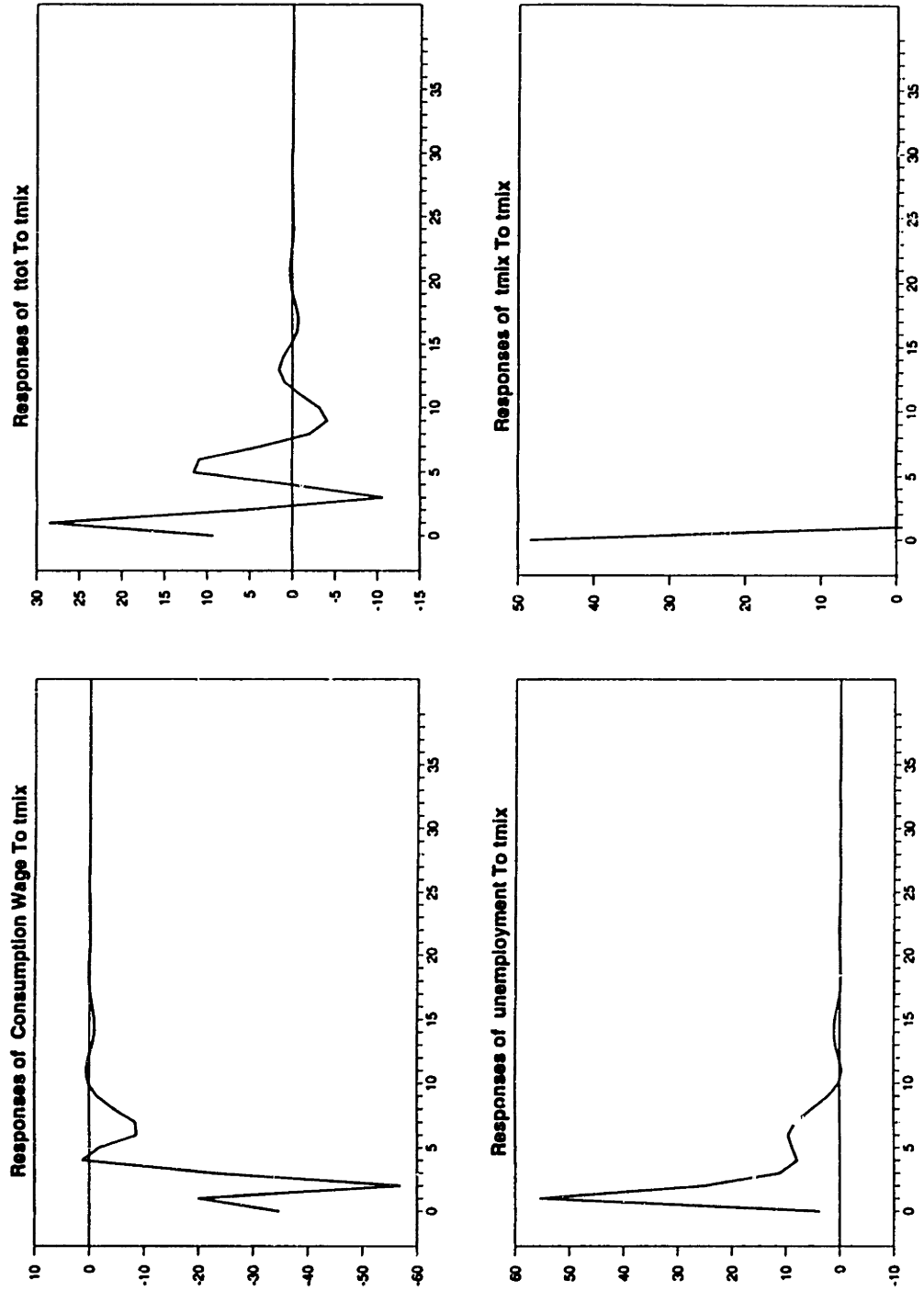


Figure 6: Alternative Model
Response to a Temporary Tax Shock

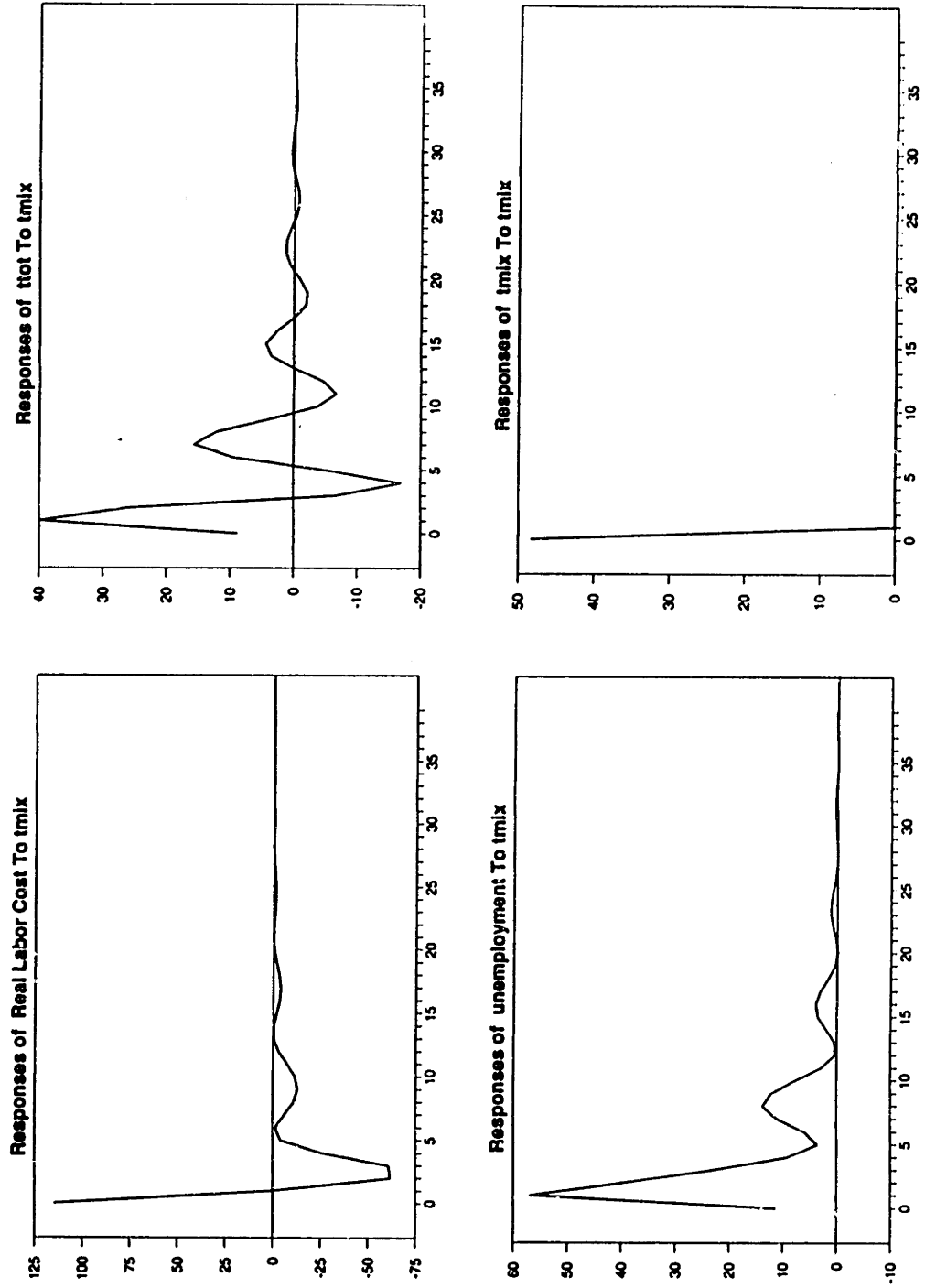


Figure 7: Alternative Model

Response to a Permanent Tax Shock

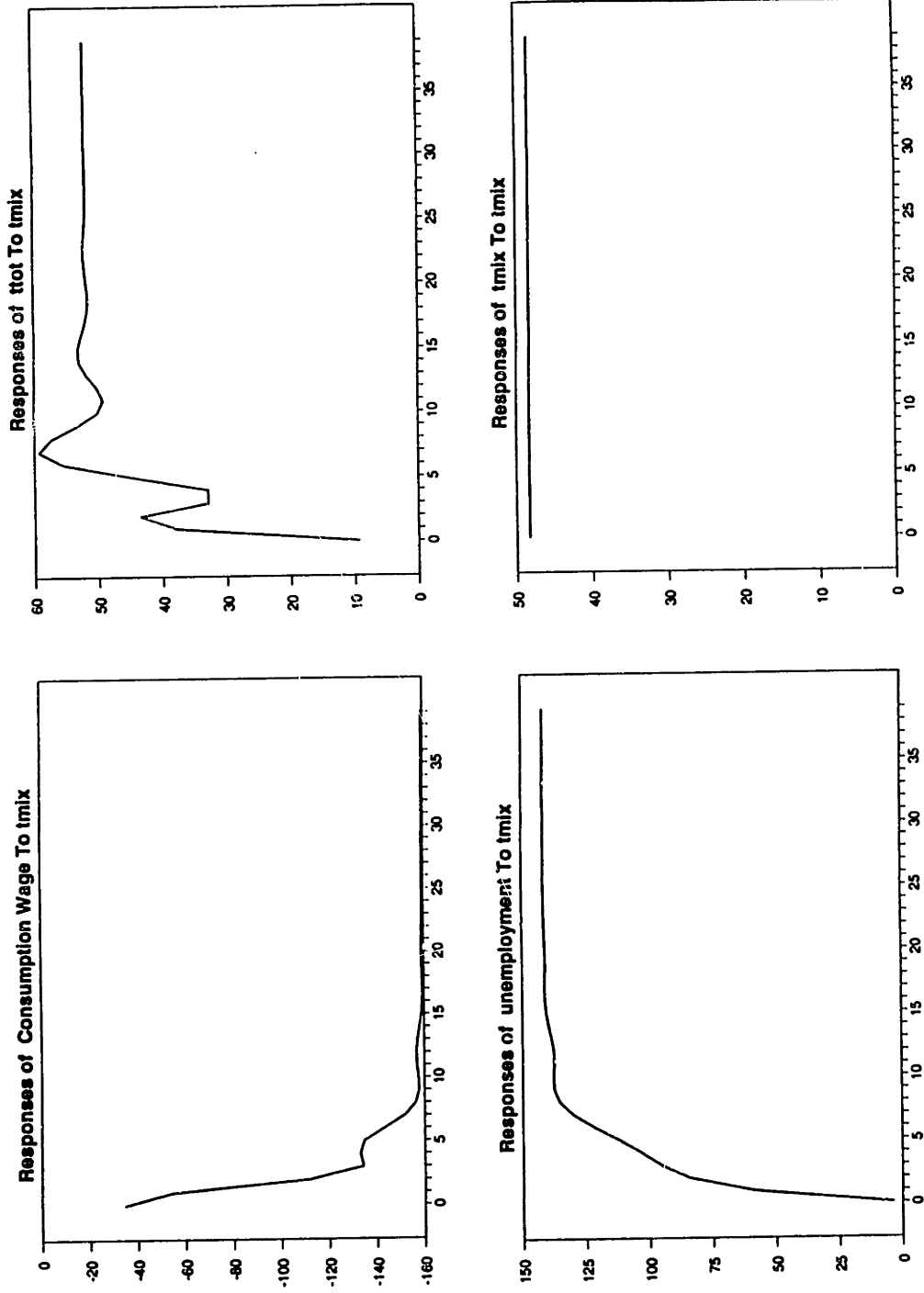
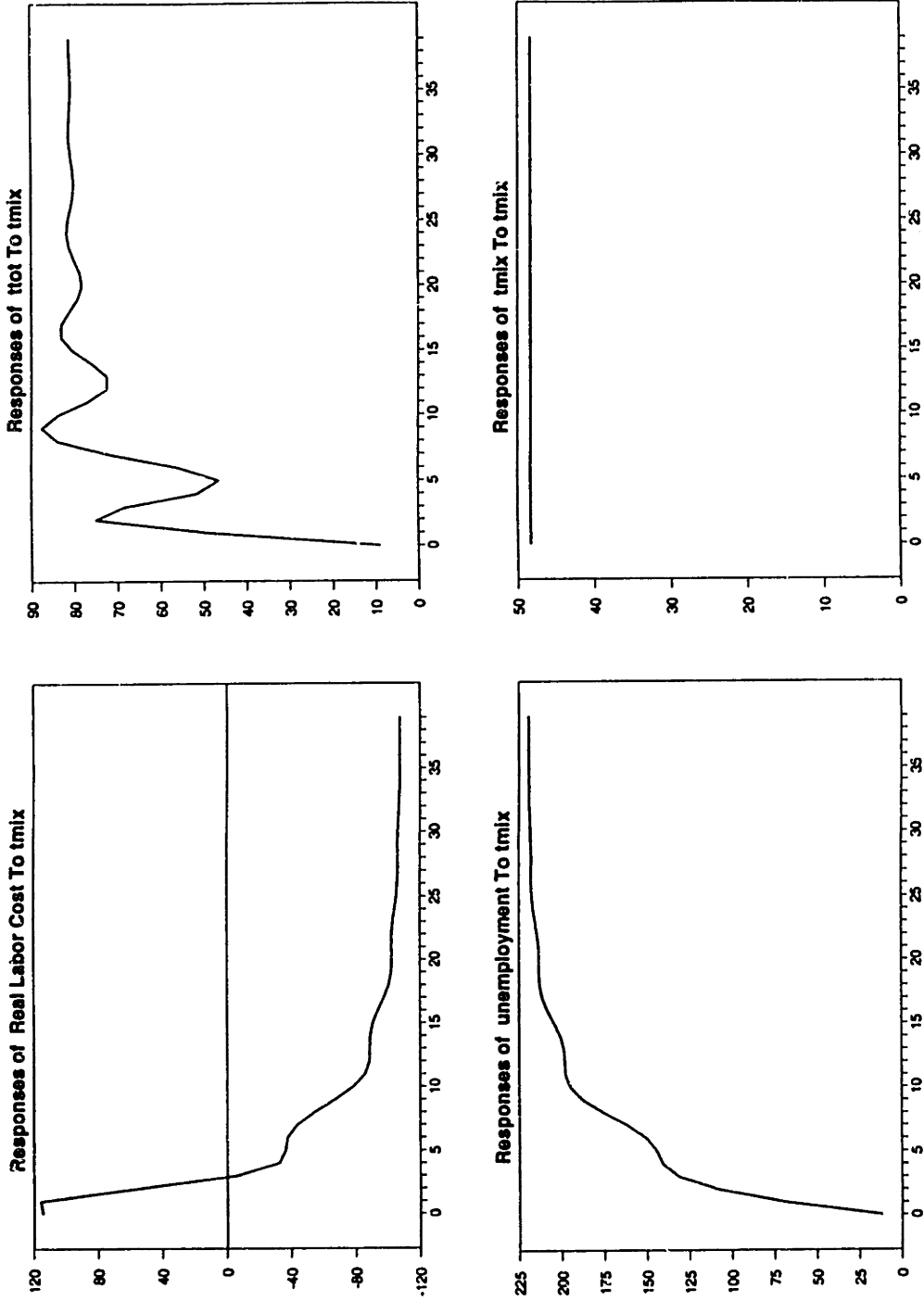


Figure 8: Alternative Model

Response to a Permanent Tax Shock



Chapter 4

The Determinants of the Reservation Wage (joint with Olivier Blanchard)

4.1 Introduction

In all models of the labor market, the reservation wage—the wage that makes workers indifferent between taking a job or remaining unemployed—is a central determinant of the actual wage, and in turn of employment/unemployment. In competitive models, the actual wage is simply equal to the reservation wage. In models with bargaining or efficiency wages, the reservation wage is one of the determinants of the actual wage. The purpose of this paper is to explore empirically the determinants of the reservation wage, and draw out the implications of our findings for wage determination.

The standard way of thinking about the reservation wage is as follows. Unemployed workers face a wage distribution, which depends in particular on their observable and unobservable (to us, not to employers) characteristics. The rate at which they get wage offers depends on labor market conditions. While waiting or searching for offers, workers draw down assets, receive unemployment and other benefits, and may get utility from leisure. In that standard model, the past does not directly matter. Bygones are bygones. More formally, given the

wage distribution that they face and the unemployment benefits that they receive, the wage that workers received in the previous job is irrelevant. Some economists believe however that this implication is counterfactual. To them, the behavior of workers laid off from high wage industries suggests that lagged wages affect reservation wages, above and beyond what they may reveal about the characteristics of the workers.

We can think of two reasons why this may occur. Firstly, workers may view, rightly or wrongly, the lagged wage as being the best indicator of their value to a potential employer. Thus they could simply set their reservation wage to equal the wage received in previous employment. A second reason is pride. Even if it is unrealistic to expect reemployment at the previous wage, pride could make it very difficult for an unemployed worker to accept an offer of anything less.

With these issues in mind, we specify the reservation wage as a function not only of the relevant distribution of wages, of labor market conditions, and of unemployment benefits, but also of the wage received in the previous job. We estimate this relation using the British household Panel Survey over four years (1991-95). That data set contains explicit information about reservation wages, labor market status, lagged wages, and can be used to construct a mean wage based on observable characteristics of each worker. The main econometric challenge is to disentangle whether the coefficient on the lagged wage reflects causality, or the fact that the lagged wage contains information about the unobservable characteristics of workers. We do so in a variety of ways, through instrumental variables, or through use of the panel data dimension of our data.

Our empirical conclusions are clear, and appear robust to a number of alternative specifications and econometric treatments. We find a large and significant effect of the mean of the distribution of wages on the reservation wage. *Ceteris paribus*, an increase in the mean of 10% increases the reservation wage by about 4%. We find a significant, but—to our surprise—a relatively small effect of the lagged wage on the reservation wage. *Ceteris paribus*, an increase in the lagged wage of 10% increases the reservation wage by only 1.5%. We also find a significant but small effect of benefits. *Ceteris paribus*, a rise in benefits received of 10% leads to a 1% increase in the reservation wage. One other surprising result is our inability to find a significant effect of labor market conditions, proxied either by a worker specific unemployment rate, or by local unemployment and vacancy rates, on the reservation wage.

These results have interesting macroeconomic implications, because the reservation wage in part determines the natural rate of unemployment.¹ Were it the case that the coefficient on the lagged wage was close to unity, reservation wages would be largely a function of the past. If the market wage is a mark up on the reservation wage, we would expect to see it following an autoregressive process with close to a unit root. Thus, changes in policy could have permanent (or at least long lasting) effects on wages and unemployment. Our results suggest that the reservation wage will adjust to any shock relatively quickly. The coefficients on the variables that reflect current reality, the level of benefits, and the expected future wage are larger than the coefficient on the historic variable, the wage in the previous job. This implies that the natural rate of unemployment will adjust relatively quickly to tax and productivity shocks.

Before proceeding, we must comment on the relationship between this paper and two other strands of the literature. There is a large literature in public finance that seeks the effect of unemployment benefits on labor market behavior, particularly the duration of unemployment spells. The paper most related to ours is Feldstein & Poterba (1984). In essence, they regress the reservation wage on the level of unemployment benefits. They find an effect roughly three or four time the size of ours. A second strand of literature that is related to our paper is the optimal search literature. The focus of this literature is not on the determination of reservation wages, however, but on the effect of reservation wages on unemployment duration. Jones (1988), for example, finds for the UK, that a 1% increase in the reservation wage leads to a 7% increase in the duration of unemployment.

4.2 Specification

A standard definition of the reservation wage is that it is the minimum wage needed to induce an individual to give up a unit of leisure. It is equal, therefore, to the marginal utility of leisure normalized by the marginal utility of the consumption of other goods i.e. the marginal rate of substitution of consumption for leisure. Anything that affects the marginal utility of leisure or the marginal utility of consumption will affect the reservation wage.

Following this line of reasoning, we see that an obvious determinant of the reservation wage

¹See Blanchard & Katz (1997) for a simple discussion of the link between reservation wages and the natural rate of unemployment.

is the individuals' valuation of leisure time. Controlling for the level of consumption of other goods, individuals will be reluctant to take up employment because it means devoting less time to other more desirable activities. The higher the value individuals place on these activities, the higher will be the reservation wage. This presumes, of course, that individuals like non-work activities more than work. It may be the case that, even ignoring the monetary benefits of work, individuals prefer work to leisure because of the opportunity to interact socially. In this case the unemployed have an excess of free time. The marginal utility of leisure is negative, at least in the neighborhood of zero hours worked. While it is difficult to think of a direct measure of the utility of leisure we can imagine that it is related to personal characteristics such as age, marital status and number and on whether the individual has dependent children or not.

The other obvious determinant of reservation wages is the level of income support an individual can expect to receive when unemployed. The more consumption of other goods the individual can have while unemployed, the more reluctant he will be to take up work, and the higher the reservation wage. Income support implies more than just the welfare benefits paid by the state. It includes also support provided in cash, or in kind, by families. This source of support is very difficult to measure, but could be very important. For example, Blanchard & Jimeno (1995) hypothesized that large intra-family transfers plays an important role in explaining the high level of Spanish unemployment.

Another source of income while unemployed is savings and access to credit. How low a wage the unemployed are prepared to accept will depend not only on the income they get from others, but on the level of their own savings and on their ability to borrow against expected future income. In reality the unemployed are likely to be severely credit constrained, unable to borrow against future income. Even if credit constrained, an unemployed individual could have enough saving to enable him to maintain living standards during a spell of unemployment. If this is so, then he will have a relatively high reservation wage. Again, however, it is unlikely to be so, as most individuals have relatively low level of liquid savings. Most individuals' savings tend to be held in the form of housing assets, which may be difficult to liquidate, or in the form of pensions, many of which cannot be run down before retirement.

The value of leisure, level of benefits, and non-labor income all determine the reservation wage in the competitive model i.e. when it is equal to the marginal rate of substitution of

consumption for leisure. In a more realistic case the reservation wage will be influenced by other factors. An individual will be more likely to turn down any job offer if he feels he is relatively likely to receive a better offer sooner rather than later. Thus, the reservation wage will probably be a negative function of the individual's expected performance in the labor market in the near future. This expected performance level can be broken into two component parts, the probability of receiving a job offer and the distribution of wage offers. Individuals will be less reluctant to turn down an offer of a job at a low wage if they believe that the probability of a better offer arriving anytime soon is low. This probability will likely be a negative function of the unemployment rate and a positive function of the vacancy rate. Similarly the reservation wage will also be a positive function of the distribution of wage offers that the individual expects to receive. The higher the mean of this distribution, and the lower its variance, the more likely is the individual to turn down a low wage offer, hence the reservation wage will be relatively high.

The reservation wage could also be a function of the wage received during any previous period of employment. This wage indicates to the individual his value to a previous employer and is, therefore, an indicator of his likely value to a future employer. If the individual receives an offer at a wage below his previous wage, he may be inclined to think that this offer is from the low end of the distribution, and therefore reject it. Furthermore, pride is likely to make any individual less likely to accept a job at a wage lower than that earned in a previous employment. We might expect both these effects to diminish over time as reality begins to bite. As length of time spent unemployed increases, the individual may revise down his wage expectations and swallow his pride.

From the discussion in the previous paragraphs we might expect the reservation wage to be determined by a function such as (4.1) where, W_{it}^L is the wage in last employment, \bar{W}_{it} is the mean of the distribution of offers, u_{it} is unemployment rate, a_{it} is asset income and b_{it} is the level of unemployment benefits. We choose the log-linear functional form so that the coefficients may be interpreted as elasticities.

$$\ln W_{it}^R = \alpha + \beta \ln W_{it}^L + \gamma \ln b_{it} + \delta \ln \bar{W}_{it} + \mu \ln a_{it} + \lambda \ln u_{it} + \varepsilon_{it} \quad (4.1)$$

4.3 Data

We conduct the analysis using a British dataset, the British Household Panel Survey (BHPS).² This panel covers 4 years from 1991-95. This dataset has three particular advantages. Firstly, it contains a wealth of information on the labor market status of respondents, enabling the difference between unemployment and non-participation to be clearly defined. Secondly, the data includes observations of an individual's reservation wage. Thirdly as the data is a panel, we may be able to control for individual specific (unobserved) effects. The major disadvantage of the data is that there are relatively few observations. After elimination of missing values we are left with 1167 observations of individuals without employment. These observations consist of 822 distinct individuals. We do not observe every individual to be unemployed in each wave. The average number of observations in the time dimension is 1.42 per individual. The panel is highly unbalanced.

Table 4.1 contains the definitions and summary statistics of the variables used in the analysis.³ The exogenous variables used here fall into two categories: human capital and time and region fixed effects. The human capital variables (*educ*, *soc*, *pasoc*, *voced*) are all related to education and occupation .

The reservation wage variable, W_{it}^R , is not imputed, it is the result of direct observation. Individuals who reported that they did not have a job, but who said that they would like one, were asked the following question:

“What is the lowest weekly take home pay you would consider accepting for a job?”

We interpret the answer to this question as being the individual's reservation wage after tax.⁴ We have observations of W_{it}^R for individuals who are unemployed and also for individuals who might be better described as non-participants or discouraged workers. The difference is that the unemployed reported that they had looked for a job within the previous four week, whereas the others reported, merely that they would “like” a job. The fact that an individual

²We are grateful to Brian Bell for providing us with regional vacancy and unemployment data for Britain.

³The summary statistics are calculated for the pooled cross section.

⁴The question would certainly be understood by the respondent to refer to the after tax wage. Tax illusion may cause problems, however. It is not clear whether, for example, individuals answered this question by first calculating a gross wage and applying some arbitrarily chosen tax rate or whether their preferences over alternative labor market states were already parameterized in terms of net wages.

said that he would like a job, and could suggest what sort of job it might be, was sufficient for him to be asked the question quoted above.

We acknowledge the potential objection that the answer to this question may not accord exactly with the theoretical concept of the reservation wage. Individuals may have little incentive to give an honest answer. Also there is the possibility that the ordering of the questions in survey may have led to some confusion.

As regards the honesty of the replies, this is a potential problem in all surveys. Two facts lead us to trust the answers in this survey. Firstly, the respondents knew that the survey was confidential. In particular they knew that the information they gave was not to be made available to tax and welfare authorities. Secondly, elsewhere in the survey many individuals who were receiving state unemployment benefits reported that they were not actively searching for work. This is despite the fact that active search is supposedly a requirement for receipt of those benefits. This suggests that respondents believed that survey was confidential.

The issue of the ordering of the question is more problematic. Before being asked the “reservation wage” question, individuals were first asked to specify the occupation that they “expected” to get. It is possible that they interpreted the subsequent “reservation wage” question as referring to the lowest wage for which they would accept that occupation, as distinct from the lowest wage they would accept for some arbitrary job. If there is some variance in the precise interpretation of this question, we believe that its answer is still indicative of an individuals relative willingness to leave unemployment. More formally, if there is an error in the W^R variable, there is no reason to expect that it is correlated with any of the regressors in (4.1). Least squares on (4.1) will still produce consistent estimates.

The wage in the last job, W^L , is calculated as the weekly wage received in the most recent spell of employment. For many, but not all the unemployed, this is equal to the wage reported at a previous wave of the panel i.e. $W_{it}^L = W_{is}$ where $s < t$. For the rest the variable is calculated from the answers individuals gave to a series of questions about their labor market activities between the current and previous waves of the panel.

The benefits variable is the level of state benefits the respondent reported receiving at time of interview. This may be different from the level of benefits to which the individual is entitled. We do not investigate the issue of benefit take up rates any further. Not all the

benefits available are formally linked to employment status. Most of the benefits, however, are means tested. Therefore they are likely to vary with employment status. About 26% of the observations in the sample are of zero benefits. We treat these individuals \$0.25 in benefits per week in order to avoid taking logs of zero.

As we discussed in the previous section, we expect labor market conditions to influence the reservation wage. For simplicity we consider two channels through which this occurs. Reservation wages will be influenced by the probability of receiving a job offer and by the expected wage associated with that offer.

We use two alternative procedures to account for the effect of the probability of receiving offers. The first method is to proxy the probability by the regional unemployment and vacancy rates. These are included as regressors in (4.1). This follows the spirit of Blanchflower & Oswald (1994). We would expect that a high unemployment rate and a low vacancy rate would make the unemployed less likely to turn down a job offer even at a low wage, for fear that a better offer is unlikely to materialize in reasonable time.

Card (1995) notes that this method suffers from the problem that there are relatively few independent observations of the regional level data. As our sample is already small, there may be insufficient variability in the unemployment and vacancy variable to identify an effect, even if it exists. Therefore we also try an alternative approach. We construct an individual specific unemployment rate. We first estimate a probit model of employment on a sample consisting of the employed and unemployed. The independent variables in this model are regional unemployment and vacancy rates, individual characteristics such as age and education, and region and time dummies and their interactions. The dependent variable is the individual's current reported employment status. We use the predicted probability of unemployment from this probit model as a regressor in (4.1). The idea is that this variable represents the probability that an arbitrary individual with the same characteristics as person i will get a job conditional on him searching.⁵ This procedure can be thought of as being a generalization of the Blanchflower & Oswald (1994) idea of using the unemployment rate for i 's region as a regressor in wage equations. It goes some way towards meeting the Card (1995) objection that there is insufficient

⁵The probability is conditional on searching because we estimate the probit model on a sample consisting of the employed and the unemployed, but not the non-participants. We then construct the predicted probability for both the unemployed and the non-participants, as we observe reservation wage for both groups.

variation in the regional unemployment variable.

We have two measures of the mean of the distribution of wage offers. The first, direct measure, is W_{it}^e , the individual's response to the question:

“What weekly take home wage would you expect to get?”

There are two obvious problems with interpreting the answer to this question. Firstly, it suffers from the same problem as the reservation wage question. It is not clear whether the expectation is taken with respect to all job offers or only over the offers relating to the previously indicated occupation of choice. Secondly it is not clear whether the expectation is conditional on the offer being acceptable i.e. the offered wage being greater than the reservation wage. We want the unconditional mean of the distribution.

Given the difficulty in interpreting the variable, W_{it}^e , we construct \hat{W}_{it} , an alternative measure of the mean of the distribution of offered wages. We first estimate a standard wage equation on a sample consisting of all the *employed*. We regress the weekly wage on education, region and time dummies and their interactions. We correct for sample selection using the two stage procedure of Heckman (1979).⁶ The \bar{R}^2 in the wage equation is 0.23 and the coefficient on the inverse mills ratio is -0.68 with a standard error of 0.02. We then use the coefficients from this regression to calculate fitted values for those who do not have a job. We interpret these fitted values, \hat{W}_{it} , as being the mean of the distribution of wage offers that an individual faces, conditional on his characteristics and the characteristics of the local labor market. This procedure has the advantage that it is not open to the kind of problems of interpretation that undermine our confidence in W_{it}^e . But there are two problems with it. Firstly the fitted values were created via a regression of the wage on dummies derived from the human capital variables together with interactions between time and region dummies. This procedure is not without controversy. Only the exogeneity of father's occupation (*pasoc*), age and the time dummies are absolutely assured. One could argue that the human capital variables and even the regional dummies are all the result of choices that are made jointly with the choice of labor market status and are therefore not exogenous.

⁶The selection probit includes variables representing the marital status, age, sex, and number of dependent children as regressors. We exclude all the human capital variables from the selection probit in order to identify the inverse mills ratio.

It can be argued, however, that, while these variables are formally the result of choices, those choices are sufficiently independent of the choice of employment status to enable the resulting variables to be treated as exogenous in practice. For example, education may be thought to be endogenous because we choose a higher level of education in anticipation that this will enable us to earn higher wages, avoid unemployment etc. But it is also plausible to suggest that the choice of education is as much a result of available opportunities, parental encouragement, personal abilities etc. To the extent that this is so, the level of education can be considered to be exogenous.

A more serious problem is that this procedure may introduce an “errors-in-variables” problem rendering OLS estimates of (4.1) inconsistent. Replacing \bar{W}_{it} with \hat{W}_{it} introduces the term $\bar{W}_{it} - \hat{W}_{it}$ into the residual of the estimated equation. This term will, almost surely, have an individual specific component μ_i . This represents that component of the expected wage that is specific to the individual and is not correlated with the observed characteristics that were used to construct \hat{W}_{it} . The actual model estimated will have the form (4.2).

$$\ln W_{it}^R = \alpha + \beta \ln W_{it}^L + \gamma \ln b_{it} + \delta \ln \hat{W}_{it} + \lambda \ln u_{it} + \mu_i + \varepsilon_{it} \quad (4.2)$$

It is probably the case that W_{it}^L will be positively correlated with μ_i , because W_{it}^L , the wage in the previous job probably reflects at least in part this individual specific component. Thus OLS estimation of (4.2) will probably yield upward biased estimates of the effect of W_{it}^L on reservation wages.

In order to combat this potential problem we use an IV procedure. We first project W_{it}^L on a set of instruments which consist of 150 dummies representing the three digit industry code of the previous job. In order for this procedure to be valid, we need that the industry code be correlated with W_{it}^L but uncorrelated with μ_i , the individual specific unobservable component of expected wages. The first of these requirements is easy to accept. The second, however, is not. To the extent that unemployed individuals are more likely to get a job in the same industry in which they were previously employed, the industry codes will be correlated with μ_i and they will not be valid instruments. If, however, we use sufficiently disaggregated industry codes, the probability of an individual returning to the same industry is minimized. At the

three digit level the probability that an unemployed individual has *exactly* the same code on reemployment, as the most recent previous job, is 34%. As we use 150 three digit industry dummies, we feel that the IV procedure is valid and yields worth-while estimates. But we do acknowledge that the procedure is not foolproof.

4.4 Empirical Results

We report the OLS estimates of equation (4.1) in Table 4.2. The first column shows the estimates of (4.1) when \bar{W}_{it} , the mean of the distribution of offered wages is proxied by W_{it}^e , the individual's subjective expectation of future wages. The estimates in the first column also allow for regional vacancies and unemployment rates to influence the reservation wage. Surprisingly, the effect of unemployment and vacancy rates is insignificant. This could indicate that local unemployment rates have no direct effect on reservation wages, perhaps only influencing reservation wages indirectly via an effect on the distribution of wage offers. It may be, however, a manifestation of the problem discussed in the last section and by Card (1995). Because they are observed at the regional level, the number of independent observations of U_{rt} and V_{rt} is only 47 and 67 respectively. Furthermore, from Table 4.1 we can see that their variance is small. This may not be sufficient to identify an effect even if one exists.

The coefficient on the expected wage variable, W_{it}^e is large and highly significant. In fact this variable alone explains most of the variation in the dependent variable, W_{it}^R . The coefficients on the "wage in the previous job" variable, W_{it}^I , and on the benefits variable, b_{it} , are small but statistically significant.

The size of the coefficient on W_{it}^e leads us to suspect that this variable may not truly capture the mean of the distribution of wage offers. It could be the case that individuals, when asked what they expect to earn, give as their answer a wage equal to their reservation wage plus 15%, for example. This sort of behavior generates a spurious correlation between the dependent variable W_{it}^R and the regressor W_{it}^e . This could fully explain the results reported in the first column of table 4.2.

In order to examine this possibility, we present, in column two of Table 4.2, the estimates of (4.1) with W_{it}^e replaced by \hat{W}_{it} , the fitted value from a wage regression. If W_{it}^e measures the

mean of the wage distribution, then the results in the first two columns of table 4.2 should not be significantly different. It is clear, however, that they are different. The magnitude of the point estimates of the effect of W_{it}^L and b_{it} have risen by factors of, approximately, 10 and 4 respectively. The coefficient on \hat{W}_{it} is two thirds of that on W_{it}^e . The \bar{R}^2 for this regression is one quarter of that in column 1. This leads us to suspect that the estimates using W_{it}^e are contaminated by a spurious correlation and therefore the estimates reported in the second column are to be preferred.

We next considered a possible solution to problem of insufficient observations of regional unemployment and vacancy rates. We re-estimate equation (4.1) with the regional variables, U_{rt} and V_{rt} , replaced by \hat{U}_{it} , our constructed individual specific unemployment rate. These estimate are presented in the third column of Table 4.2. The coefficients on the variable are virtually unchanged from those of column 2. The \bar{R}^2 is similarly unchanged. Furthermore, the coefficient on \hat{U}_{it} is not significantly different from zero. This suggests that unemployment rates do not directly influence the formation of reservation wages.

We next consider the possibility that the wage in previous job does not exert an influence on the reservation wage, independent of that exerted by the mean of the distribution. This could be the case if the wage in the last job is drawn from the distribution which has \bar{W}_{it} as its mean. Both variables could be picking up the effect of personal characteristics on the reservation wage even if previous employment per se had no effect on the reservation wage. Therefore we re-estimated the regression excluding the lagged wage variable. These results are presented in the fourth column of Table 4.2. These results should be compared with those in column 2 of Table 4.2, where the regressors are identical but for the inclusion of W_{it}^L . The coefficients on unemployment and vacancy rates remain insignificant. The coefficient on \hat{W}_{it} , the constructed mean of the distribution of wage offers, has risen, however, and is significantly different from that in column 2. The explanatory power of the model, as given by the \bar{R}^2 , is cut in half by the exclusion of W_{it}^L . This suggests that while there is some degree of positive collinearity between W_{it}^L and \hat{W}_{it} , the wage received in the previous job does exert an independent influence on the formation of reservation wages.

As explained in the last section, we might expect that OLS estimation of (4.1) is inconsistent because W_{it}^L is correlated with the residual when \hat{W}_{it} is a regressor. We report Instrumental

Variable estimation of equation (4.1) in table 4.3. The columns of Table 4.3 correspond to columns 2 and 3 of Table 4.2, with the exception that W_{it}^L is first projected onto 150 industry code dummies. The effect of this IV procedure is to *increase* the point estimate of the coefficient on W_{it}^L by one third. This increase is statistically significant. The point estimate of the coefficient on benefits falls, but is not significantly different from the OLS estimates. Similarly the point estimate of the coefficient on \hat{W}_{it} rises, but not by a statistically significant amount. As in the case of the OLS estimates the unemployment and vacancy variables are insignificant

The increase in the coefficient on W_{it}^L is curious. As explained in section three we would have expected IV to reduce the estimate this coefficient relative to the OLS estimate. Further work needs to be done in order to explain exactly why the IV estimate is larger. It is worth noting, however, that both estimates of the influence of W_{it}^L on reservation wages are relatively small.

An alternative method of dealing with the individual specific unobservable is to make use of the panel aspect of the data. We should be able to difference out the individual effect using the “within groups” estimator. We present these results in the first column of Table 4.4. The results are less than impressive. Almost all of the regressors are insignificant. Collectively they explain only 2% of the variation within groups. On reflection this is not surprising. We have very few individuals in the dataset who have had more than one spell of unemployment. The average number of observations per individual in the time dimension is less than 1.5. Basically our panel is a cross section.

For the sake of completeness we report GLS estimates of a random effects model in the second and third columns of table 4.4. The GLS method suffers from the same problem as OLS, namely that μ a component of the residual, could be correlated with a regressor, W_{it}^L . We attempt to overcome this by instrumenting for the lagged wage using industry code dummies as before. The result is reported in the third column of table 4.4. These results are not very different from those reported in tables 4.2 and 4.3 for the pooled cross sections.

An interesting extension is to look at how these results vary by sex. The estimates reported previously made no attempt to distinguish between the sexes, apart from the inclusion of sex dummy as a regressor in both the wage equation and the selection probit used to calculate the fitted value \hat{W}_{it} . Labor economists tend to view the labor supply of men and women as

being qualitatively different. Therefore we report in Table 4.5 the results from estimation of equation (4.1) on separate sub-samples of men and women. We also add an extra regressor, *kids*, the number of dependent children in the household, as we suspect that this may influence the behavior of women especially.

The results are quite striking. Dividing the sample by sex gives very different results. The coefficients on W_{it}^L and b_{it} are very different. Their coefficients from the full sample regressions do not equal the average of the coefficients estimated over the two sub-samples. This suggests that estimates over the full sample are picking up some spurious correlation between sex and the lagged wage and benefit variables.

If we assume that women have lower wages in general, then W_{it}^L will be negatively correlated with the sex dummy, where female is coded as one and male as zero. It is also probable that women have lower reservation wages than men, if only because they can expect a lower wage upon employment. Thus, the sex dummy will be negatively correlated with the reservation wage.⁷ The exclusion of a variable that is negatively correlated with both reservation wage and the lagged wage will generate a spurious positive correlation between the lagged wage and the reservation wage. This explains why the coefficient on the lagged wage falls once we split the sample by sex.

The change in the coefficient on the benefits variable could have a similar explanation, if we believe that women receive systematically lower benefits than men. This is actually observed in this dataset⁸, but it is not clear why it should be so. It may simply be the case that benefits paid to a household with both a male and female adults tend formally to be paid to the male as "head of household".

The mean wage variable behaves as one would expect. The coefficient estimated from the full sample is roughly equal to the average of coefficients estimated on the two sub-samples. The effect for females is slightly higher than for males, but not significantly so. The negative effect of asset income on the reservation wage is significant only for men. Similarly, the presence of children raises the reservation wage of men, but lowers that of females.

⁷The correlation between the sex dummy (with female coded as one) and the reservation wage is -0.38 . Similarly the correlation with the lagged wage is -0.32 .

⁸The correlation between sex and benefits is -0.28 .

4.5 Macro Implications

In order to illustrate the macro implications of the results presented in the previous section, consider the imposition of a income tax in a labor market with involuntary unemployment. Suppose further that the involuntary unemployment results from a Shapiro & Stiglitz (1984) model of efficiency wages.⁹ Employers have imperfect information regarding workers level of effort. This causes them to pay a premium in order to induce workers to exert effort. This ensures that equilibrium wage is above the market clearing level, leading to involuntary unemployment.¹⁰

The labor market can be described by equation (4.3), where the market wage is some multiple of the reservation wage and a standard labor demand curve. There is involuntary unemployment because some workers, who are prepared to accept to work at the going wage ($W > W^R$), will not be offered a job in equilibrium.

$$\ln W(1 - \tau) = \ln W^R + \theta \quad (4.3)$$

In this context workers are paid a markup on their reservation wage in order to discourage them from shirking. The efficiency wage premium declines as unemployment rises, because higher levels of unemployment act as a deterrent against shirking.

In order to illustrate the policy implications played by these models and the role played by reservation wages, consider the impact on the natural rate of an increase in τ , the tax on wage income. Intuitively, if the burden of the taxes falls entirely on the workers, then the cost of labor does not rise and the tax has no implications for unemployment.¹¹ Workers, seeking to preserve the markup of net wage on the fixed reservation wage, shift some of the burden of taxes onto employers in the form of a higher gross wage. Firms respond to an increase in the cost of labor by cutting back on hires.

This holds for a fixed reservation wage. But, if the reservation wage itself changes in response to the tax, then the effect of the tax on the natural rate of unemployment turns out to be very

⁹In the actual model presented in Shapiro & Stiglitz (1984), they assume, for simplicity, that the labor supply curve is vertical. The reservation wage is not well defined in this case.

¹⁰Discussion of other examples can be found in Bean (1994), Blanchard & Katz (1997) and Layard et. al. (1991).

¹¹Of course, individuals whose after tax wage has fallen may withdraw from the labor force, leading to a fall in *employment*. These individuals, however, not unemployed; they are nonparticipants.

different. Consider the following simple example. Assume that the reservation wage is equal to net income when unemployed and that unemployment benefits, b , are taxable at the same rate as wage income, as in equation (4.4).

$$W^R = (1 - \tau)b \quad (4.4)$$

Substituting (4.4) for W^R in the wage setting equation (4.3) results in an expression for the equilibrium wage that is independent of τ . Thus taxes will have no effect on equilibrium wages or unemployment. In this simplistic case the reservation wage adjusts immediately and completely to the change in taxes. Workers have no ability to pass on any of the burden of taxes to employers. Firms faced with unchanging cost of labor do not change employment levels.

In a more realistic case, we might expect any adjustment in the reservation wage to take time. How this adjustment takes will be an important determinant of the long run response of unemployment to real shocks such as tax changes. Bean (1994) and Blanchard & Katz (1997) point out that we might expect that the workers bear the entire burden of the tax in the long run. Their intuition is as follows. A permanent increase in taxation will reduce permanent income and consumption. This will increase the marginal utility of consumption relative to the marginal utility of leisure. This in turn implies that the reservation wage will fall. It is not hard to design a specific set up where the net result is no change in the mark-up and therefore the wage. Thus the incidence of the tax falls completely on workers. This would imply that even a permanent increase in taxes would have only a temporary effect on unemployment.

Much depends on the exact form of (4.3). As explained earlier, if reservation wages are primarily a function of the level of benefits, then they are likely to adjust quickly to any changes in taxes or productivity. Thus, the change in the natural rate of unemployment brought about by the change in taxation, is likely to be small and not long lasting. Alternatively, if the reservation wage is primarily a function of the wage in the previous job, the effects of changes in taxation on the natural rate of unemployment could be very long lasting. Substituting W_{it}^L for W_{it}^R in (4.3) leads to an expression for the market wage that is an autoregressive process with a coefficient close to unity.¹² In this case the reservation wage adjusts slowly leading to

¹² $W_{it}^L \approx W_{it-1}$

large changes in the natural rate. The unemployed are holding out for a wage equal to the wage they received in the previous employment, even though the tax increase has made that net wage economically infeasible. Unemployment will persist until reservation wages adjust to the new reality.

4.6 Conclusions

This paper set out to find the determinants of the reservation wage and to indicate what the structure of reservation wages implies for the evolution of the natural rate of unemployment. We find that the level of benefits, the wage in a previous job and the expected future wage are all important determinants of the reservation wage. Surprisingly, we find that unemployment rates have no influence on reservation wages. Our empirical conclusions are clear, and appear robust to a number of alternative specifications and econometric treatments. We find a large and significant effect of the mean of the distribution of wages on the reservation wage. *Ceteris paribus*, an increase in the mean of 10% increases the reservation wage by about 4%. We find a significant, but—to our surprise—a relatively small effect of the lagged wage on the reservation wage. *Ceteris paribus*, an increase in the lagged wage of 10% increases the reservation wage by only 1.5%. We also find a significant but small effect of benefits. *Ceteris paribus*, a rise in benefits received of 10% leads to a 1% increase in the reservation wage. One other surprising result is our inability to find a significant effect of labor market conditions, proxied either by a worker specific unemployment rate, or by local unemployment and vacancy rates, on the reservation wage.

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Table 4.1: The BHPS Data

Variable	Definition	Mean	Variance
age	age at interview	36.76	13.47
month	month of interview	9.43	1.82
year	year of interview	93.11	0.80
region	region	8.55	5.81
b_{it}	benefits	183.30	232.72
W_{it}	usual weekly wage		
W_{it}^R	reservation wage	111.21	74.52
W_{it}^e	expected wage	144.31	104.81
\hat{W}_{it}	constructed mean wage	169.08	69.45
W_{it}^L	wage in previous job	158.71	129.65
U_{rt}	Regional unemp. rate	9.82	1.09
V_{rt}	Regional vacancy rate	0.58	0.22
\hat{U}_{it}	constructed unemp. rate	9.68	6.14
educ	level of education	1.8	1.55
voced	vocational education dummy	3.64	1.28
soc	occupation code	5.72	2.3
pasoc	father's occupation	3.64	1.28
race	ethnic background	1.12	0.77
sex	sex	0.50	0.50

1. Statistics are calculated for the pooled cross section

Table 4.2: OLS Estimation

Dependent Variable: $\ln W_{it}^R$

Regressor	(1)	(2)	(3)	(4)
$\ln W_{it}^L$	0.020 (0.009)	0.224 (0.017)	0.226 (0.018)	- -
$\ln b_{it}$	0.047 (0.011)	0.187 (0.023)	0.182 (0.022)	0.221 (0.019)
$\ln \hat{W}_{it}$	- -	0.421 (0.074)	0.421 (0.074)	0.391 (0.064)
$\ln W_{it}^e$	0.877 (0.015)	- -	- -	- -
$\ln U_{rt}$	-0.133 (0.115)	-0.102 (0.158)	- -	- -
$\ln V_{rt}$	0.06 (0.021)	-0.137 (0.047)	- -	- -
$\ln \hat{U}_{it}$	- -	- -	0.491 (0.287)	0.441 (0.238)
$\ln a_{it}$	-0.008 (0.006)	-0.045 (0.015)	-0.043 (0.014)	-0.028 (0.012)
constant	0.327 (0.168)	0.625 (0.530)	1.709 (0.803)	1.560 (0.653)
N	1350	1160	1160	1160
\bar{R}^2	0.814	0.224	0.220	0.086

1. Standard errors are in parentheses

Table 4.3: IV Estimation

Dependent Variable: $\ln W_{it}^R$

	(2)	(3)
$\ln W_{it}^L$	0.411 (0.037)	0.409 (0.037)
$\ln b_{it}$	0.202 (0.023)	0.199 (0.023)
$\ln \bar{W}_{it}$	0.454 (0.075)	0.455 (0.075)
$\ln W_{it}^e$	- -	- -
$\ln U_{rt}$	-0.219 (0.161)	- -
$\ln V_{rt}$	-0.155 (0.048)	- -
$\ln \hat{U}_{it}$	- -	0.416 (0.291)
$\ln a_{it}$	-0.040 (0.014)	-0.037 (0.015)
constant	-0.166 (0.552)	0.496 (0.400)
N	1160	1160
\bar{R}^2	0.178	0.168

1. Standard errors are in parentheses

2. IV has W_{it}^L instrumented by industry code

Table 4.4: Panel Data Estimation

Dependent Variable: $\ln W_{it}^R$

	Within	GLS	GLS-IV
$\ln W_{it}^L$	0.060 (0.068)	0.208 (0.020)	0.387 (0.041)
$\ln b_{it}$	0.072 (0.040)	0.154 (0.022)	0.158 (0.023)
$\ln W_{it}$	0.257 (0.322)	0.387 (0.081)	0.421 (0.082)
$\ln u_{it}$	0.741 (0.522)	0.479 (0.282)	0.489 (0.283)
$\ln a_{it}$	0.000 (0.036)	(0.034) (0.151)	(0.030) (0.015)
constant	4.408 (1.778)	2.094 (0.806)	1.116 (0.833)
N	797	797	797
\bar{T}	1.455	1.455	1.455
R^2	0.180	0.224	0.161

1. Standard errors are in parentheses

2. GLS is the standard Random Effects model

3. IV has W_{it}^L instrumented by industry code

Table 4.5: Estimation By Sex

Dependent Variable: $\ln W_{it}^R$

	ALL		Male		Female	
	OLS	IV	OLS	IV	OLS	IV
$\ln W_{it}^L$	0.227 (0.018)	0.397 (0.037)	0.142 (0.027)	0.137 (0.041)	0.107 (0.025)	0.234 (0.058)
$\ln b_{it}$	0.183 (0.023)	0.197 (0.023)	0.072 (0.020)	0.077 (0.029)	0.089 (0.032)	0.089 (0.031)
$\ln W_{it}$	0.432 (0.074)	0.469 (0.075)	0.371 (0.078)	0.437 (0.078)	0.528 (0.112)	0.503 (0.111)
$\ln u_{it}$	0.485 (0.286)	0.405 (0.289)	0.038 (0.305)	-0.071 (0.309)	0.735 (0.410)	0.685 (0.408)
$\ln a_{it}$	-0.046 (0.015)	-0.044 (0.015)	-0.046 (0.016)	-0.0401 (0.016)	-0.008 (0.020)	-0.011 (0.021)
Kids	-0.035 (0.017)	-0.049 (0.017)	0.094 (0.019)	0.095 (0.020)	-0.076 (0.026)	-0.086 (0.026)
constant	1.683 (0.802)	0.485 (0.833)	1.918 (0.855)	1.33 (0.895)	2.44 (1.150)	1.896 (1.171)
N	1160	1160	573	576	587	591
R^2	0.222	0.19	0.179	0.15	0.099	0.095

1. Standard errors are in parentheses

2. IV has W_{it}^L instrumented by industry code