Unemployment and Growth Dynamics: Theory and OECD Evidence

Thesis submitted for the degree of
Doctor of Philosophy (PhD) by Ravi Balakrishnan,
registered at the London School of Economics

April 1999

Abstract

We study unemployment and growth dynamics. A search theoretic approach, augmented by exogenous and endogenous growth considerations, is used. We apply a variety of macro-econometric tools, across OECD countries, namely: structural vector autoregression (SVAR) analysis; simulations; frequency domain analysis and panel data regression analysis, to test out a variety of hypotheses drawn from the theoretical literature.

First, we look at unemployment dynamics, using a search model and an SVAR methodology, and discover that the European Community and the US have faced similar shocks, mainly aggregate ones, but have reacted very differently. The exception is Spain, where most of the unemployment dynamics have been driven by reallocation. Overall, this implies that EEC economies might be 'dynamically sclerotic' when compared to the US, though simulations do not confirm this result.

Next, we re-examine the link between growth and unemployment. Using: frequency domain analysis, panel data regression analysis and looking at cross correlations, we find that the interactions are weak, with at best a marginally significant negative effect of growth on unemployment. This is consistent with theories that predict capitalization effects dominate creative destruction, in the effect of growth on unemployment. It is not consistent with theories that imply a strong effect of unemployment on growth, through: loss of skills; learning by doing; cleansing effects and savings effects. Even when the capitalization effect is significant, it is not very large. A 1% increase in steady state growth would only reduce equilibrium unemployment by 1%.

Finally, we look at the links between growth, R&D and job flows, as an alternative way to isolate creative destruction effects. We find that creative destruction mechanisms are only important for US, i.e. for a country on the technological frontier.

Contents

List of Tables

List of Figures

0.1 Acknowledgments

Most importantly, I would like to thank two people in particular: my supervisor, Chris Pissarides, for advice and guidance over the years; and Claudio Michelacci, with whom I co-authored the second chapter. I also thank those who helped by their comments or criticisms, notably: Charlie Bean, Giuseppe Bertola and Steve Nickell, and more generally all who gave a part of their time to discuss the ideas in this dissertation . I greatly appreciated the chance to work in the Centre of Economic Performance at the LSE and at the European University Institute. Financial support from the ESRC and the CEP is greatly acknowledged.

Chapter 1

Introduction

There can be few questions of more importance, in economics, than how to increase growth and reduce unemployment, in a sustainable way. After the global boom in the 1950s and 60s, there was a period when the World Economy became less robust, in response to two major oil price shocks. There was a global productivity slowdown and particularly in Europe, unemployment took off. Low unemployment and high growth have never been taken for granted since. Some questions have been answered, but many puzzles still remain. As Blanchard and Katz (1996) noted, in reference to the huge cross country differences in unemployment dynamics,

'many suspects have been identified, none has been convicted.'

The aim of this thesis, is to help answer the questions of how to sustain growth and keep unemployment low. We do this against a backdrop of an OECD data set. This is not because developing countries are not equally important, just that the data available for the OECD is much more comprehensive and of a higher quality[1].

This thesis will document and evaluate, how and why unemployment and growth evolve over time, and if there is any relationship between the two. Below, I discuss the theoretical considerations and empirical techniques which provide the foundations of this thesis, before going on to describe how the rest of the thesis is organized.

[1]Though more recent data sets, for example Maddison (1994), Summers and Heston (1992) and Barro and Lee (1993) do provide rich data for developing countries aswell.

1.1 Theoretical considerations

1.1.1 The Labour Market

Although we use a variety of models of the labour market, throughout this thesis, the most common one utilizes a search and matching framework. Modern search theory has its roots in the early 80s through a series of pioneering papers by Diamond (1982), Mortensen (1982a,b) and Pissarides (1984a,b) (see Mortensen and Pissarides 1999 for an evaluation of what phenomena in the labour market search models can and cannot explain). The basic formulation that is utilized in this thesis, is based on Pissarides' (1990) model of equilibrium unemployment, as extended by Mortensen and Pissarides (1994) to allow for job destruction. The approach interprets unemployment as the consequence of the need to reallocate workers across activities and the fact that the process takes time. The model is founded on two constructs, a matching function that characterizes the search and recruitment process by which new job-worker matches are created and an idiosyncratic productivity shock that captures the reason for resource allocation across alternative activities. Given these concepts, decisions about the creation of new jobs, about recruiting and search effort, and about the conditions that induce job-worker separations can be formalized.

Existing employment relationships command monopoly rents because of search and recruiting investments, hiring and firing costs, and other forms of match-specific human capital formation. The surplus that accrues is allocated between the parties to the employment relationship by a wage contract. Given a particular wage rule, employers provide jobs and recruit workers while workers search for employment. At the same time, an existing employer-worker match ends when sufficiently bad news arrives about their expected future. These job creation and job destruction decisions generate worker flows into and out of employment which depend on the current value of the employed stock. When the two flows differ, employment dynamics are set in motion which, under a reasonable set of conditions, lead to a unique steady-state employment level. These properties characterize the equilibrium model of job creation and job destruction.

This framework allows one to clearly discriminate between *aggregate* and *reallocative* shocks. An aggregate shock affects the average profitability of jobs: a positive shock will increase the profitability of jobs and thus increase the incentive to create new ones. At the same time, the shock reduces the incentive to destroy the old ones, so that job creation and job destruction tend to move in opposite directions. A reallocative shock on the other hand, affects the dispersion of productivities across jobs. For example, a positive reallocative shock will increase, for a given average productivity, productivity in some firms and will reduce it in others. More jobs will be created in high productivity sectors. At the same time, more jobs will be destroyed in low productivity ones, so that job creation and destruction tend to move in the same direction. We make use of this identification when we look at unemployment dynamics in chapter 2.

The framework also allows us to analyze the effect of growth on unemployment. This is split up into two effects (see Aghion and Howitt 1994 and Mortensen and Pissarides 1998). The *creative destruction effect* is when productivity growth occurs through the destruction of low productivity jobs and their replacement by new high productivity ones elsewhere in the economy, thus increasing the inflow rate into unemployment. The *capitalization effect* is where an increase in the growth rate increases the present discounted value of the profits from creating a new job slot, leading firms to open more vacancies increasing the rate of job creation and thus ultimately reduce unemployment. We discuss and test the relevance of these effects in chapters 4 and 5.

1.1.2 Growth

We consider both exogenous and endogenous growth models. To find effects of growth on unemployment, we only require a search theoretic framework and exogenously given growth. To generate effects of unemployment on growth that are *permanent* though, we require a model of endogenous growth. Once we allow for endogenous growth, there are many ways in which unemployment can effect growth, such as: *loss of skills*, *learning by doing*, *savings* and *cleansing effects.* We evaluate such effects in chapters 4 and 5 using a variety of endogenous growth models, some with optimizing Ramsey frameworks and some within an overlapping generations structure.

We focus on two main engines for growth: physical capital accumulation and R & D. Romer (1986) formalized the idea that physical capital accumulation could affect the steady state growth rate via an externality. Most of the models of endogenous growth based on physical capital, that we review, use his formulation. Schumpeter (1942) was one of the first to write about the importance of innovation in the growth process. This line of reasoning suggests that R&D should be important, as increasing R&D should increase the probability of making an innovation. Aghion and Howitt (1992, 1998) have formalized this intuition in models of growth through creative destruction. We test some important hypotheses deriving from these models in chapters 4 and 5.

This thesis is really about trying to discriminate between differing hypotheses concerning the evolution of unemployment and growth. This requires an way of testing and it is to this that we now turn.

1.2 Econometric considerations

This thesis is about studying macroeconomic evolutions and thus we tend to focus on macroeconometric modes of empirical analysis. The main techniques used are: structural vector autoregression (SVAR) analysis, simulations, spectral analysis and panel data analysis. I briefly motivate each one of these in turn.

1.2.1 SVAR analysis

Standard macroeconomic theory represents the equilibrium dynamics of an economic variable, as the joint outcome of exogenous structural shocks and a transmission mechanism that allows for these shocks to propagate in the economic system. The structural VAR (SVAR) methodology, pioneered among others by Bernanke (1986) and Blanchard and Quah (1989), seems well suited to testing whether the evolution of macroeconomic variables in different countries are: due to *exposure to* different shocks, or *reacting* differently to the same shocks. In fact, if a structural VAR (SVAR) is estimated, the impulse response functions represent how shocks propagate in the economic system, while the variance decompositions weight the contribution of each shock in the forecasting error of the relevant variables. This seems particularly suited to analyzing unemployment dynamics, which have differed markedly in the EEC and the US. We carry out such an exercise in chapter 2.

1.2.2 Simulations

Often models lead to predictions which are ambiguous if one keeps working at a very general level of abstraction. To get some testable hypotheses one often calibrates a model with certain parameter values obtained by inference using other techniques. For example, when calibrating search models, a matching elasticity of 0.4 is often chosen, as estimated by Blanchard and Diamond (1990). Once a model has been calibrated we can simulate it to generate variables which mimic the data the model is trying to explain. We use this technique in chapter 2 to see if the predictions of search based labour market models are born out in the results of the SVAR approach.

1.2.3 Spectral analysis

Frequency domain analysis allows one to look at the relationship between macroeconomic variables at *all frequencies*. A very arbitrary split, for macroeconomic variables, might be that: low frequency movements are equivalent to movements in the equilibrium of the process; medium frequency movements equivalent to business cycle induced fluctuations and high frequency movements highlight seasonal trends. By looking at *phase* and *coherence* diagrams, we can get an understanding of the correlation and lead/lag structure between two variables, at all frequencies. This could be particularly useful in studying the relationship between growth and unemployment, as we may expect the relationship to be different at different frequencies. At business cycle frequencies, we may expect *Okun's Law* to dominate the relationship between output and unemployment. At lower frequencies, we may expect: capitalization effects, creative destruction effects, loss of skills, learning by doing, savings effects and cleansing effects to play a part in the relationship between growth and unemployment. Thus the relationship at business cycle frequencies could be very different to that at lower frequencies. In chapter 3, we look at this issue by applying a variety of time and frequency domain methods to growth and unemployment evolutions.

1.2.4 Panel Data Regression analysis

A common finding in OECD studies of growth and unemployment, is the prevalence of country specific effects. This is not surprising, as institutional structures such as: employment protection, union coverage, benefit durations and labour taxes can vary a lot, even amongst a seemingly homogenous group like the OECD. As Nickell (1997) has noted though, these institutions have evolved very slowly since the 1960s. Thus we can maybe consider them as country-specific effects that have not varied much over time. Panel data analysis is ideally set up for this problem, as it allows one to explicitly control for country specific effects. In chapter 5, we utilize data from: the CEP-OECD data set, the Barro-Lee data set, the NSF(1996) and the OECD database on unemployment benefit entitlements and replacement rates, to estimate a system of growth and unemployment equations and test the interactions between growth and unemployment, controlling for institutional effects.

1.3 Structure of the Thesis

Below, I briefly summarize the structure and results of the remaining chapters.

1.3.1 Chapter 2 - Unemployment Dynamics

The European Community and the US have experienced vastly different unemployment dynamics over the last two decades. This chapter investigates whether these differences are due to exposure to different shocks, or reacting differently to the same shocks. With the premise of a search theoretic framework and a structural VAR methodology, the chapter robustly identifies aggregate versus reallocative shocks. With the exception of Spain where most of the dynamics seem to be driven by reallocation, it is found that most differences in unemployment dynamics arise because of differences in responses to shocks. In particular, the US Labour market is quicker to adjust than the European Community. This implies that EEC economies might be dynamically 'sclerotic', even if the size of the steady state labour market flows give the impression that European Labour markets are quite active. This speed of adjustment ranking though seemingly intuitive, are not reflected in simulations of a simple search model. Calibrated 'US' and 'European' economies appear to have very similar speeds of adjustment in the simulations. This difference in what the data suggests and what the simulations imply will hopefully be solved in future work.

1.3.2 Chapter 3 - Growth and Unemployment: the facts re-examined

This chapter re-examines the facts about the bivariate link between growth and unemployment. This is achieved using both *time domain* methods, i.e. granger causality tests and cross correlations; and *frequency domain* methods. Amongst other things, we find a high degree of correlation between unemployment and growth at equilibrium and low business cycle frequencies, with no noticeable shift in the relationship as one progresses from equilibrium frequencies to business cycle frequencies. Further, granger causality tests suggest that we cannot rule out unemployment and growth feeding back into each other.

1.3.3 Chapter 4 - Models of the Growth/Unemployment Dynamic

In this chapter, we review various classes of models which can result in interactions between growth and unemployment, namely: search models, overlapping generations models, optimizing Ramsey models, efficiency wage models and educational models. We then evaluate the models in light of the bivariate evidence documented in the previous chapter. This suggests that at longer horizons, the relationship between growth and unemployment is dominated by growth affecting unemployment rather than vice versa. This is because growth is highly stationary with low levels of persistence, whereas unemployment is a highly persistent process. Further, cross correlations suggest that capitalization effects are more important than creative destruction effects. At medium run horizons, a cleansing type effect seems to be very pervasive.

1.3.4 Chapter 5 - A Multi-Variate Evaluation of the Growth/Unemployment Dynamic

In the final chapter, we take account of institutions explicitly and estimate unemployment and growth equations using panel data. Considerations in previous chapters suggested growth and unemployment feedback into each other. This could lead to the problem of *simultaneity bias* in the regression estimates. We solve this problem by estimating the unemployment and growth equations as a *system*. We also look at the relationship between growth and

R&D and growth and job flows. We discover that the interactions between growth and unemployment are weak. Further analysis of R&D and job flows evidence suggests that R&D models of growth and creative destruction mechanisms may be important in countries on the technological frontier, such as the US, but not so prevalent in other OECD countries. Also, results from estimating the growth and unemployment system, suggest that changes in the investment share do not have significant effects on growth. This is consistent with Jones's (1995a) criticism of endogenous models of growth based on physical capital accumulation.

1.4 Overall Conclusions

Overall, the evidence from this thesis is suggestive of the following:

- Most differences in unemployment dynamics arise because of differences in responses to shocks not exposure to different shocks. Further, EEC economies might be dynamically 'sclerotic' when compared to the US, though simulations do not confirm this latter result.
- The interactions between growth and unemployment are weak. Only the effect of growth on unemployment is ever significant and then only in one specification. If this specification is the true one, the effect is negative, suggesting capitalization dominates creative destruction, but not very high, a 1% increase in steady state growth only reduce equilibrium unemployment by 1%.
- The links between growth and R&D and growth and job flows, suggest that only for the US, the technological leader, are R&D and creative destruction important factors in economic growth.
- The finding that investment is not significant in determining steady state growth, is consistent with Jones's (1995a) criticism of endogenous models of growth based on physical capital accumulation. In fact, this thesis suggests that neither physical capital accumulation nor R&D have been the main factors in determining steady state growth, for most of the OECD, post WWII.

Chapter 2

Unemployment Dynamics across OECD Countries

2.1 Introduction

Over the last two decades unemployment has increased dramatically within the European Community (EC). It started at less than 3% of the workforce before the first oil price shock, peaked at 11% in 1985 and is now around 10%. This phenomenon has not been replicated in the US. The US has also experienced a rise in unemployment over some of this period, but nowhere near as marked as that for the EC. Many theories have been produced to explain the differences, in the time path of unemployment, between the two sides of the Atlantic. These huge differences in the dynamics of unemployment, however, remain a major puzzle for macroeconomists (see Bean 1994). "Many suspects have been identified, none has been convicted" (Blanchard and Katz 1996).

Standard macroeconomic theory represents the equilibrium dynamics, of an economic variable, as the joint outcome of exogenous structural shocks and a transmission mechanism that allows for these shocks to propagate in the economic system. Equilibrium unemployment has taken a very different time path in the European Community as compared to the US. This paper tests whether these differences are due to *exposure* to different shocks, or *reacting* differently to the same shocks or a combination of the two.

The structural VAR (SVAR) methodology, pioneered, among others, by Bernanke (1986) and Blanchard and Quah (1989), seems well suited to the above question. In fact, if a structural VAR (SVAR) is estimated, the impulse response functions represent how shocks propagate in the economic system, while the variance decompositions weight the contribution of each shock in the forecast error of the relevant variables. For the exercise to be meaningful, however, the shocks must have a robust economic interpretation: that is the call for a strong theoretical framework. We choose a search theoretic one (see Pissarides 1990) and we use flow data, from and into unemployment (see Burda and Wyplosz 1994), to identify aggregate versus reallocative shocks. An aggregate shock affects the average profitability of jobs: a positive shock will increase the profitability of jobs and thus increase the incentive to create new ones. At the same time, the shock reduces the incentive to destroy the old ones, so that inflows into and outflows from the unemployment pool, tend to move in opposite directions. A reallocative shock on the other hand, affects the dispersion of productivities across jobs. For example, a positive reallocative shock will increase, for a given average productivity, productivity in some firms and will reduce it in others. More jobs will be created in high productivity sectors. At the same time, more jobs will be destroyed in low productivity ones, so that the unemployment flows tend to move in the same direction. We start from a two variable SVAR specification and then augment it by introducing additional labour force shocks, identified as skill unbiased and skill biased shocks. We think of the former as a shock that, in the long run, is neutral on the level of the unemployment rate and of the latter as a shock that, for given size of the labour force, affects unemployment flows in the same way as a reallocative shock.

A related exercise was carried out by Blanchard and Diamond (1989, 1990). They estimated a three variable SVAR with unemployment, vacancies and the labour force. Their experiment was carried out for the US only. They found that, except at long durations, reallocative and labour force shocks contributed little to the fluctuations in the unemployment or vacancy rate. This paper differs in three respects. Firstly we make use of flow as well as stock data. In fact, Hosios (1991), Mortensen and Pissarides (1994) and Caballero and Hammour (1994) argue for the need to look at labour market flows, to properly identify reallocative versus aggregate shocks. Once the job destruction rate is endogenized, it is no longer possible to properly identify these shocks by looking at movements in unemployment and vacancies alone (see Hosios 1991). Secondly, the analysis is cross-country. We estimate SVARS for: the US, the UK, Germany, France and Spain for the period 1972-1990, so that the main purpose of the paper is to compare across countries. We also extensively check for robustness using different structural restrictions, and different variables in our VAR specification. Finally, we perform simulations of a simple search model as a final check of the interpretation of the results.

The main results of the paper can be summarized as follows:

- European economies seem to respond slower to shocks than the US. This implies that EEC economies might be dynamically "sclerotic", even if the size of the steady state labour market flows might give the impression of the European labour market being quite active (see Burda and Wyplosz 1994, OECD, 1994a, 1994b, Garibaldi et al., 1996, Alogoskoufis et al. 1995 and Bertola and Rogerson 1996). This result is not confirmed in the simulations of calibrated 'US' and 'European' economies which is very surprising and we hope to investigate further in future work.

- Different economies seem to be subject to the same structural shocks, mainly aggregate ones. Spain is the only exception, where reallocative shocks predominate. This difference may be due to the reallocation of workers, from the agriculture to the manufacturing sector, after the Franco's reign, in Spain (see Marimon and Zilibotti (1996) and Dolado and Jimeno (1997)). The simulations suggest that the results from the

VAR based on a normalization in rates, are more reliable than results based on data normalized by the labour force. The results though hold for both specifications.

- Shocks that are identified to affect all skill levels equally and not to have a long run impact on unemployment, do not appear to have had much influence for any of the countries considered.

- For all countries in the sample, the reallocative component can be split into a labour side skill biased component and a firm side reallocative component. This implies that skill biased technological progress (see Katz and Murphy 1992 and Juhn et al. 1993) might explain some of the unemployment problems of OECD economies.

Section II introduces aggregate and reallocative shocks in a search theoretic framework, and section III summarizes the SVAR methodology. Section IV documents the data. Section V reports the results for the two variable SVAR under different specifications. Section VI extends the analysis, by introducing labour force shocks into the model and considering both a three and four variable SVAR . Section VII simulates a search model and compares the results to those from the SVAR. Section VIII summarizes the results and considers the implications.

2.2 A Search Theoretic Framework

In this section we sketch a model of the labour market with search frictions. We use the model to derive the implications of aggregate and reallocative shocks for the dynamics of labour market flows. The analysis draws on Pissarides (1990) and Mortensen and Pissarides (1994).

2.2.1 The theoretical Set-up

The labor market consists of firms and workers. We assume they are both risk-neutral and maximize expected returns in output units, discounted at rate $r > 0$. Each firm has one job that can be in one of two states: filled and producing or vacant and searching. Jobs that are not actively producing or searching for a match, are destroyed. Similarly, workers can be either unemployed and searching, or employed and producing. As in Jovanovic (1979, 1984), we keep the simplifying assumption of equating wages to the reservation utility of workers, or that firms can extract all the surplus from a match. This implies, as in Jovanovic, that if h is the common alternative value of a worker's time, that his wage w once employed will also be equal to h[1].

Each job is characterized by a fixed irreversible technology and produces a quantity of goods equal to $P + \sigma\iota$. P and σ are common to all jobs. ι is job specific and represents an idiosyncratic component of productivity. P is the aggregate component of productivity that does not affect the dispersion of productivity. A change in P affects, in a similar way, the profitability of *all* jobs and it is thus called an *aggregate shock*. The parameter σ reflects dispersion, with an increase in σ representing a symmetric mean preserving spread in the job-specific shock distribution, or equivalently an increase in the cross sectional variance of the productivity of jobs. A change in σ is a *reallocative shock*. For example, an increase in σ corresponds to a positive reallocative shock: productivity in some firms rises while it falls in others.

The process that changes the idiosyncratic component of productivity is assumed to be a Poisson process, with rate of arrival μ. When there is a change, the new value of ι is a drawing from the fixed distribution $G(\cdot)$, which has finite upper support $\bar{\iota}$, no mass points, zero mean and unit variance. σ is therefore the standard deviation of the idiosyncratic component

[1] In the search literature wages are usually chosen so as to share at all times the surplus from a job match in fixed proportion, usually via a Nash bargain, see for example Pissarides (1990). We do not pursue this line of research here to save on notation and space. The identifying assumption of aggregate versus reallocative shocks does not depend on this simplifying assumption.

of productivity $\sigma\iota$.

As in Mortensen and Pissarides (1994), firms create jobs that have productivity equal to the upper support of the distribution of productivities $P + \sigma\bar{\iota}$. Once a job is created, however, the firm has no choice over its productivity. Thus job productivity is a stochastic process, with the initial condition being the upper support of the distribution and the terminal state being the reservation productivity R that leads to job destruction. In fact, existing filled jobs are destroyed only if idiosyncratic component of their productivity falls below some critical number $R < \bar{\iota}$. Therefore, the rate at which existing jobs are destroyed is $\mu G(R)$.

As workers are heterogeneous and firms post vacancies to operate specific jobs, matching a worker with a vacancy is costly and requires time. Because of this, the model is usually closed through a useful tool: the matching function[2], that is a stable, concave, homogenous-of-degree-one aggregate relation, $H = m(U, V)$, linking the unemployment pool U and the stock of vacancies, V, with the number of new hirings H. The matching function allows one to represent two key characteristics of the labour market: the fact that workers and firms are heterogeneous so that search is costly and time consuming; and the fact that different firms might compete for the same workers. The transition rate for vacancies is $q(\theta) = \frac{m(U,V)}{V} = m(\frac{U}{V}, 1) = m(\frac{1}{\theta}, 1)$, where $\theta = \frac{V}{U}$, while the rate at which unemployed seekers meet vacancies is $\alpha(\theta) = \frac{m(U,V)}{U} = m(1, \theta)$.

2.2.2 The Formal Model

The assumption that vacancies cost χ per unit of time and that jobs are created at the upper support of the distribution of the productivity distribution,

[2]See Jackman, Layard and Pissarides (1986), Pissarides (1986), Blanchard and Diamond (1989,1990) and Burda and Wyplosz (1994) for empirical evidence on the existence of stable aggregate matching functions. Caballero and Hammour (1990, 1996) show how a matching function is not required to close the model, as a search theoretic framework just asks for some mechanism that makes it progressively less profitable to post vacancies at a given level of unemployment. In their set up, creation costs provide this.

imply that

$$rV = -\chi + q(\theta)\left[J(\bar{\iota}) - V\right]$$

where V and $J(\iota)$ are respectively the asset values of a vacancy and of a filled job with idiosyncratic component ι. As in Pissarides (1990) and Burda and Wyplosz (1994), jobs are created until all rents are exhausted. This implies the value of posting a vacancy must reach zero, so that the following *free entry condition* holds:

$$\frac{\chi}{q(\theta)} = J(\bar{\iota}) \tag{FE}$$

Since firms have the option of closing jobs at no cost, a filled job continues in operation for as long as it is profitable. Hence, filled jobs are destroyed when a productivity shock y arrives that makes $J(y)$ negative. Given the Jovanovic assumption that workers are paid their marginal product h, for any realization ι, $J(\iota)$ solves the Belman equation

$$(r+\mu)\,J(\iota) = P + \sigma\iota - h + \mu\int_{-\infty}^{\bar{\iota}} \max\left[J(y),0\right]\,dG\left(y\right). \tag{2.1}$$

Since $J(\iota)$ is monotonically increasing in ι, there is a unique reservation productivity R that solves $J(R) = 0$ such that jobs that get a shock $\iota < R$, are destroyed. The condition $J(R) = 0$ and the fact that $J'(y) = \frac{\sigma}{r+\mu}$, implies, after integration by parts, that R solves

$$P + \sigma R = h - \frac{\sigma\mu}{r+\mu}\int_{R}^{\bar{\iota}} \left[1 - G\left(y\right)\right]\,dy \tag{DE}$$

so that $\forall\iota > R$

$$J(\iota) = \sigma\frac{(\iota - R)}{\mu + r} \tag{2.2}$$

while $J(\iota) = 0$ if $\iota \leq R$. Equation (FE) together with (DE) given the constraint imposed by either (2.1) or (2.2) completely solves the model in the two endogenous variables, θ and R. Given equation (FE), θ reflects *market profitability*: the higher the profitability of a job, the bigger the incentive to enter the market and the higher is θ. R is a reservation productivity and reflects the option of firms to keep operating: the bigger the value of the option, the lower the value of R.

Let us indicate, respectively, with E_t and U_t, the number of employed and unemployed workers. We then obtain that the inflow into unemployment, *in*, and the outflow from unemployment, *out*, are equal to

$$\begin{aligned} in &= \mu G(R) E_t && (2.3) \\ out &= p(\theta) U_t. && (2.4) \end{aligned}$$

$\mu G(R)$ is the inflow rate into unemployment. It is increasing in R: the higher the reservation productivity R, the bigger the fraction of firms that are destroyed. $P(\theta)$ is the outflow rate from unemployment. It is increasing in θ: the bigger the value of θ, the higher the probability of exiting from the unemployment pool.

In this framework, it is possible to think of shocks affecting either firms or the labour force. In this section we focus on shocks of the first kind, while we analyze shocks of the second kind in section 2.6.

An aggregate shock affects in a similar way the profitability of all jobs, both the operating and non operating ones. This is equivalent to a change in P. Differentiating (FE) and (DE) with respect to P, it can be seen that

$$\begin{aligned} \frac{dR}{dP} &= -\frac{\sigma^{-1}}{1-\frac{\mu}{r+\mu}\left[1-G(R)\right]} < 0 \\ \frac{d\theta}{dP} &= \frac{[q(\theta)]^2}{q'(\theta)\chi(\mu+r)}\frac{dR}{dP} > 0 \end{aligned}$$

as it follows from the fact that $q'(\theta) < 0$. As a result, a positive aggregate shock that increases the profitability of jobs, increases the incentive to create new ones and thus $p(\theta)$ rises. At the same time, the shock reduces the incentive to destroy the old ones , thus $\mu G(R)$ falls. This implies that, for given dynamics of the labour force, inflows into the unemployment pool would fall, while outflows would rise.

A positive reallocative shock will increase, for a given average productivity, productivity in some firms and will reduce it in others. Intuitively, a positive reallocative shock increases the cross sectional variance of the productivity of jobs and it is equivalent to an increase in σ. Differentiating (2.1) with respect to σ, we obtain

$$\begin{aligned}\frac{dJ(\iota)}{d\sigma} &= \frac{\iota}{r+\mu}+\mu\int_R^{\bar{\iota}}\frac{dJ(y)}{d\sigma}\,dG(y)\\ &= \frac{\iota}{r+\mu}+\frac{\mu}{(r+\mu)\left[r+\mu G(R)\right]}\int_R^{\bar{\iota}}y\,dG(y)\end{aligned}$$

that is positive for any ι greater than zero as $\int_{-\infty}^{\bar{\iota}}y\,dG(y)=0$ by assumption. Therefore, equations (FE) and (DE) imply that

$$\begin{aligned}\frac{dR}{d\sigma} &= \frac{(P-h)\,\sigma^{-2}}{1-\frac{\mu}{r+\mu}\left[1-G(R)\right]}>0\\ \frac{d\theta}{d\sigma} &= -\frac{\left[q(\theta)\right]^2}{q'(\theta)\chi}\frac{dJ(\bar{\iota})}{d\sigma}>0\end{aligned}$$

In other words, an increase in σ leads to an increase in θ which will have a positive affect on $p(\theta)$. More jobs will be created in the high productivity sectors. At the same time more jobs will be destroyed in the low productivity ones, as R increases and thus $\mu G(R)$ rises. Inflows into and outflows from the unemployment pool will simultaneously rise so that, ceteris paribus, worker flows should move in the same direction[3]. We use this result to identify an aggregate versus a reallocative shock in the context of structural VAR methodology.

One final point worth mentioning, is the distinction between worker, job and unemployment flows. In the model analyzed above, they coincide exactly. This is not the case in the real world and we talk more about the empirical implications of this in section 2.4. Theoretically though, it is also important to draw a distinction between the various flows. Mortensen (1994)

[3]It should also be noted that the result does not depend on the assumption that jobs are created at the upper support of the distribution of productivities. In fact the value of a job $J(\iota)$ at any idiosyncratic productivity $\iota > 0$ increases: a firm always has the option to stop losses when things go wrong. That is why an an increase in idiosyncratic volatility σ generally raises the value of a job and increases θ.

and Pissarides (1994) model on-the-job search with this in mind. More explicitly, Burda and Wyplosz (1994) model the distinction between a job and a worker-firm match. It seems that our identifying restrictions would extend to their set-up as well, once the destruction margin is modelled in the same way as in this section: on impact an aggregate (reallocative) shock will tend to move unemployment flows in opposite (same) directions[4].

2.3 The Structural VAR Methodology

Let Y_t, ϵ_t be two vectors containing, respectively, the observed values of our variables, assumed to be covariance stationary, and the structural disturbances.

From the assumption that Y_t is a stationary process, it follows that there exists a Wold Decomposition with white noise disturbances η_t such that $Y_t = C(L)\eta_t$, where $E(\eta_t \eta_t') = \Omega$ If, moreover, we assume that the relationship between the structural disturbances ϵ_t and the observed outcomes Y_t has a linear moving average (MA) representation, it follows that

$$Y_t = C(L)\eta_t = B(L)\epsilon_t, \; B(0) = B_0, \tag{2.5}$$

where $B(L)$ is a (potentially) infinite order matrix polynomial in the lag operator L, describing the dynamic effects, on Y_t, of the structural disturbances ϵ_t. From equation (2.5), it follows that $\eta_t = B_0\epsilon_t$ and $B_i = C_i B_0$, where B_i, C_i are, respectively, the matrix coefficients associated with the terms of order i in the polynomials $B(L)$, $C(L)$.

In the analysis, we assume that the structural disturbances are uncorrelated white noise errors of unit variance. Though this is standard in the VAR

[4]This is not the same thing as saying that in response to an aggregate shock, unemployment flows must move in opposite directions over the adjustment path. In fact, Burda and Wyplosz (1994) show that a sufficiently big adverse aggregate shock raises the unemployment stock and makes unemployment flows move together over the adjustment path. Still, on impact, an adverse aggregate shock raises unemployment (the destruction margin rises), while the outflow rate falls.

literature, it is not a trivial assumption and requires some justification. A simple justification often invoked in the SVAR literature (see Blanchard and Quah 1989), is that the structural shocks, by their very nature, are fundamental shocks without a common cause and should therefore be treated as orthogonal. It certainly seems possible though, that many shocks that have impacted on the world economy in the post war period, have both aggregate and reallocative components. For example, the oil price shocks of 1972 and 1979. If this is the case, the assumption of orthogonality is still tenable with shocks having both aggregate and reallocative components, provided the reallocative component depends on the *magnitude* of the aggregate shock and not its *direction*, i.e. not whether it is a positive or negative aggregate shock[5]. Over a long enough time period, the fundamental shocks should include a random mix of positive and negative aggregate shocks. Thus the correlation between aggregate and reallocative shocks should be zero, or close enough to zero.

This is equivalent to noting that even if the aggregate $\tilde{P}_t$ and reallocative $\tilde{\Sigma}_t$ shocks are not stochastically independent, they might still be uncorrelated. For example, suppose that the aggregate shock $\tilde{P}_t$ is symmetric and that the absolute size of $\tilde{\Sigma}_t$ and $\tilde{P}_t$ are related as follows:

$$E\left(\tilde{\Sigma}_t \mid \tilde{P}_t\right) = b\left(\tilde{P}_t^2 - \sigma\right)$$

where $b > 0$ and $\sigma = E\left(\tilde{\Sigma}_t^2\right)$. In other words the reallocative component is related to size of the aggregate component and not its direction. Then:

$$E\left(\tilde{\Sigma}_t \tilde{P}_t\right) = 0$$

so that $\tilde{\Sigma}_t$ and $\tilde{P}_t$ are uncorrelated even if not stochastically independent. If so, the orthogonality assumption is still a reasonable one. We still have

[5]It should be noted that Caballero and Hammour (1994) argue that the direction could matter, to the extent that there is usually more reallocation in a recession than in a boom, due to cleansing type effects. One could argue though that this not a reflection of the asymmetry of reallocative shocks, but more of an asymmetry in the reaction to the shock. In other words, that the perceived costs of adjusting to the shock could be lower in a recession.

to be careful about this interpretation of aggregate and reallocative shocks and its relation to those described in the search framework earlier. In the search framework, the reallocative shock was purely a shock to the dispersion of the idiosyncratic component of productivity and did not depend on the aggregate shock at all. Above we are arguing for a reallocative shock made up of two components:

$$\epsilon_{re} = \phi(\mathrm{mod}(\epsilon_{ag}) + \epsilon_1$$

In other words, a component which depends on the size of the aggregate shock and one which does not. Now provided ϵ_{re} and ϵ_{ag} are uncorrelated, then the identification restrictions discussed below will allow us to derive impulse responses and variance decompositions for reactions to ϵ_{re} and ϵ_{ag}. But in terms of the reallocative shock, we may be more interested in ϵ_1, as the other part of the reallocative shock is caused by the aggregate shock and thus in some way is less of a fundamental shock. Thus it may be the case that the variance decompositions put too much weight on fundamental reallocative shocks, by including the component which depends on the magnitude of the aggregate shock. We could still argue that looking at the impact of the total reallocative component is interesting. As though part of it may be fundamentally caused by an aggregate shock, it is the transmission of this shock via reallocation which is causing the effect on unemployment. So provided we are aware that under this interpretation, the variance decompositions are assigning which shocks *explain* unemployment rather than which shocks are the *initial impulse* to unemployment, the variance decompositions are meaningful.

Again, we can provide a different decomposition of aggregate and reallocative shocks that gets over this problem. In the real world we can think of shocks as always being a combination of aggregate and reallocative shocks, oil price shocks in the 70s being examples with a big component of both types of shock. But just because these shocks happen at the same time does not mean that they are correlated. Different shocks will have a different mix of aggregate and reallocative components. In fact we can think of a shock as a random drawing from the distribution of aggregate shocks and a random drawing from the distribution of reallocative shocks, with both shocks being independent of each other. This is a meaningful decomposition as though the shocks may happen at the same time, they have very different dynamics on job flows and very different policy implications. Under this decomposition the shocks are independent and there will be a direct correspondence from the shocks discussed under a search framework, to the shocks identified in an SVAR. Though if we believe that reallocation is *caused* by aggregate shocks, it is quite difficult to sustain that the shocks are independent of each other and therefore accept this decomposition.

The point of the above discussion, is just to highlight the fact that the orthogonality of shocks is not an innocuous assumption and depending how we decompose shocks to be consistent with this, will affect how we interpret the resulting variance decompositions from the SVAR analysis.

From this, it follows that:

$$B_0 B_0' = E(\eta_t \eta_t') = \Omega. \tag{2.6}$$

The dynamics of the coefficient B_i represent the speed of adjustment to a given a shock. The greater the speed, the faster they decay. The contribution of a shock to the underlying dynamics of a variable, is given by the contribution of the shock to the variance of the forecasting error of the variable at different leads (forecasting variance decomposition). In what follows we draw on the theoretical structure, introduced in the previous section, to estimate an SVAR as in equation (2.5). We consider different restrictions and different vectors of variables Y_t, to identify the matrix B_0 through equation (2.6) and check for robustness of the results.

2.4 Data Description

The French data came from the Ministère du Travail, the German data from the Bundesanstalt fur Arbeit, the Spanish data from the Bank of Spain, the

UK data from the Employment Gazette and the US data from the Employment and Earnings survey.

The UK, German and French unemployment flow data are registry or claimant count based, whereas the Spanish and US data are labour force survey based. All data has been seasonally adjusted. One caution should be mentioned. The vacancy data also is often not as comprehensive as one would like. For example, the US series is based on the help-want index of advertised vacancies and the UK series is of job centre reported vacancies. Both series may only capture up to a third of the total vacancy stock.

The data is on: inflows to, I_t , and outflows from, O_t, unemployment; vacancies V_t; and the labour force, L_t, and is quarterly for the period 1972:3 -1989:4 for France, Germany and Spain, but extended to 1997:4 for the US and the UK. A balanced sample was chosen as far as possible as some of the tests, for example comparing the impulse responses of the European countries relative to the US, can only be meaningful if performed over a balanced sample. Considering the data for the US and UK could be updated much further, we decided it was worth doing so for these two countries.

Various integration and cointegration tests were performed. All variables were found to be $I(1)$, with inflows and outflows, standardized by the labour force, cointegrated with a cointegrating vector of approximately $(1,-1)$[6]. This is unsurprising, given that flows into and out of unemployment are large relative to the stock of unemployment. Thus any sharp movements in *netflows* should cause a sharp movement in the stock of unemployment. A perfunctory look at unemployment data for most countries, quickly shows that this rarely occurs. Also intuitively, an increase in inflows causes a rise in unemployment. Given the matching function, and ceteris paribus, this should lead to an increase in matchings or outflows. See figure 2.5 for graphs of inflows and outflows normalized by L_t.

[6]The flows to and from unemployment are likely to be measured with significant error. The strong cointegrating relationship between them could be partly due to this, though it is likely that the fact that unemployment is slow moving is far more important in explaining it.

One final point on the data should be made. In the model we analyzed in section 2.2, unemployment, job and worker flows coincided exactly. This is not the case in reality. The flows we have are inflows to and outflows from unemployment. These are not the same as job destruction and job creation rates. Inflows are made up of job destruction, quits into unemployment and new entrants to the labour force. Outflows are made up of job creation and exits from unemployment to out of the labour force. It is then a reasonable question to ask if the identification of aggregate and reallocative shocks in our model, extend to a theoretical set-up where these distinctions are explicitly taken into account. There are good reasons to believe that it does. Burda and Wyplosz (1994) detail how, for Europe at least, job separations are much larger than the flow of new entrants to the labour force: the majority of workers who leave unemployment do so because they have found a job. Moreover, they highlight that quits into unemployment represent a minor component of total unemployment inflow. Further, they show that exits from unemployment to employment, in European data, are numerically larger than exits from the labour force. For example in Germany, 60-70% of outflows are attributable to new employment. For the US the picture is not so rosy. Clark and Summers (1979) attribute up to half the unemployment flows in the US to entry and exit from the labour force. However, for given dynamics of the labour force, on impact a reallocative (aggregate) shock will tend to move unemployment flows in the same (opposite) directions. Moreover, we also introduce additional labour force shocks, in section 2.6, to correct for possible discrepancies in the dynamics of jobs versus worker flows. As it will be seen later, the robustness of the main broad results suggest that the main conclusions would have been no different if we had explicitly considered the distinction between unemployment, job and worker flows.

2.5 Estimating Aggregate and Reallocative Shocks

The considerations in section 2.2 suggest a very strong theoretical restriction. In response to an aggregate shock, flows into and out of the unemployment pool should move in the opposite direction; while in response to a reallocative shock, they should move in the same direction. If we write the contemporaneous effects matrix as:

$$B_0 = \begin{bmatrix} \sigma_1 & \sigma_2 b_{12} \\ \sigma_1 b_{21} & \sigma_2 \end{bmatrix},$$

equation (2.6) imposes that the coefficient b_{12} and b_{21} must satisfy the following relation

$$b_{12} = \frac{\Omega_{12} - \Omega_{11} b_{21}}{\Omega_{22} - \Omega_{12} b_{21}}, \tag{2.7}$$

while the two coefficient σ_1, σ_2 are also defined as function of b_{12} and b_{21} only.

In what follows, we consider different restrictions on the parameters b_{12} and b_{21} such that (2.7) holds and the two coefficients are of opposite signs. b_{12} and b_{21} having opposite sign is a direct implication of our identification scheme for aggregate and reallocative shocks. We look at different combinations of b_{12} and b_{21} as a check of the robustness of our results to slight perturbations.

As the objective of the paper is to compare across countries, we would like the variable to be scale free. (2.3) and (2.4) suggest two possible standardizations to analyze the flows: one in terms of the labour force, the other in terms of rates. Therefore, and as an additional check of robustness, we consider two different two variable SVAR specifications:

- In order to keep track of the dynamics of the unemployment rate, we consider a specification with outflows over labour force, $\frac{O_t}{L_t}$, and inflows over labour force, $\frac{I_t}{L_t}$. The variables seem to be integrated of order one and cointegrated with cointegrating parameter equal to (1,-1) (see the consideration of the previous section and figure 2.5 to illustrate the cointegration relationship). Since Y_t must be covariance stationary, we consider

$$Y_t = \begin{bmatrix} \Delta \frac{I_t}{L_t} \\ \frac{O_t}{L_t} - \frac{I_t}{L_t} \end{bmatrix},$$

where Δ indicates the first difference operator and $\frac{O_t}{L_t} - \frac{I_t}{L_t}$ measures net flows, nf_t. Moreover we recover as a proxy of the impact on the unemployment rate at time t, the sum of the impact on $\frac{I_t}{L_t} - \frac{O_t}{L_t}$.

- Our second specification uses the outflow rate,$\frac{O_t}{U_t}$, and the inflow rate, $\frac{I_t}{E_t}$ (inflows over employment,E_t). The two variables seem to be integrated of order one and not cointegrated. Therefore, we also consider as an alternative

  $$Y_t = \begin{bmatrix} \Delta \frac{I_t}{E_t} \\ \Delta \frac{O_t}{U_t} \end{bmatrix}.$$

  As the dynamics of the unemployment rate, u_t, are approximately given by $\Delta u_t = \frac{I_t}{E_t}(1 - u_t) - \frac{O_t}{U_t} u_t$, we also consider a measure of the forecasting variance decomposition for the changes of the unemployment rate, given by the average between the ones of inflow and outflow rate with weight equal to $(1 - u_t)$ and u_t respectively[7].

2.5.1 Identification

In the 2 variable SVAR, only one identification restriction is required to exactly identify the matrix B_0 in equation (2.5). In the first specification outlined above, we consider

$$Y_t = \begin{bmatrix} \Delta \frac{I_t}{L_t} \\ \frac{O_t}{L_t} - \frac{I_t}{L_t} \end{bmatrix},$$

[7] In tables 2.4-2.11 the results are obtained posing a standardizing value of $u_t = 0.07$. This value represents the approximate average of the unemployment rate of the countries considered for the sample chosen. We tried different values, choosing the average unemployment rate for each country, not across the whole sample, but found the results were virtually identical, as the weights u_t and $1 - u_t$ do not vary much.

where $\frac{O_t}{L_t} - \frac{I_t}{L_t}$ measures net flows nf_t. An aggregate shock will cause $\Delta\frac{I_t}{L_t}$ and nf_t to move in the opposite direction, whereas a reallocative shock will cause them to move in the same direction. The logic is the one outlined in section 2.2. Consider a positive reallocative shock that increases the productivities in some sectors and reduces it in others (an increase in the variance of the productivities of jobs σ). This will cause the inflow into unemployment to rise ($\Delta\frac{I_t}{L_t}$ is positive) because of the contribution of declining sectors. Outflows will also rise, both because of the underlying trend linking the unemployment flows (cointegration) and because of the contribution of the expanding sectors. This causes outflows to increase more than what it would have done in the absence of the shock, i.e. nf_t is positive. Thus $\Delta\frac{I_t}{L_t}$ and nf_t move in the same direction. An analogous argument can be applied to aggregate shocks.

We identify the SVAR by choosing combinations of b_{12} and b_{21} such that (2.7) holds and the coefficients have opposite sign. Thus we impose *impact* restrictions on the SVAR. We report the results for $b_{21} = 1, 30$ and 60 to cover the range of values for which the coefficients have opposite sign (see figure 2.6 for the $b_{12,}$ b_{21} locii, for all the countries, with the normalization by the labour force).

For the second normalization, a similar procedure is carried out, we simply identify an aggregate shock as one which causes $\Delta\frac{I_t}{E_t}$ and $\Delta\frac{O_t}{U_t}$ to move in opposite direction on impact and a reallocative shock to move them in the same direction on impact. We follow the same procedure for choosing b_{12} and b_{21} as above.

2.5.2 Results

The appendix gives the recursive chow tests, variance covariance decompositions, the impulse response functions and the speed of adjustment rankings for the two different two variables VAR specifications[8]. The results are re-

[8] All the VARs in the paper were estimated with two lags. Standard Durbin Watson tests performed well. We also carried out some maximum likelihood tests against specifi-

ported during the sample period 1972:3-1989:4 for France, Germany and Spain and updated until 1997:4 for the UK and US. In an earlier version of this chapter, all results were reported for the sample period 1972:3-1989:4. Only the updated results are reported here for the US and UK, though I will discuss the few differences there were between the initial sample results and the updated results, in the main text below, for these two countries.

The updated sample size allows us to test for structural change in the UK economy. It has been often argued that the UK labour market has evolved over the 1980s and 1990s due to the reforms implemented under Mrs. Thatcher. Many believe that the UK switched onto a more dynamic adjustment path, due to these reforms, during the 1990s and that the shock which was the impulse, was the UK leaving the ERM in the final quarter of 1992. We test this hypothesis by performing structural stability tests around this time. We perform recursive Chow tests for a structural break from 1990:1 to 1993:2 (a couple of quarters after the ERM exit). We do the same test for the US, to make sure that any structural break is unique to the UK during this period and could not be explained by some common factor affecting many countries.

The results for both specifications are reported in **Figures 2.1-2.8.** The graphs plot the value of the F statistic of the chow test, for a particular point in time, normalized by the value of 1% significance. Thus any point value below one can be interpreted as not rejecting the null hypothesis of no structural break. A 1% significance level is chosen as opposed to a 5% level, due to considerations discussed in Hendry (1996) of multiple testing when the tests overlap. By performing Chow tests recursively, we are increasing the chance of finding some structural break and thus we must alter

cations with longer lags. Our specification beat the one with three lags, while the results were mixed for lags longer than four. In these cases, however, the VARs seemed to be overparametrized as the impulse responses looked unstable. We therefore relied on the principle of parsimony by choosing the specification with the smaller number of lags. We also looked at subsample stability tests, within a country, looking at the AR estimates of each equation separately. In general, the null hypothesis that no structural break had taken place before and after the 80's was not rejected.

the significance levels for the individual chow tests to adjust for this. We are performing chow tests recursively over 10 quarters, for which the Bonferroni bound for Type 1 errors with an individual significance level of 5% would be 40%. Thus to keep the overall possibility of Type 1 errors down, Hendry suggests using an individual significance level of 1% or lower. Referring to figures 2.1-2.8, it is very clear that there is no evidence of any structural change for the US economy, from either specification. At face value, the same result seems to hold for the UK. But looking a bit closer, the inflow equation for both specifications is close to the rejection level during the early 90s for the UK, but nowhere near the rejection level for the US. This may be consistent with the hypothesis that the UK has evolved, but has not changed fundamentally enough to put itself onto a new adjustment path. Certainly, there does not seem to be strong case for a new adjustment path after the UK left the ERM. Overall it is difficult to reject the null of no structural change in the UK economy. This is consistent with the fact that the results below have not changed much once we updated the sample for the US and UK.

Table 2.3 documents the impact effects, standard deviations and the long run impacts of the shocks, using the standardization by the labour force. With the exception of Spain, it can be seen that in general the long run impact of a shock, of unit standard deviation, is higher for aggregate shocks than for reallocative shocks[9]. This is consistent with the Variance Decomposition evidence (discussed later), that shows that aggregate shocks dominate, at least at long lags, with the exception being Spain. Also the impact effects, of a unit standard deviation shock, are very similar for France and Germany. Spain shows higher impact effects for both shocks. Finally, it is worth noting that the size of the reallocative shocks (σ_1) are much larger in Spain than in other countries.

Table 2.4 documents the dynamic speed of adjustment to the shocks.

[9]Though for the UK, with $b_{21} = 60$ the opposite is true, but only just. This is different from results for the initial sample where aggregate shocks were larger for all values of b_{21}, for the UK.

The entries show the values of the norm of the ranked eigenvalues of the VAR(1) representation of the VAR, for different specifications. In the long run, the dynamics of the system are dominated by the eigenvalue with the greatest norm. Thus, we consider this the appropriate measure to capture the long run speed of adjustment of the system[10]. As clearly illustrated, the US is quickest. The ranking over France, Germany, the UK and Spain, though, depends on which normalization we use. If standardized by the labour force, Germany is next, followed by France, Spain with the UK last. If we use the specification in terms of rates, the UK, Germany and Spain are quicker than France.

The US showing the quickest adjustment will not surprise many. It is often argued that the US has a more flexible labour market than the EC: with low welfare payments of a short duration, small firing costs and little trade union influence. Several authors have noted that steady state job flows are remarkably similar across the two sides of the Atlantic (OECD, 1994a, 1994b, Garibaldi et al., 1996, Alogoskoufis et al. 1995 and Bertola and Rogerson 1996). Burda and Wyplosz (1994) also note how worker flows are large in Europe and because of this they argue that European Labour markets are quite active. The results of this section suggest, however, that European labour markets are dynamically "sclerotic", even if steady state flows might give the impression of the European labour market being quite active.

Germany being so high in the rankings may surprise a few. This may be due to: its comprehensive apprentice system (see Lynch 1994); its alleged corporatist structure and nominal wage flexibility (see Bruno and Sachs (1985)). In comparison to France, Germany also does not have an explicit minimum wage and apprentices often work at considerably lower than market wages[11]. All theses factors, may allow a faster adjustment to shocks than is often

[10]This implies that the long run speed of adjustment of the system is independent of the the values of b_{12} and b_{21}chosen.

[11]In France, an explicit minimum wage (SMIC) binds at a high proportion of the average wage.

perceived, for Germany, given its other institutional facets like strong trade unions.

The UK may have been expected to have been second after the US in the rankings. This is certainly not the case in the normalization by the labour force and is again repeated in the three and four variable case (see next section). Our initial thoughts were that this ambiguity maybe because of the Thatcher labour market reforms in the UK causing a structural change. But the above structural stability tests suggest that this is not the case. Further the fact that the ranking has not changed for the UK in either specification once we have updated the data, suggests the specification differences are driving the ambiguity rather than any structural change.

Tables 2.5-2.9 show the variance decompositions of the (approximated) unemployment rate, for the two different specifications for each country. With the exception of Spain, it is found that aggregate shocks tend to dominate, with reallocative shocks being important on impact, but with diminishing influence over time.

For Spain, reallocative shocks dominate but more so using the labour force normalization. For France, we find that aggregate shocks dominate, but with reallocative shocks having a significant effect on impact. Even at long lags, reallocative shocks explain about 40% of the movement in unemployment for France[12]. Germany produces similar results to France, only that aggregate shocks dominate even more so. Again on impact, reallocative shocks have a significant influence on unemployment, but this drops to about 20% at long lags. For the US and UK, aggregate shocks dominate, but less so in the updated results reported here than in estimations based on earlier samples. Reallocative shocks have stronger impact effect in the results reported here. Also, for the UK under the normalization by labour force for $b_{21} = 30, 60$, aggregate and reallocative shocks have more or less equal effect, even at long

[12]It must be noted that in the normalisation in terms of rates, with $b_{21} = 60$, we get the rather spurious result that reallocative shocks dominate. We do not think this is contradicting the previous results, as the impulse responses oscillate a lot and seem very unstable for this case.

lags.

In **Tables 2.9-2.11** we formally test the underlying hypothesis that the structures of the economies, as revealed by the impulse responses, are fundamentally different in the US and Europe. We do this by looking at the impulse responses of a country *relative* to those of the US and the accompanying confidence intervals[13]. The tables are for the specification over the labour force, with results given for the different values of ${b_{21}}^{14}$. The first number in each box represents the difference in the impulse response of the unemployment rate of the country minus that of the US, calculated at different leads. The second number is equal to (one half) the size of the corresponding 95% confidence interval, calculated using a bootstrapping technique with 1000 replications[15].

Referring to Tables 2.9-2.11, it is easy to notice a well known problem with this class of tests: the standard errors are very large. Thus, the confidence intervals are correspondingly wide and it is very difficult to get statistically significant results. Nevertheless, some interesting findings do come out. The only country for which a reallocative shock is significantly different from the US, at any lead, is Spain. Further, Spain is the only country for which aggregate shocks show a significant difference at long leads. This is consistent with the view that the power of this test is very low. Thus only

[13]All results are reported on the balanced sample 1972:3-1989:4 except for the UK/US comparison, where we use the updated sample.

[14]Similar results holds for the specification in terms of rates.

[15]The standard errors in table 6 are calculated using a bootstrapping technique with 1000 replications. The underlying assumption is that the Wold innovations are not only uncorrelated over time, but also identically and independently normally distributed with variance equal to the sample variance. From this distribution, we resample a number of Wold innovations equal to the one in the original sample. For each replication, we then estimate the MA representation of the VAR and obtain the implied structural impulse responses for unemployment. The first number is equal to, the average over all replications of, the difference between the impulse response of the unemployment rate of the country minus that of the US. The second number, band ($\pm$), in table 6 is equal to (one half) the size of the interval. This represents the range over which we are 95% confident that the difference between the impulse response, of the unemployment rate of the country, minus that of the US lies.

large differences will show up as being significantly so. We noted earlier that Spain was an exception, in that reallocative shocks dominate. The evidence presented here is consistent with this finding, in that it is the only country which shows significant differences in its responses relative to the US. On the whole, aggregate shocks show more significant differences, with all countries showing significant differences up to two quarters after a shock. France ranks after Spain, in showing the most significantly different aggregate shocks. The differences are significant up to five quarters, but thereafter remain close to significance. For both reallocative and aggregate shocks, the UK and Spain have bigger *absolute* differences relative to the US.

Summary

The above analysis of the tables suggests the following. Aggregate shocks dominate across countries, the important exception being Spain. There is some variation in the importance of reallocative shocks (excluding the obvious example of Spain) across countries, with France showing them to have more influence when compared to Germany. The explanation for the predominance of reallocative shocks in Spain, could be the reallocation of workers from the agriculture to the manufacturing sector, after Franco's reign (see Marimon and Zilibotti (1996)).

Independent of the specifications, the US labour market is quicker to adjust than European economies. There is also a ranking inside European economies with Germany quicker than other continental European countries even if still slower than the US. Finally, structural stability tests find it difficult to reject the hypothesis of no structural change for the UK.

2.6 Labour Force Shocks

The two variable VAR specifications, have given us some interesting results. In order to investigate if the results are driven by the particular specifications chosen, we augment them by considering, in more detail, the labour force.

First, we show how the theoretical set-up can account for labour force shocks. These can be of two types, either affecting the size or the composition of the labour force. We then draw on these theoretical considerations to identify a *skill unbiased labour force shock,* which represents changes in the size of the labour force alone; and a *skill biased shock* that deals with the compositional change alone.

2.6.1 Theoretical Labour Force considerations

In practice, workers can be in one of three states: working in a firm, unemployed or out of the labour force. Unemployed workers can either be actively searching or stop searching and go out of the labour force. There are, in fact, vast movements in and out of the labour force which we hope to capture better by explicitly using the labour force as a variable.

The reallocative and aggregate shocks, considered previously, are shocks directly affecting the firm. To complete the model, we must consider shocks that directly affect the labour force. These can be of two types, either affecting the size or the composition of the labour force. Thus we consider two further shocks which characterize these two effects separately. The skill unbiased labour force shock represents changes in the size of the labour force alone, and the skill biased shock deals with the compositional change alone.

In the model outlined in section two, no shock had a permanent effect on the unemployment rate. This is, however, the result of the particular model specification chosen there. For example, Acemoglu (1996) shows that once the choice of technology is made endogenous and firms freely choose their optimal levels of capital, multiple equilibria can arise in the basic model. If so, change in the aggregate conditions (change in P or σ) can shift the economy from one equilibrium to the other. However, if the matching function has constant returns to scale, changes in the size of the labour force L_t, alone, represent just a change in the scale of the economy. Given the assumption that no job can exploit economies of scale, L_t can never have long run effects on the level of unemployment. In fact, there is a large body of evidence, across countries, that suggests that the unemployment rate is untrended in the long run despite huge increases in the size of the labour force. Moreover, economies with very different labour force sizes have very similar unemployment rates (see i.e. Layard, Nickell and Jackman 1991).

We therefore identify the skill unbiased labour force shock by imposing that it has no long run effect on the unemployment rate. This shock is introduced for two reasons: firstly because it allows us to evaluate if labour force influences affect unemployment dynamics in the short run; and secondly because it might correct for possible discrepancies in the dynamics of jobs versus worker flows. It gauges what is the short run contribution of structural shocks that do not exhibit permanent effects, on the level of the unemployment rate.

Even if changes in the size of the labour force do not a have long run impact on the unemployment rate, changes in the composition of the labour force might. Acemoglu (1997, 1998) shows that firms can react to changes in the composition of the labour force, by 'directing' technological change towards specific skills. More specifically, when the composition of the labour force changes, the nature of the equilibrium might change, with firms starting to create separate jobs for the skilled and unskilled.

To consider the effects of a skill biased technological shock, we modify the model in section 2.2 as follows. We assume that each worker is endowed with a given amount of skill x. The skill x is worker specific and can be transferred from one job to the other. We indicate, with $F(\cdot)$, the distribution function of skills x in the labour force. The productivity of a job, once it is operated by a worker with skill x, is given by the sum of three components $P+\sigma\iota+\lambda\iota x$. P, σ and λ are common to all jobs, while ι is an idiosyncratic component of productivity that, as before, evolves according to a Poisson process with rate of arrival μ. The third component is new. It captures *mismatch.* In a Walrasian economy, with no frictions, high productivity workers (high x) should be matched with high productivity firms, (high ι). In a market with search frictions this is not always the case and high productivity workers can be operating jobs hit by a negative idiosyncratic shock. λ captures this effect, measuring the size of the *skill mismatch.* When λ is equal to zero, there is no skill mismatch and the allocation of worker-skills to jobs has no effect on productivity. When λ is high, the social cost of allocating 'good' workers to 'bad' jobs is high. A change in λ is a *skill biased* labour force shock. For example, an increase in λ corresponds to an increase in skill mismatch or the social cost of misallocating skills.

Given these additional assumptions, equations (DE) and (2.2) become equal to

$$P + \sigma R + \lambda R x = h - \frac{\mu\left(\sigma + \lambda x\right)}{r+\mu}\int_{R}^{\bar{\iota}} \left[1 - G\left(y\right)\right] dy \qquad (DE')$$

so that $\forall \iota > R$

$$J(\iota, x) = \left(\sigma + \lambda x\right)\frac{\left(\iota - R\right)}{\mu + r} \qquad (2.8)$$

while $J(\iota, x) = 0$ if $\iota \leq R$, where now both the asset value of a job and the reservation productivity depend on x. Differentiating (DE') and (2.8) with respect to λ and σ, we then obtain that

$$\frac{dR}{d\lambda} = \frac{x\left(P-h\right)}{\left(\sigma+\lambda x\right)\left\{1 - \frac{\mu}{r+\mu}\left[1 - G\left(R\right)\right]\right\}} = x\frac{dR}{d\sigma}$$

$$\frac{dJ(\iota, x)}{d\lambda} = \frac{x\left(\iota - R\right) - \left(\sigma + \lambda x\right)\frac{dR}{d\lambda}}{\mu + r}$$

and

$$\frac{dJ(\iota, x)}{d\sigma} = \frac{\left(\iota - R\right) - \left(\sigma + \lambda x\right)\frac{dR}{d\sigma}}{\mu + r}.$$

Therefore, the three equations together imply that

$$\frac{dJ(\iota, x)}{d\lambda} : \frac{dR}{d\lambda} = \frac{\left(\iota - R\right)}{\left(\mu + r\right)\frac{dR}{d\sigma}} - \frac{\left(\sigma + \lambda x\right)}{\left(\mu + r\right)} = \frac{dJ(\iota, x)}{d\sigma} : \frac{dR}{d\sigma}. \qquad (2.9)$$

That is the relative impact of a skill biased labour force shock (change in λ) on the destruction margin R and on the overall profitability of the job $J(\iota, x)$, is equal to that of a reallocative shock (change in σ).

(2.9) suggests a possible way of identifying a skill biased labour force shock: for given size of the labour force, a skill biased labour force shock has similar effects on unemployment flows as a reallocative shock. This symmetry is appealing as skill mismatch and reallocative shocks are really compositional effects, the former being on the labour force side, the latter being on the firm side.

2.6.2 Augmented VARs

Given the labour force considerations documented above, we consider extending our empirical evaluation by augmenting our previous VAR analysis. We do this by adding variables to the VARs, to capture labour force size and skill effects. We include the total labour force and the stock of vacancies to achieve this. Vacancies are an important addition, as they captures firm-side *demand.* In particular, if the work force has a lower average level of skill, then firms may put out less vacancies, as the potential profit stream from a job will have fallen (Pissarides 1992). This illustrates how introducing vacancies as an additional variable, may capture skill compositional changes better.

We first consider a three variable SVAR, with

$$Y_t = \begin{bmatrix} \Delta \frac{I_t}{L_t} \\ \frac{O_t}{L_t} - \frac{I_t}{L_t} \\ \frac{\Delta L_t}{L_t} \end{bmatrix}.$$

Each of the variables in Y_t is found to be stationary, according to preliminary statistical investigation.

This specification allows one to recover, perfectly, the unemployment rate u_t as

$$\Delta u_t = \frac{I_t}{L_t} - \frac{O_t}{L_t} - \frac{\Delta L_t}{L_t} u_t, \tag{2.10}$$

once a standardizing value for u_t is chosen [16].

[16] In the table 1.12, the results are obtained posing a value of $u_t = 0.07$. Changing this standardized value does not change the results, as the size of $\frac{\Delta L_t}{L_t}$ is small with respect to that of unemployment flows.

We have argued in section 2.6.1, that there are two elements to labour force changes: a size effect and a compositional effect reflecting the skill make up of the labour force. To capture both these effects, we estimate a four variable SVAR with

$$Y_t = \begin{bmatrix} \Delta \frac{I_t}{L_t} \\ \frac{O_t}{L_t} - \frac{I_t}{L_t} \\ \frac{\Delta L_t}{L_t} \\ \Delta \frac{V_t}{L_t} \end{bmatrix}.$$

V_t represents vacancies at time t. Vacancies standardized by the labour force, $\frac{V_t}{L_t}$, were found to be $I(1)$ and so were entered in differences in the SVAR. The effects on the unemployment rate are recovered as in the three variable case above.

2.6.3 Identification

For the three variable SVAR, three independent identification restrictions are required to exactly identify the matrix B_0, in equation (2.5). We identify the reallocative and aggregate shocks, by imposing that the relative impact of both a reallocative and an aggregate shock, on inflows $\Delta \frac{I_t}{L_t}$ and on net flows $nf_t = \frac{O_t}{L_t} - \frac{I_t}{L_t}$, in the three variable case, is equal to that of the two variable case. We believe this to be a reasonable procedure, because we are using the 3 and 4 variable SVARS first to check the robustness of the 2 variable SVAR results and second to isolate labour force influences in the dynamics of the unemployment rate. We draw on the considerations in section 1.6.1 to identify the third shock and we impose that it has no long run effect on the level of the unemployment rate. We call this a *skill unbiased labour force shock*, its role being to correct for the behavior of inflow and outflows that can be driven by changes in the labour force, rather than changes in the creation and destruction of jobs.

For the four variable SVAR, six independent identification restrictions are required. We use the three given above and hence require three more. We identify the fourth shock, *the skill biased labour force shock*, by imposing that its relative impact on inflows $\Delta\frac{I_t}{L_t}$ and on net flows, $nf_t = \frac{O_t}{L_t} - \frac{I_t}{L_t}$, is equal to that of a reallocative shock. The justification draws on equation (2.9): reallocative shocks and skill biased shocks are really both compositional effects, the former being on the firm side and the latter being on labour force side. Both shocks are really about mismatch and therefore we would expect similar effects on inflows and outflows. Moreover we impose that a skill biased shock has no effect on the size of the labour force on impact. This is simply an orthogonalization, to separate out the size and compositional effects of a labour force change. The third required identifying restriction is delivered directly by the assumption that a skill unbiased labour force shock has no long run impact on the unemployment rate. This implies that it can not have a long run effect on the level of vacancies, standardized by the labour force, as well.

2.6.4 Results

Tables 2.12 and 2.13 show how the results, from the two variable VARs, extend to this case as well[17]. The relative weight of aggregate versus reallocative shocks is changes little in the variance decomposition of the unemployment rate, as does the speed of adjustment ranking[18]. In particular, we do not find

[17]Recursive chow tests were also performed for the the 3 and 4 variable VARs, though they are not reported here, but are available on request. Again it was very difficult to find evidence of structural breaks in the flows equations or the vacancy equation for either the UK or US. There was some evidence of instability in the labour force growth equation, but this was evidenced both for the US and UK, which suggests that it is a problem of modelling labour force growth, rather than of structural change specific to the UK. Given also that the identification of reallocative versus aggregate shocks does not depend on any reaction of the labour force, its seems hard to believe that this could cause any loss of confidence in the SVAR derived results of the importance of the two shocks relative to each other.

[18]There are slight exceptions here. The three variable results for Spain suggest that aggregate shocks dominate. This goes against the results for the two and four variable cases. We believe the result does not contradict the previous ones, for the same reasons that were suggested for France, in the two variable case with $b_{21} = 60$, namely that the impulse response functions oscillate a lot and seem very unstable for this case. Also, in the four variable VAR, France has a higher speed of adjustment than Germany and the UK a slightly higher figure than for Spain

that the speed of adjustment ranking is affected. Moreover, the role of the skill unbiased labour force shock, on the variance covariance decomposition of the unemployment rate, is very small, so that most of its dynamics are driven by shocks that have permanent effects. One interesting result to notice, is the difference in the importance of the skill biased shock between France and Germany. In France it has more influence on the variance decomposition of unemployment than for Germany (approx 25% in France as opposed to 5% in Germany at long lags). This is consistent with the two variable SVAR results where reallocative shocks were more important in France than in Germany. The importance of the skill biased shock in France suggests that skill biased technical progress might explain more unemployment in France than other OECD countries, particularly when compared to Germany. The contrast with Germany may be due to the factors mentioned in section 2.5.2.

2.7 Simulations

In this section, we simulate a simple version of the search theoretic framework to see if the results suggested by the VAR analysis, above, are consistent with simulations of the underlying theoretical model that we used to justify the identification restrictions.

Search models are non linear models of the labour market. The VAR methodology imposes a linear structure onto the dynamics of the variables considered. We noted in section 2.3 that there always exists a linear Wold Decomposition of any stationary process. This is the fundamental decomposition used in most VAR analysis. There also exists many non linear decompositions of a stationary process. The question is are we losing much by imposing a Wold Decomposition onto a labour market which may be better forecasted by a non linear process? We analyze this question by simulating a version of the Mortensen and Pissarides (1994) model of the labour market which is exposed to purely aggregate shocks. We recover the inflows and outflows from the unemployment pool, predicted by the simulations, and use them as inputs into an SVAR as modelled in section 2.5. To test how well a linear VAR is representing the market, we compare the impulse responses from the VAR to those from the simulations for an aggregate shock. We also check the variance decompositions derived from the SVAR. The extent to which reallocative shocks play a role is evidence of how misleading the procedure is, as the simulated results are purely driven by aggregate shocks. Many recent papers (Mortensen and Pissarides 1994, Mortensen 1994 and Cole and Rogerson 1998) have argued that a variant of the search model exposed to aggregate shocks can perform well in matching business cycle facts for the US. Thus we perform this test for a calibrated baseline economy, based on the US economy.

One of the most important findings of the previous sections was that the US economy had a higher speed of adjustment than the European economies and this was robust to the identification restrictions, as it only depended on the unrestricted VAR representation. We can use a simulated search model to try explain this, by calibrating the search model differently to correspond to differences in the US and Europe. In particular, following Mortensen and Pissarides (1999b) and Mortensen and Millard (1997) we can vary the firing tax and unemployment benefits. To this end, we can simulate search models for 'US' and 'European' economies exposed to aggregate productivity shocks, recover the inflows and outflows and use them to form a VAR representation, from which we can estimate speeds of adjustment.

In this section we firstly extend the model of section 2.5 to allow us to perform the simulations. We then perform the simulation exercises proposed above.

2.7.1 The Model

We extend the previous model by introducing some institutional variables and introducing an aggregate shock. We propose that after the initial wage w_0 has been agreed by the matched worker and employer, the firm must pay a set up cost k, which includes the cost of hiring, training and other forms of match specific investment. As before, when $\iota < R$, then the job is destroyed, but now the firm has to pay a firing cost T. We introduce unemployment benefit, by the symbol b. Also, let δ represent the exogenous turnover rate, or the rate of voluntary quits into unemployment. To introduce aggregate shocks, we model P as a jump process characterized by η, a Poisson arrival rate, and $H : \mathcal{R} \rightarrow [0,1]$, a conditional distribution function. Although simple, this approach captures the main features of cyclical shocks, i.e. that there is a positive probability less than one that a boom or a recession will end within any finite period of time. Since we are not varying the reallocative component σ, we set it equal to 1 to save on notation.

The free entry condition becomes:

$$\chi\theta(P) = \alpha(\theta(P))\{J_0(P) - k\} \tag{2.11}$$

where J_0 is the value of a job just filled. In other words, the introduction of creation costs just reduces the value of forming a vacancy by k. Notice how all variables to be determined are now indexed by the state of aggregate productivity, as it now can vary. The job destruction condition will now become:

$$J\left(R(P), P\right) = -T \tag{2.12}$$

So jobs are only destroyed when there value no longer exceeds the cost of paying the firing cost.

In section 2.5, we made a simplifying assumption about wages to save on notation and space. We are afforded no such luxury here. Thus following the search literature, for example Pissarides (1990), we assume wages are chosen via a nash bargain[19], which shares the surplus from a job match in a fixed proportion between the worker and employer. Let $W(\iota, P)$ denote the asset value of a job match, with idiosyncratic productivity ι, to a worker and $W_0(P)$ denote the initial value before an idiosyncratic shock has hit the job. Further, let $U(P)$ be the asset value of being unemployed.

[19] So threat points are equal to the option of looking for an alternative match partner.

The initial and continuing match surplus in equilibrium are:

$$\begin{aligned} S_0(P) &= J_0(P) - k + W_0(P) - U(P) \\ S(\iota) &= J(\iota, P) + T + W(\iota, P) - U(P) \end{aligned} \tag{2.13}$$

The difference between the initial wage bargain and subsequent renegotiation arises for two reasons. First creation costs are 'sunk' in the latter case but 'on-the-table' in the former. Second, termination costs are not incurred if no match is formed initially but must be paid if an existing match is destroyed. The standard Nash solution to the bargaining problem is the following:

$$\beta(J_0(P) - k) = (1 - \beta)(W_0(P) - U(P)) \tag{2.14}$$

$$B(J(\iota, P) + T) = (1 - \beta)(W(P) - U(P)) \tag{2.15}$$

where β, the worker's bargaining power is the resulting worker's share of match surplus.

It can be shown, by writing down conditions for $(J(\iota, P), W(P), U(P))$ and summing them up, that the equilibrium surplus value of a match is given by:

$$\begin{aligned} (r + \delta + \mu + \eta)S(\iota, P) &= P + \iota + (r + \delta)T - b + \alpha(P)\beta S_0(P) \\ &\quad + \mu \int_{R(P)} S(z, P)dG(z) + \eta \int_{R(z)} S(\iota, z)dH(z/P) \end{aligned} \tag{2.16}$$

$$S_0(P) = S(\bar{\iota}, P) - T - k \tag{2.17}$$

where $H(z/P)$ is the conditional distribution of the next arrival of the aggregate productivity parameter given its current value P.

Making use of the free entry condition, equation (2.11), and the solutions to the wage bargaining problem, equation (2.14), we can show that the job meeting rate, $\alpha(P)$, solves the following:

$$\frac{\alpha(P)}{\theta(P)}\{(1 - \beta)S_0(P) - k\} = \chi \tag{2.18}$$

Also the job destruction condition can be rewritten as:

$$S(R(P), P) = 0 \tag{2.19}$$

An equilibrium is a solution to equations (2.16), (2.17), (2.18) & (2.19). Mortensen (1994) develops a method for solving the above system, once the model has been calibrated. Then it is straight forward to simulate the model and to recover the dynamics for employment, unemployment and the inflows to and from unemployment.

2.7.2 Calibrating the model

To model the evolution of aggregate productivity, we follow previous studies in this area (Mortensen (1994), Mortensen and Pissarides (1994) and Millard, Mortensen and Rosenblat (1996)) and suppose that the aggregate productivity follows the following first order autoregressive process:

$$P_t = \rho P_{t-1} + (1-\rho)\mu + v_t \text{ with } E(v_t) = \sigma_v^2 \tag{2.20}$$

We follow Millard, Mortensen and Rosenblat (1996) in setting ρ and σ_v to equal 0.95 and 0.047 respectively[20]. Chari, Christiano and Kehoe (1991) show how a continuous Markov process can be modelled as a finite state Markov chain. Mortensen (1994) and Mortensen and Pissarides (1994) use a three state approximation. We follow Millard, Mortensen and Rosenblat (1996) and use a 17 state approximation. The reason for this is the approximation of equation (2.20) gets better as we increase the number of possible states. Also Millard, Mortensen and Rosenblat (1996) show that the simulated results for unemployment tend to be very jerky, when compared to the data, if the number of possible states is small. 17 states is chosen as a balance between getting a good fit of the data and saving on CPU time.

A matching function of the Cobb-Douglas form is assumed with elasticity with respect to unemployment equal to ζ, i.e. $q(\theta) = \theta^{-\zeta}$. The distribution

[20] These values are chosen to set the autocorrelation and variance of aggregate consumption in a baseline model for the US, equal to that in detrended data, as reported by Merz (1994).

of idiosyncratic shocks is assumed to be uniform on the support $[\gamma, 1]$, i.e. $F(x) = \frac{x-\gamma}{1-\gamma} \; \forall \; x \in [\gamma, 1]$. The parameters for a 'US' baseline economy, calibrated on quarterly data, are reported below[21]. The value of income while unemployed and the minimum match product γ, are chosen so that the average unemployment rate and average duration of an unemployment, for the simulated model, are 6.5% and 3 months respectively. These are post war averages for the US. The other parameter values are the same as those justified in Mortensen and Millard (1997).

Baseline parameter values

discount rate: $r = 0.01$ per quarter

matching elasticity: $\zeta = 0.4$

recruiting cost: $c = 0.33$ per worker

creation cost: $k = 0.275$ per worker

productivity shock frequency: $\lambda = 0.66$

minimum match product: $\gamma = 0.66$ per quarter

value of income while unemployed: $b = 0.53$

worker's share: $\beta = 0.3$

firing cost: $T = 0$

To obtain parameters that reflect a 'European' economy, we follow Mortensen and Pissarides (1999a) and maintain the same values for all parameters except for unemployment income b and the firing cost T which we chose to yield an average unemployment rate of 7.8%, but an average duration of 9 months. 7.8% is the unemployment average for the big five European countries over the last 30 years, namely: the UK, France, Germany, Italy and Spain. The results, $b = 0.61$ and $T = 1.45$ are consistent with the fact that unemployment compensation and the implicit cost of employment protection are both higher in Europe than in the US and the fact that unemployment spells are much longer in Europe.

[21] The software used to perform the calibrations and simulations below, is called 'Flows' and was developed by Stephen Millard and Tanya Rosenblat. I thank Stephen Millard for access to it.

2.7.3 Results

We perform the simulations to create a sample size similar to that used in this paper, i.e. for a baseline sample of 70 observations. The simulations are performed 500 times.

First experiment

For the first experiment, on the baseline 'US' economy, the impulse responses for the simulated economy are shown in **figures 2.11-2.14** (let us refer to them as unfiltered responses). We show the responses of unemployment, the inflow rate, the outflow rate and the level of outflows The responses for the level of inflows are very similar to that for the rate of inflow and are thus not shown[22]. The shock is a negative one and interesting features to notice is the speed at which inflows react compared to outflows. The inflow rate is back to the level before the shock hit after approximately 2 quarters, whereas the outflow rate has not reached its initial level after 20 quarters. This is consistent with the job destruction spikes we see at the start of a recession in the data. As Mortensen and Pissarides (1994) note, the job destruction rate leads the job creation rate as a cause of the rise in unemployment and the speed of change at the start of a recession. Also worth noting is that the level of outflows (also outflows normalized by the labour force in this model) fall for 1 period, then quickly rise and overshoot their final equilibrium. The fall is due to the fall in the outflow rate and the subsequent rise is due to the vast increase in unemployment caused by the job destruction spike. This phenomenon has also been noted by Burda and Wyplosz (1994) Mortensen (1994) and Cole and Rogerson (1998). It suggests that using flows in levels terms, or normalized by the labour force, to identify aggregate shocks by the opposing effects it has on the flows is only robust if imposed on the impact effect as suggested in the discussion in section 2.2.2. The dynamics of unemployment destroy this negative correlation at some point after the

[22] In the search model used, the labour force is normalised to unity, and thus the level of inflow is the same as the inflow normalized by the labour force.

impact of the shock. The simulations suggest the negative correlation is destroyed as soon as the second period after the shock.

Figures 2.15-2.16 and **Table 2.15** show the impulse responses (let us refer to them as the filtered responses) and variance decompositions once the simulated data has been put into the VARs, as specified in section 2.5. For the rates specification, the responses are for a negative aggregate shock. They show the same features as the unfiltered responses in that the outflow rate takes a lot longer to converge to its initial level than the inflow rate. The inflow rate has a sharp spike, gets back close to its initial level before the shock after 2 periods, before slowly moving back to the initial equilibrium. Thus the inflow rate filtered response is similar but not quite as quick as the unfiltered response. The variance decompositions also suggest that aggregate shocks contribute over 90% to the variance of unemployment at all leads. Thus there does not seem to be a large error in the assignment of which shocks are more important in the specification in terms of rates.

The filtered responses for the normalization by the labour force show the response to a positive aggregate shock. Since the VAR representation implies equal but opposite effects for positive or negative shocks, we can impute the effects of a negative shock. Thus again it can be seen that inflows have a spike, before coming back to near its initial value after 2 periods and then slowly adjusting to its pre-shock value. Outflows show the property of having an initial negative impact, before quickly shifting to a positive effect, and in fact overshooting the final equilibrium, due to the increase in unemployment, i.e. a very similar reaction to the unfiltered response. The variance decompositions suggest that aggregate shocks dominate on impact, explaining around 90% of unemployment, but over time reallocative shocks become more important, in the end explaining up to 57% of the variance of unemployment. Clearly this is a surprising result given the data are purely generated by an aggregate shock. I believe it can be explained by looking at the filtered response for a reallocative shock. The responses of inflows and unemployment are very strange and volatile. Take the reaction of inflows to a positive reallocative shock. It is positive on impact, as expected, and then switches between being positive and negative for four periods. I believe the filtered responses for a reallocative shock are spurious after impact because the SVAR is trying to identify a shock that is not there. In this situation the variance decompositions after impact are also misleading. The results from this specification suggest one has to be careful when interpreting the variance decompositions when the variables are normalized by the labour force. Though, the fact that the results earlier in the paper also hold for the specification in terms of rates, gives us confidence that they are still valid.

One important property of the VAR based responses I alluded to before is the symmetry of the response to positive and negative shocks. This is a property not shared by search models. As noted in Davis and Halitwanger (1992, 1998) Mortensen and Pissarides (1994) and Mortensen (1994) job destruction is certainly not symmetric. It increases more rapidly and by more at the start of a recession than it decreases at the start of a boom. Also because of this, unemployment will rise quicker in a recession in response to a negative aggregate shock, than it will fall in a boom in response to a positive shock. This is because job destruction can happen immediately in a recession, but job creation takes time in a boom, due to matching frictions. Further, as noted by Mortensen (1994) the overshooting in the level of outflows is likely to be less in the case of a positive shock, as unemployment falls less at the start of a boom than it rises at the start of a recession, due to the job destruction spikes. What the VAR responses are doing is averaging asymmetric positive and negative responses to form a symmetric one. Since job destruction spikes tend to be large relative to job destruction troughs, this suggests that the filtered impulse responses more closely characterize negative aggregate shocks than positive ones, at least for a short time period after the shock[23].

[23]This asymmetry is likely to be less prevalent in continental European countries. As Garibaldi (1998) argues on one side we find the North American and British experience, where job destruction is more volatile than job creation and job reallocation moves countercyclically. On the other side we find the Continental Europe experience, where job reallocation tends to be acyclical and the fluctuations in job creation and destruction are less pronounced.

Country	Specification	1st	2nd	3rd	4th
U.S.	$\frac{I_t}{L_t}, \frac{O_t}{L_t}$	.6702	.4011	.4011	.0984
	$\frac{I_t}{E_t}, \frac{O_t}{U_t}$	.9139	.2959	.1475	.1230
EU	$\frac{I_t}{L_t}, \frac{O_t}{L_t}$	.685	.685	.3169	.3169
	$\frac{I_t}{E_t}, \frac{O_t}{U_t}$	.9128	.2975	.2261	.0754

Table 2.1: **Speed of adjustment ranking for the unemployment rate (ranked eigenvalues): two variables (simulated data) VAR.** The entries show the values of the norm of the ranked eigenvalues of the VAR representation, of the VAR for different specifications for the simulated data.

Second experiment

In this experiment we estimate speeds of adjustment from the VAR representation of the simulated data for the baseline 'US' economy and the calibrated 'European' economy. The results are given in table 2.1 above.

The results are very surprising at first sight. The highest eigenvalue is virtually identical in both specifications for the US and European economies. This suggests there speed of adjustment rankings are very similar. This is very much at odds with the evidence provided earlier which suggested that one of the most robust results of the paper was that the speed of adjustment was higher in the US as it did not depend on the identification assumptions and was a common finding across all specifications. In fact in other ways the model performs well in simulating the differences between the US and Europe. In table 2.2 we show the means for inflows and outflows normalized by the labour force for the simulated economies and the US and Germany. It can be seen that the model simulations replicate the large differences in absolute levels of the flows between the US and a typical European country, for example Germany.

Possible explanations are:

- The model is in some way not capturing the processes generating the data, for example the fact that there is no labour force growth in the model. This rules out movements in and out of the labour force (which

Country	mean ($\frac{I}{L}$)	mean ($\frac{O}{L}$)
U.S.	0.081	0.081
Germany	0.029	0.028
US (simulated)	0.067	0.067
EU (simulated)	0.026	0.026

Table 2.2: **Flows in the simulated data and real data**

do not net out), which are large in the US (see Clark and Summers (1979)) and may be part of its quick adjustment process. Perhaps more important is the way firing costs have been modelled. We have modelled them as a fixed certain cost that varies across countries. Garibaldi (1998) argues that we should model firing and job destruction as costly and lengthy, at least in Continental Europe. He argues that this can explain some of the differences we see in job flow dynamics between Anglo-Saxon economies and Continental European economies, which will not show up in models simulated with fixed certain firing costs. In particular, he shows that increased firing costs, due to the lower chance of getting *firing permissions,* reduces the volatility of job destruction relative to job creation.

- In our calibrations, the US and European economies only differed in their unemployment benefits and firing costs. Maybe there are other more important differences, like in creation costs or the worker share which could explain differences in speeds of adjustment. I feel though that this explanation is unlikely as benefits and firing costs were chosen as they have often been argued to the most important differences between Europe and the US. For example Mortensen and Pissarides (1999b) argue that the US would have experienced a similar rise in unemployment to Europe had unemployment compensation and employment protection policies been at European levels. Also in simulations not reported here, I changed other policy variables, but found few differences when the European economy was calibrated on the same average duration and unemployment.

- We have only looked at a simulated economy exposed to aggregate shocks. Maybe introducing reallocative shocks could make a difference.

- Maybe our measure of speed of adjustment is not capturing adjustment properly.

We hope to able to discriminate between these various hypotheses in future work,

Summary

The simulations suggest the VAR procedure performs well, in representing a non linear search model, on some dimensions but not on others. It seems to perform well in illustrating the job destruction spikes we see in the data, at least for the US, and the switching prevalent in the response of the level of outflows. The symmetry assumption is not held up in simulations of the search model though and this suggests that, if job destruction spikes are large and pronounced, VAR based impulse responses are more accurate for negative rather than positive aggregate shocks. The variance decompositions suggest one needs to be careful in interpreting results based on a specification based on a normalization by the labour force, though the fact that the results earlier in the chapter were also based on a rates specification, gives us confidence that they are still valid. The speed of adjustment experiment provides a surprising result in that there is no difference for the US and European economy. Finally, we have only considered aggregate shocks. It could be argued that reactions to reallocative shocks could be even more non linear than to those of aggregate shocks. We hope to introduce reallocative shocks and solve the speed of adjustment paradox in future work.

2.8 Conclusions

The European Community and the US have experienced vastly different unemployment dynamics over the last two decades. This paper has investigated whether these differences are due to exposure to different shocks, or reacting differently to the same shocks. With the premise of a search theoretic framework and a structural VAR methodology, the paper has robustly identified aggregate versus reallocative shocks. With the exception of Spain where most of the dynamics seems to be driven by reallocation, it is found that most differences in unemployment dynamics arise because of differences in responses to shocks. In particular, European economies seem to respond slower to the same shock, when compared with the US. This implies that EEC economies might be dynamically "sclerotic" even if the size of the steady state job flows might give the impression of the European labour market being quite active. Simulations of a search model though cannot replicate the speed of adjustment rankings. For calibrated US and European economies we do not find a difference in the speed of adjustment ranking. In future work, we hope to resolve this paradox.

In order to check for robustness we have introduced additional labour force shocks identified, respectively, as a skill unbiased and a skill biased component. We have shown that skill unbiased labour force shocks do not appear to have much influence in any of the countries considered, so that most structural shocks exhibit permanent effects on the level of the unemployment rate. The skill biased component seems to be relevant in accounting for unemployment dynamics. This implies that skill biased technological progress might explain some of the unemployment problems of OECD economies.

Country	b_{21}	b_{12}	σ_1	σ_2	$b_{21}\,\sigma_1$	$b_{12}\,\sigma_2$	$-B_{21}(1)\sigma_1$	$-B_{22}(1)\sigma_2$
U.S.	60	-1.32	0.003	0.245	0.21	-0.32	0.401	0.605
U.S.	30	-1.31	0.007	0.247	0.21	-0.32	0.395	0.601
U.S.	1	-1.00	0.114	0.302	0.11	-0.30	0.175	0.700
U.K.	60	-1.34	0.002	0.112	0.15	-0.16	0.964	0.946
U.K.	30	-1.31	0.005	0.114	0.14	-0.15	0.949	0.961
U.K.	1	-0.77	0.074	0.169	0.07	-0.130	0.387	1.294
Spain	60	-4.96	0.007	0.123	0.42	-0.61	0.547	0.086
Spain	30	-4.76	0.014	0.128	0.42	-0.61	0.545	0.092
Spain	1	-1.640	0.310	0.320	0.310	-0.525	0.432	0.347
France	60	-1.21	0.003	0.169	0.18	-0.20	0.288	0.329
France	30	-1.20	0.006	0.171	0.18	-0.21	0.283	0.649
France	1	-0.801	0.090	0.229	0.090	-0.184	0.119	0.421
Germany	60	-1.11	0.003	0.178	0.18	-0.20	0.243	0.517
Germany	30	-1.09	0.006	0.180	0.18	-0.20	0.236	0.520
Germany	1	-0.762	0.084	0.233	0.084	-0.178	0.008	0.571

Table 2.3: **Standardization over L_t.** The first four columns summarise the impact effects and standard deviations of the shocks, that is the coefficient b_{12}, b_{21}, σ_1, σ_2 in the main text once a VAR with two lags is run. The last two columns document the long run impacts on the unemployment measure. The term $B_{ij}(1)$ indicates the element in rows i and column j of the structural matrix polynomial $B(L)$, in equation (5), evaluated at $L = 1$. **Note:** The elements in the first column of the matrix B_0 and $B(L)$ refer to the reallocative shock, the ones in the second to the aggregate shock.

Country	Specification	1st	2nd	3rd	4th
U.S.	$\frac{I}{L}, \frac{O}{L}$	.601	.446	.446	.424
	$\frac{I_t}{E_t}, \frac{O_t}{U_t}$	.432	.432	.330	.220
U.K.	$\frac{I}{L}, \frac{O}{L}$	.880	.294	.251	.251
	$\frac{I_t}{E_t}, \frac{O_t}{U_t}$	.685	.590	.234	.170
Spain	$\frac{I}{L}, \frac{O}{L}$	.806	.806	.455	.323
	$\frac{I_t}{E_t}, \frac{O_t}{U_t}$	.805	.805	.471	.426
France	$\frac{I}{L}, \frac{O}{L}$	.815	.815	.602	.419
	$\frac{I_t}{E_t}, \frac{O_t}{U_t}$	.861	.861	.739	.302
Germany	$\frac{I}{L}, \frac{O}{L}$	.667	.573	.542	.542
	$\frac{I_t}{E_t}, \frac{O_t}{U_t}$	.759	.759	.433	.223

Table 2.4: **Speed of adjustment ranking for the unemployment rate (ranked eigenvalues): two variables VAR.** The entries show the values of the norm of the ranked eigenvalues of the VAR representation, of the VAR for different specifications. All VARs are run with two lags.

VD leads	$\frac{I}{L}, \frac{O}{L}$			$\frac{I}{N}, \frac{O}{U}$								
	b_{21}	VD of $\sum \frac{(I_t - O_t)}{L_t}$		b_{21}	VD of $\frac{I}{N}$		VD of $\frac{O}{U}$		effect on Δu_t			
		RE	AG		RE	AG	RE	AG	RE	AG		
1	1	12	88	-25	46	54	12	88	43	57		
15		6	94		23	77	2	98	22	78		
30		6	94		23	77	2	98	22	78		
1	30	41	59	-30	60	40	5	95	66	44		
15		30	70		36	64	0	100	33	67		
30		30	70		35	65	0	100	33	67		
1	60	42	58	-35	69	31	1	99	64	46		
15		31	69		45	55	2	98	42	58		
30		31	69		45	55	2	98	42	58		

Table 2.5: **Country: U.S.** VD stands for forecasting variance decomposition of the (approximated) unemployment rate, RE for reallocative shock, AG for aggregate shock. For the specification with outflow and inflow rates, we also consider, as a measure of the forecasting variance decomposition for the unemployment rate, the average between the ones of inflow and outflow rate with weight equal to $(1-u_t)$ and u_t, respectively, where a standardizing value of 0.07 is chosen for u_t. All VARs are run with two lags.

VD leads	$\frac{I}{L}$, $\frac{O}{L}$			$\frac{I}{N}$, $\frac{O}{U}$						
	b_{21}	VD of $\sum \frac{(I_t - O_t)}{L_t}$		b_{21}	VD of $\frac{I}{N}$		VD of $\frac{O}{U}$		effect on Δu_t	
		RE	AG		RE	AG	RE	AG	RE	AG
1	1	16	84	-10	3	97	91	9	9	991
15		9	91		4	96	80	20	19	91
30		8	92		5	95	79	21	10	90
1	30	61	38	-30	39	61	48	52	40	60
15		50	50		9	91	34	66	11	89
30		50	50		8	92	32	68	10	90
1	60	63	37	-60	75	25	25	85	71	29
15		52	48		39	61	6	94	37	63
30		51	49		37	63	5	95	35	65

Table 2.6: **Country: U.K.** VD stands for forecasting variance decomposition of the (approximated) unemployment rate. For the specification with outflow and inflow rates, we also consider, as a measure of the forecasting variance decomposition for the unemployment rate, the average between the ones of inflow and outflow rate with weight equal to $(1 - u_t)$ and u_t, respectively, where a standardizing value of 0.07 is chosen for u_t. All VARs are run with two lags.

VD leads	$\frac{I}{L}, \frac{O}{L}$			$\frac{I}{N}, \frac{O}{U}$						
	b_{21}	VD of $\sum \frac{(I_t - O_t)}{L_t}$		b_{21}	VD of $\frac{I}{N}$		VD of $\frac{O}{U}$		effect on Δu_t	
		RE	AG		RE	AG	RE	AG	RE	AG
1	1	48	52	-10	51	49	84	16	53	47
15		58	42		71	29	83	17	72	28
30		59	41		74	26	83	17	74	26
1	30	92	8	-30	83	17	51	49	81	19
15		95	5		94	6	50	50	90	10
30		96	4		96	4	50	50	93	7
1	60	92	8	-60	94	6	34	66	90	10
15		96	4		98	2	33	67	93	7
30		97	3		99	1	33	67	94	6

Table 2.7: **Country: Spain.** VD stands for forecasting variance decomposition of the (approximated) unemployment rate. For the specification with outflow and inflow rates, we also conside,r as a measure of the forecasting variance decomposition for the unemployment, rate the average between the ones of inflow and outflow rate with weight equal to $(1 - u_t)$ and u_t, respectively, where a standardizing value of 0.07 is chosen for u_t. All VARs are run with two lags.

VD leads	$\frac{I}{L}, \frac{O}{L}$			$\frac{I}{N}, \frac{O}{U}$						
	b_{21}	VD of $\sum \frac{(I_t - O_t)}{L_t}$		b_{21}	VD of $\frac{I}{N}$		VD of $\frac{O}{U}$		effects on Δu_t	
		RE	AG		RE	AG	RE	AG	RE	AG
1	1	13	87	-10	0	100	83	17	6	94
15		7	93		2	98	60	40	6	94
30		7	93		1	99	59	41	5	95
1	30	52	48	-30	47	53	17	83	45	55
15		42	58		43	57	4	96	40	60
30		42	58		41	59	3	97	38	62
1	60	53	47	-60	84	16	0	100	78	22
15		43	57		79	21	6	94	74	26
30		43	57		78	22	6	94	73	27

Table 2.8: **Country: France.** VD stands for forecasting variance decomposition of the (approximated) unemployment rate. For the specification with outflow and inflow rates, we also consider, as a measure of the forecasting variance decomposition for the unemployment rate, the average between the ones of inflow and outflow rate with weight equal to $(1 - u_t)$ and u_t, respectively, where a standardizing value of 0.07 is chosen for u_t. All VARs are run with two lags.

VD leads	$\frac{I}{L}, \frac{O}{L}$			$\frac{I}{N}, \frac{O}{U}$						
	b_{21}	VD of $\sum \frac{(I_t-O_t)}{L_t}$		b_{21}	VD of $\frac{I}{N}$		VD of $\frac{O}{U}$		effects on Δu_t	
		RE	AG		RE	AG	RE	AG	RE	AG
1	1	11	89	-40	1	99	65	35	5	95
15		0	100		2	98	41	59	5	95
30		0	100		2	98	39	61	5	95
1	30	47	53	-50	7	93	49	51	10	90
15		18	82		9	91	26	74	10	90
30		18	82		9	91	24	76	10	90
1	60	49	51	-60	17	83	35	65	18	82
15		19	81		19	81	15	85	19	81
30		19	81		19	81	13	87	19	81

Table 2.9: **Country: Germany.** VD stands for forecasting variance decomposition of the (approximated) unemployment rate. For the specification with outflow and inflow rates, we also consider, as a measure of the forecasting variance decomposition for the unemployment rate, the average between the ones of inflow and outflow rate with weight equal to $(1 - u_t)$ and u_t, respectively, where a standardizing value of 0.07 is chosen for u_t. All VARs are run with two lags.

Country	C.I.	Aggregate Shock				Reall. Shock			
		Leads:				Leads:			
		2	**5**	**15**	**30**	**2**	**5**	**15**	**30**
UK	resp	0.19	0.04	-0.43	-0.72	0.00	-0.03	-0.17	-0.26
	band($^+_-$)	0.08	0.24	0.75	1.51	0.07	0.17	0.37	0.59
Spain	resp	0.03	0.37	0.49	0.49	-0.26	-0.32	-0.32	-0.31
	band($^+_-$)	0.12	0.30	0.56	0.66	0.13	0.24	0.33	0.34
France	resp	0.25	0.35	0.40	0.41	0.00	-0.01	0.00	0.01
	band($^+_-$)	0.10	0.32	0.60	0.70	0.01	0.17	0.24	0.27
Germany	resp	0.22	0.24	0.23	0.22	0.04	0.10	0.13	0.13
	band($^+_-$)	0.10	0.34	0.69	0.82	0.09	0.184	0.25	0.27

Table 2.10: **US vs Europe, Comparison of Impulse Responses:** This table is for the specification over the labour force, with $b21 = 1$. The first number, in each box, represents the difference of the impulse response, of the unemployment rate of the country, minus that of the US, calculated at different leads. The second, labelled band($^+_-$), is one half of the size of the corresponding 95% confidence interval. band($^+_-$) is calculated using a bootstrapping technique with 1000 replications.

Country	C.I.	Aggregate Shock				Reallocative Shock			
		Leads:				Leads:			
		2	**5**	**15**	**30**	**2**	**5**	**15**	**30**
UK	resp	0.21	0.11	-0.23	-0.44	0.03	-0.09	-0.44	-0.64
	band($^{+}_{-}$)	0.07	0.24	0.60	1.09	0.07	0.19	0.57	1.11
Spain	resp	0.22	0.57	0.69	0.70	-0.32	-0.24	-0.20	-0.20
	band($^{+}_{-}$)	0.12	0.28	0.53	0.65	0.12	0.28	0.46	0.54
France	resp	0.26	0.37	0.41	0.42	0.04	0.05	0.06	0.06
	band($^{+}_{-}$)	0.09	0.30	0.55	0.65	0.09	0.21	0.37	0.43
Germany	resp	0.22	0.23	0.20	0.18	0.06	0.10	0.11	0.10
	band($^{+}_{-}$)	0.10	0.33	0.71	1.26	0.10	0.23	0.41	0.60

Table 2.11: **US vs Europe, Comparison of Impulse Responses:** The table is for the specification over the labour force, with $b21 = 30$. The first number, in each box, represents the difference of the impulse response, of the unemployment rate of the country, minus that of the US, calculated at different leads. The second, labelled band($^{+}_{-}$), is one half of the size of the corresponding 95% confidence interval. band($^{+}_{-}$) is calculated using a bootstrapping technique with 1000 replications.

Country	C.I	Aggregate Shock				Reallocative Shock			
		Leads:				Leads:			
		2	**5**	**15**	**30**	**2**	**5**	**15**	**30**
UK	resp	0.22	0.11	-0.22	-0.45	0.03	-0.09	-0.45	-0.67
	band($\pm$)	0.07	0.23	0.62	1.35	0.07	0.19	0.61	1.31
Spain	resp	0.23	0.57	0.69	0.69	-0.31	-0.24	-0.20	-0.20
	band($\pm$)	0.13	0.27	0.47	0.51	0.12	0.27	0.41	0.43
France	resp	0.26	0.37	0.41	0.41	0.03	0.04	0.06	0.06
	band($\pm$)	0.10	0.29	0.51	0.57	0.09	0.21	0.36	0.39
Germany	resp	0.22	0.22	0.20	0.19	0.06	0.10	0.10	0.10
	band($\pm$)	0.10	0.32	0.64	0.76	0.09	0.22	0.38	0.43

Table 2.12: **US vs Europe, Comparison of Impulse Responses:** The table is for the specification over the labour force, with $b21 = 60$. The first number, in each box, represents the difference of the impulse response, of the unemployment rate of the country, minus that of the US, calculated at different leads. The second, labelled band($\pm$), is one half of the size of the corresponding 95% confidence interval. band($\pm$) is calculated using a bootstrapping technique with 1000 replications.

Country	Number of Variables	Leads:	Aggr. shock	Reall. shock	Skill Mism. shock	Skill Neutr. shock
U.S.	3 Vars.	1	0.90	0.10	-	0.00
		15	0.97	0.03	-	0.00
		30	0.97	0.03	-	0.00
U.S.	4Vars.	1	0.71	0.24	0.01	0.04
		15	0.71	0.25	0.04	0.00
		30	0.71	0.25	0.04	0.00
U.K.	3 Vars.	1	0.65	0.34	-	0.01
		15	0.81	0.19	-	0.00
		30	0.81	0.19	-	0.00
U.K.	4 Vars.	1	0.93	0.02	0.05	0.00
		15	0.96	0.01	0.03	0.00
		30	0.96	0.01	0.03	0.00
Spain	3 Vars.	1	0.77	0.22	-	0.01
		15	0.65	0.34	-	0.01
		30	0.65	0.35	-	0.00
Spain	4 Vars.	1	0.34	0.25	0.39	0.02
		15	0.41	0.21	0.37	0.01
		30	0.42	0.21	0.37	0.00
France	3 Vars.	1	0.64	0.31	-	0.05
		15	0.63	0.36	-	0.01
		30	0.63	0.37	-	0.00
France	4 Vars.	1	0.65	0.01	0.30	0.04
		15	0.64	0.13	0.23	0.00
		30	0.64	0.13	0.23	0.00
Germany	3 Vars.	1	0.56	0.42	-	0.02
		15	0.80	0.19	-	0.01
		30	0.80	0.19	-	0.01
Germany	4 Vars	1	0.59	0.21	0.18	0.02
		15	0.71	0.22	0.06	0.01
		30	0.71	0.22	0.06	0.01

Table 2.13: **Forecast Variance Decomposition of the Unemployment rate** (three and four variables VAR). The coefficient b_{21} is chosen to be equal to 30. All VARs are run with two lags.

Country	N. of Var.	1st	2nd	3rd	4th	5th	6th	7th	8th
U.S.	3 vars.	.592	.476	.476	.420	.420	.390	-	-
	4 vars.	.569	.569	.556	.492	.492	.485	.449	.074
U.K.	3vars.	.879	.391	.391	.283	.269	.269	-	-
	4 vars.	.871	.485	.485	.389	.389	.323	.192	.192
Spain	3vars.	.857	.857	.537	.486	.486	.456	-	-
	4 vars.	.881	.881	.638	.601	.556	.556	.479	.479
France	3vars.	.823	.823	.472	.221	.221	.215	-	-
	4vars	.804	.804	.763	.763	.556	.556	.361	.331
Germany	3vars.	.662	.627	.627	.596	.375	.031	-	-
	4vars.	.832	.832	.682	.617	.617	.589	.398	.062

Table 2.14: **Speed of adjustment ranking for the unemployment rate (ranked eigenvalues): three and four variables VAR.** The entries have the same meaning as the ones in the two variable case (table 6). All VARs are run with two lags.

VD leads	$\frac{I}{L},\frac{O}{L}$			$\frac{I}{N},\frac{O}{U}$						
	b_{21}	VD of $\sum\frac{(I_t-O_t)}{L_t}$		b_{21}	VD of $\frac{I}{N}$		VD of $\frac{O}{U}$		effects on Δu_t	
		RE	AG		RE	AG	RE	AG	RE	AG
1	30	11	89	-15	4	96	13	87	5	95
15		48	52		7	93	20	80	8	92
30		57	43		7	93	20	80	8	92

Table 2.15: **Country: Baseline economy** VD stands for forecasting variance decomposition.

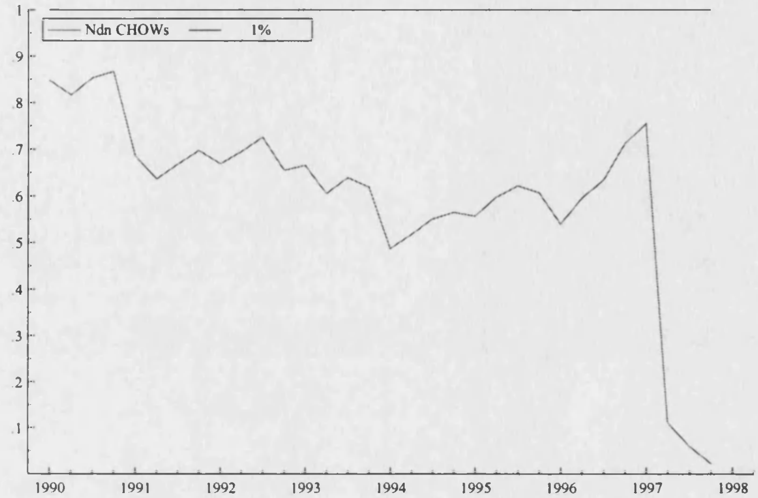

Figure 2.1: {UK} recursive chow test for the inflow equation (normalized by the labour force)

Figure 2.2: {UK} recursive chow test for the netflow equation

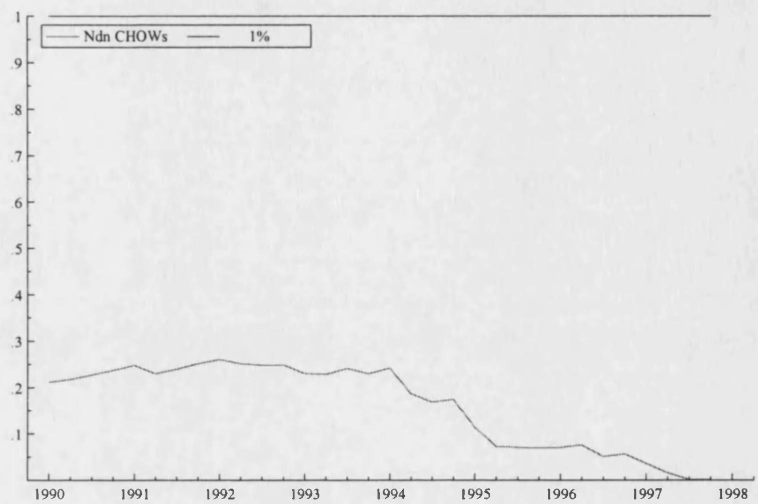

Figure 2.3: {US} recursive chow test for the inflow equation (normalized by the labour force)

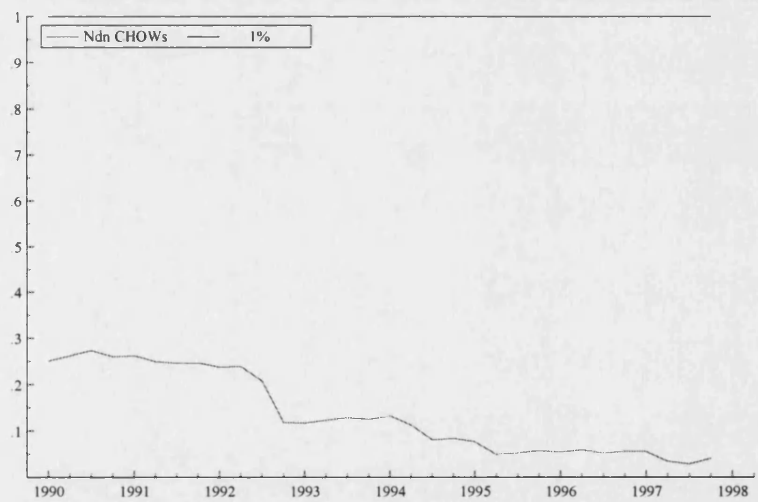

Figure 2.4: {US} recursive chow test for the netflow equation

Figure 2.5: {UK} recursive chow test for the inflow rate equation

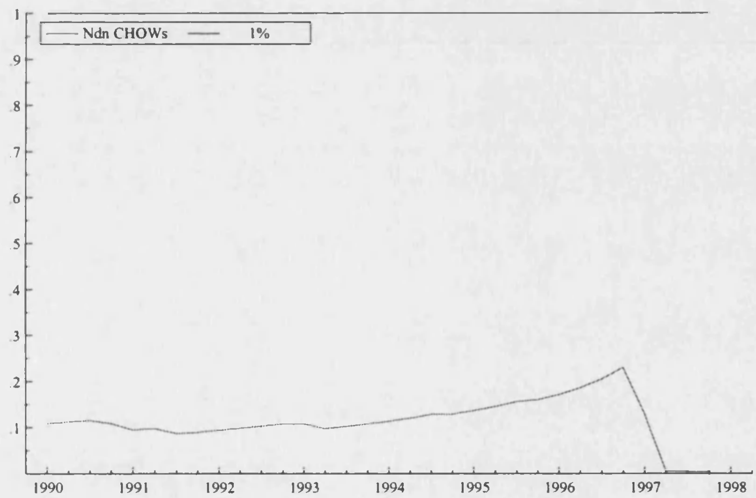

Figure 2.6: {UK} recursive chow test for the outflow rate equation

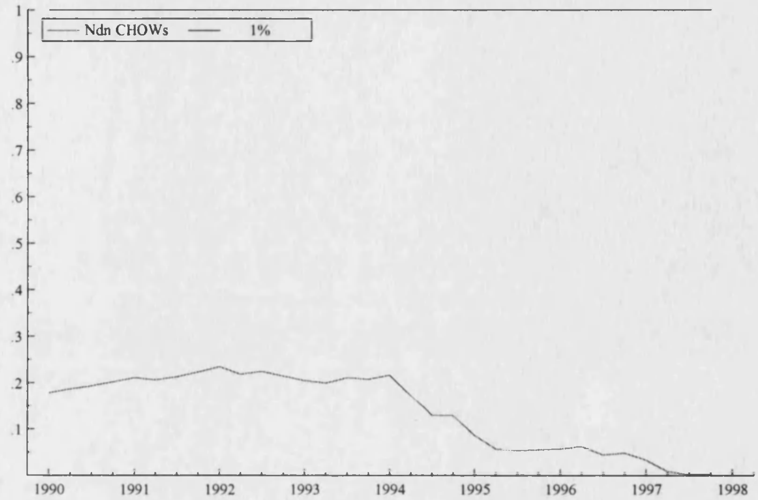

Figure 2.7: {US} recursive chow test for the inflow rate

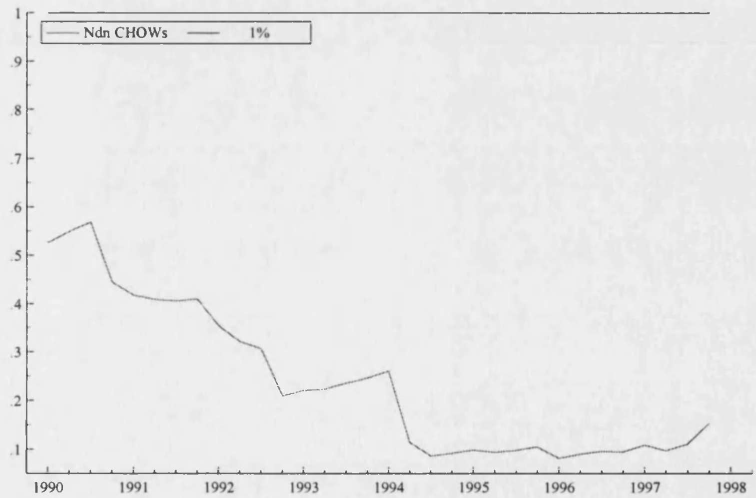

Figure 2.8: {US} recursive chow test for the outflow rate equation

Inflows into and Outflows from the Unemployment Pool

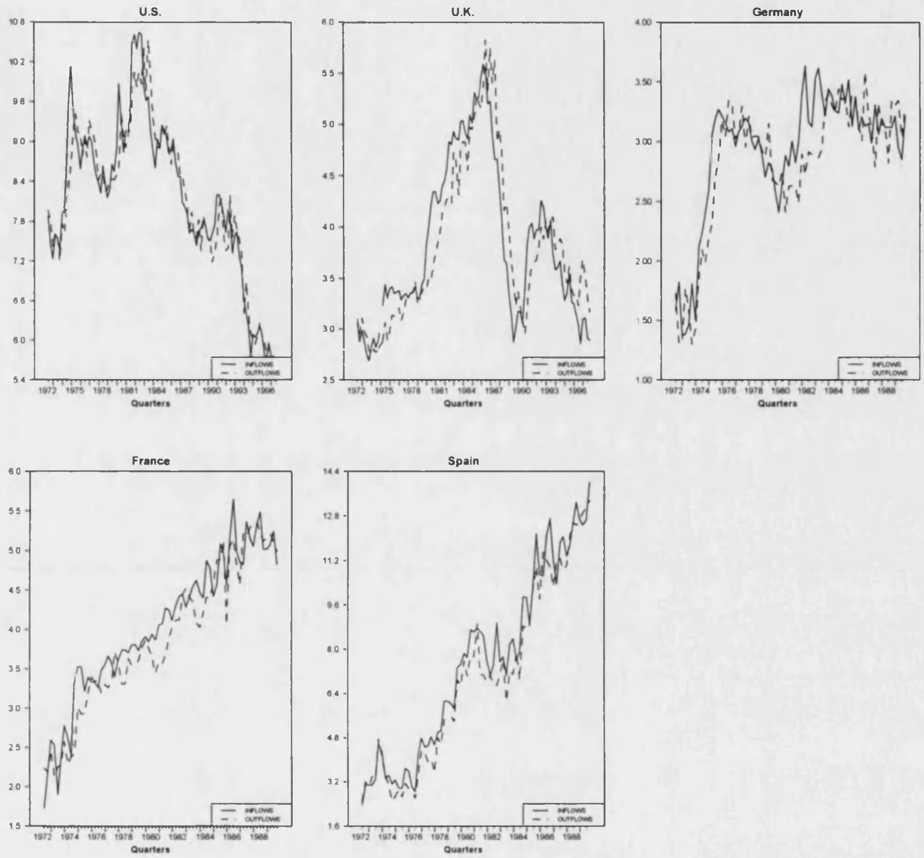

Figure 2.9: The graphs show the dynamics for the level of the inflows into, $\frac{I_t}{L_t}$, and the outflows from the unemployment pool, $\frac{O_t}{L_t}$, standardized by the labour force. The data are quartely and refer to the period 1972:3 -1989:4 except for the US and UK, for which the period is 1972:3 to 1997:4

Range for Parameter Values (b12 vs. b21)

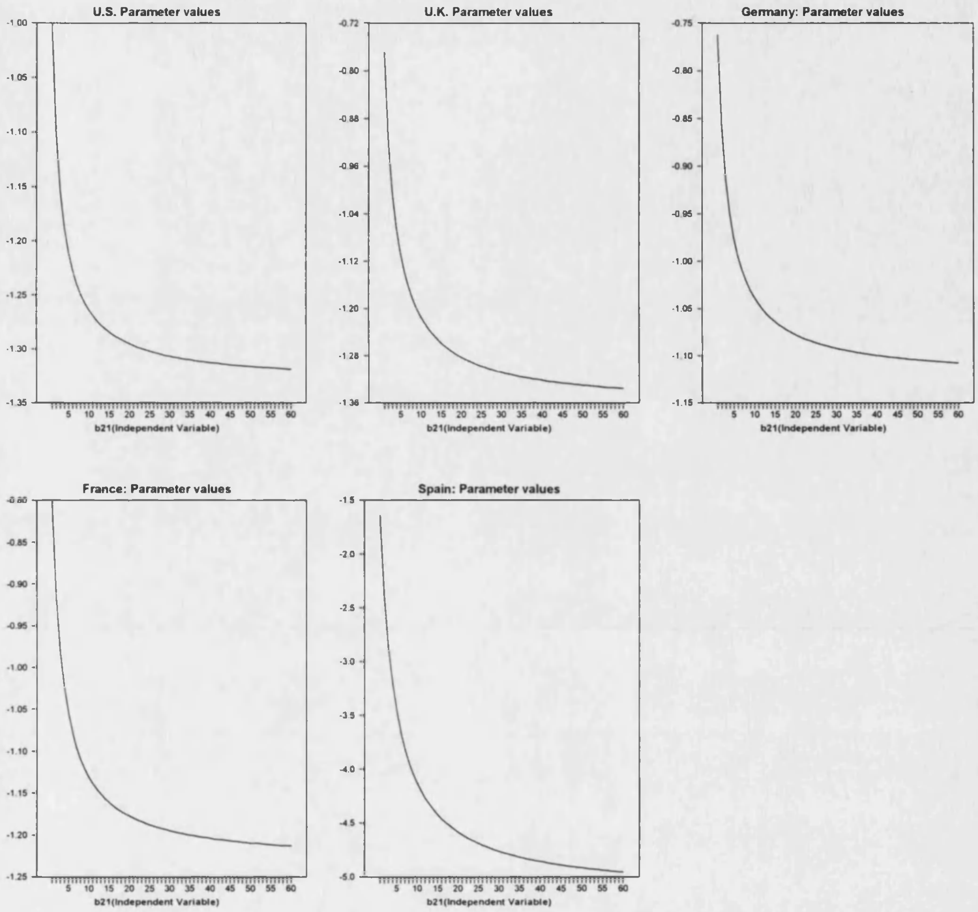

Figure 2.10: The graphs show the relation between b_{12} and b_{21}, as given by equation (2.7) in the main text, for the two variables specification with $\frac{O_t}{L_t} - \frac{I_t}{L_t}$ and $\frac{I_t}{L_t}$ as independent variables. The end point for the sample is 89:4, except for the US and UK for which it is 97:4.

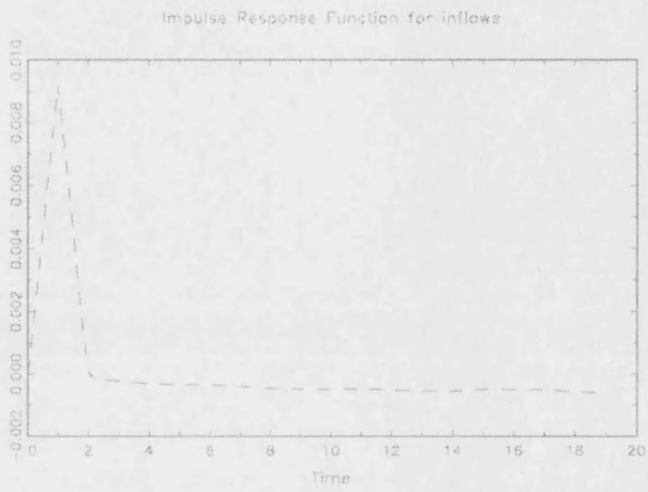

Figure 2.11: (baseline economy) impulse response to an aggregate shock of the simulated inflow rate

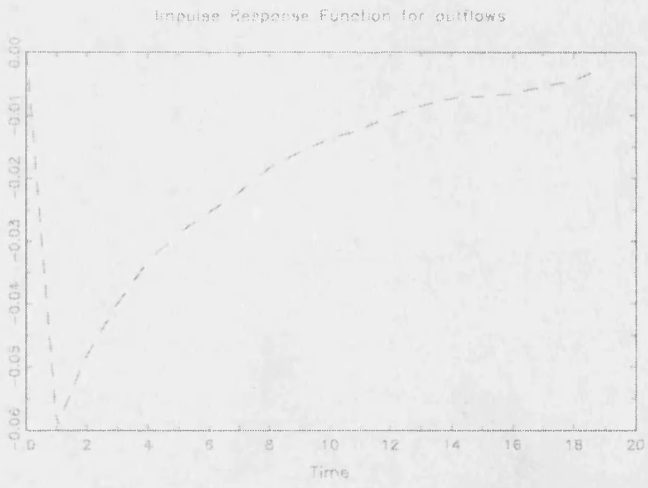

Figure 2.12: (baseline economy) impulse response to an aggregate shock of the simulated outflow rate

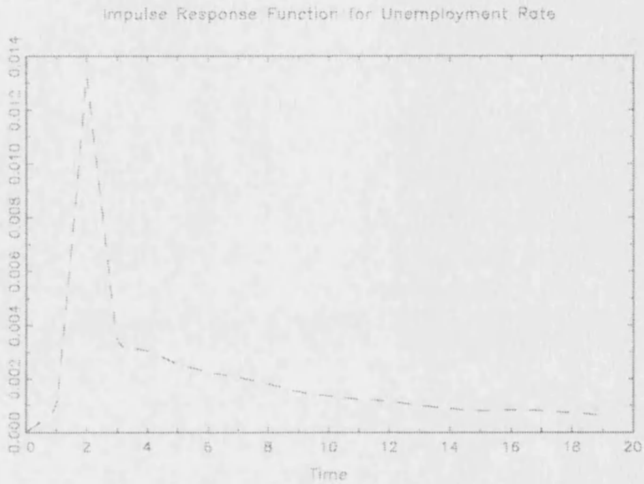

Figure 2.13: (baseline economy) impulse response to an aggregate shock of the simulated unemployment rate

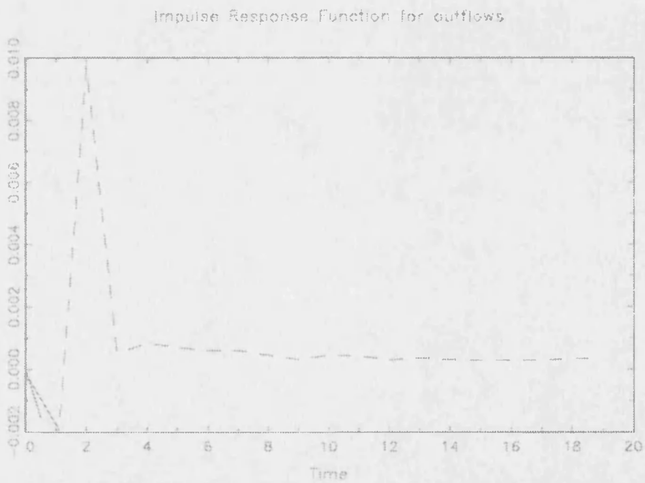

Figure 2.14: (baseline economy) impulse response to an aggregate shock of simulated outlflows

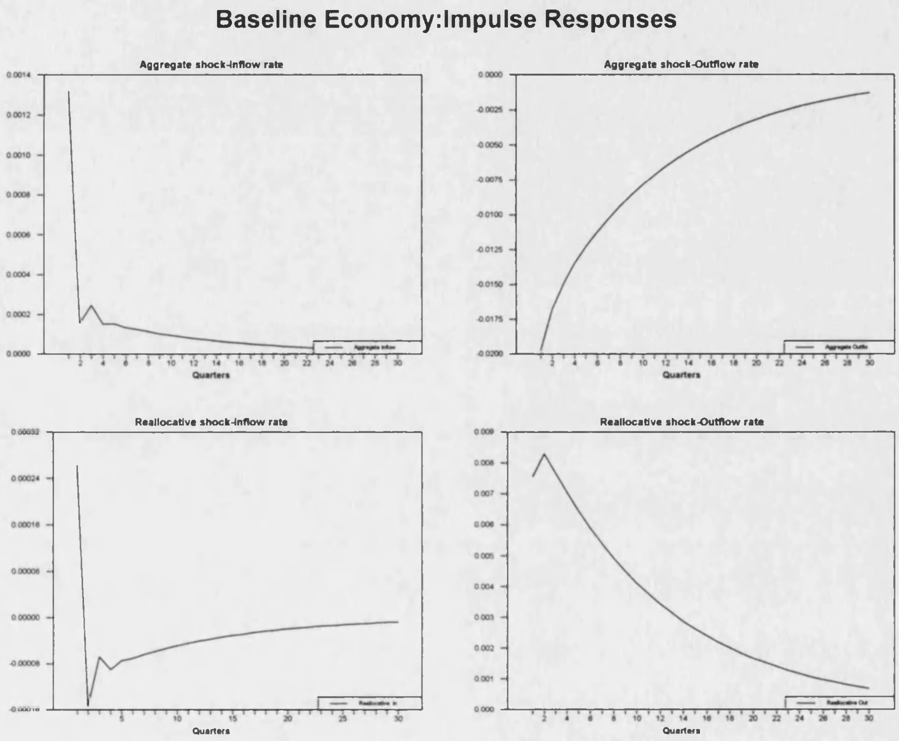

Figure 2.15: (baseline economy) impulse responses for the normalization in rates, $b_{21} = -15$.

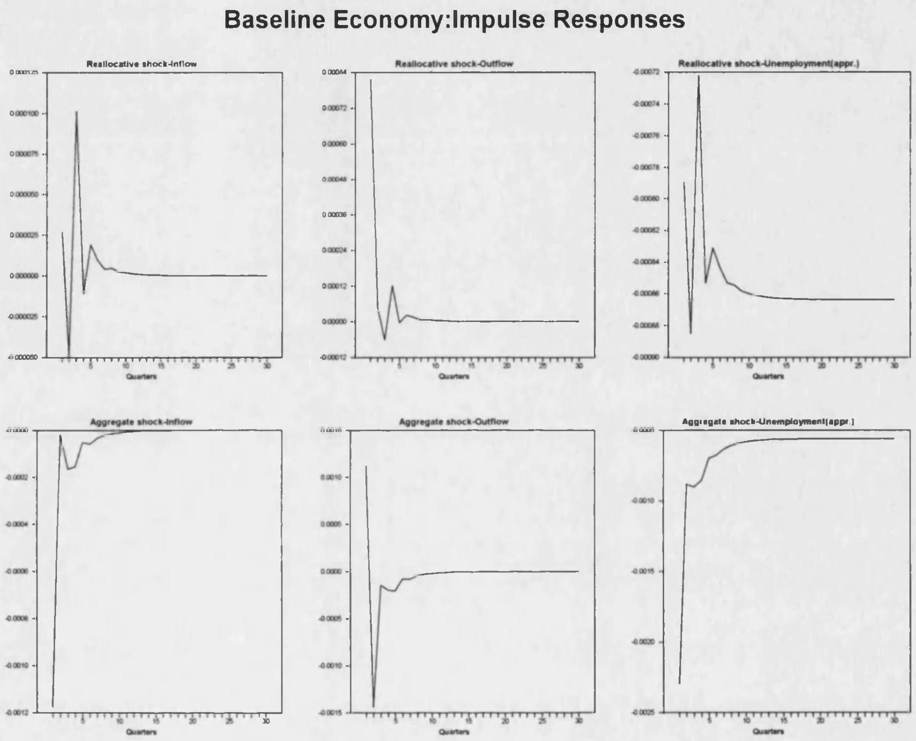

Figure 2.16: (baseline economy) impulse responses for the normalization by the labour force, $b_{21} = 30$.

Chapter 3

Growth and Unemployment: A Re-examination of The Facts

3.1 Introduction

The aim of the following chapter is to document the facts about growth and unemployment and their bivariate relationship.

In the past, the received wisdom has been that interactions between output, or productivity, and unemployment were only significant at frequencies associated with the business cycle. The relationship between output and growth at these frequencies were generally associated with *Okun's Law.* The correlation of productivity and unemployment was also expected to be negative over the business cycle. This is due to two reasons: labour hoarding by firms during recessions and the importance of technological shocks in generating economic fluctuations. At lower frequencies, for example interactions between equilibrium output or equilibrium growth and unemployment, there was often believed to be no relationship. According to neoclassical growth theory, equilibrium productivity growth is purely determined by the exogenous rate of labour-augmenting technical progress. Further, a well documented stylized fact is that the unemployment rate is untrended in the long run (LNJ 1991). This was seen as evidence that output cannot have a great effect on the equilibrium unemployment rate. Institutional factors, for example: the benefit regime; the wage bargaining system and minimum wages, were viewed as far more important.

However, over the last decade, vast progress has been made in understanding the mechanisms of growth. Endogenous growth theory as pioneered by Romer (1986) and Lucas(1988), has helped explain the non convergence in growth rates which often shows up in the data. This is achieved by endogenizing the source of growth of per capita income in the steady state, namely technical progress or the accumulation of knowledge. The accumulation of knowledge is now seen as not simply exogenously given, but depending on many factors which are endogenous up to a point, for example : formal education, on the job training, basic scientific research, learning by doing, process innovations and product innovations. This has led to many policy implications as to what factors can increase average growth rates of many economies.

There has also been a growing theoretical literature detailing interactions between steady state growth and equilibrium unemployment. Search theoretic models illustrate how changes in steady state growth can affect the equilibrium unemployment rate. Two main effects are uncovered: *a capitalization effect* and *a creative destruction effect.* Endogenous growth models, with some kind of labour market friction, show how changes in equilibrium unemployment can affect the steady state growth rate. There are various mechanisms via which this can happen: *loss of skills; learning by doing; the cleansing effect* and *savings.* An evaluation of the various models which link growth and unemployment will be carried out in the next chapter. The purpose of this chapter is to accumulate evidence on the *direct* link between growth and unemployment which will allow such an evaluation.

As Bean and Pissarides (1993) rightly comment, a simple graph looking at the cross sectional relationship between growth and unemployment does not reveal much of a relationship (see section 3.2). This could be due to not controlling for important differences in institutional features across countries, which I will address in another chapter, or that a simple cross sectional graph does not provide enough detail to uncover any relationship. In this chapter I use frequency domain analysis, as well as standard time domain analysis, to try to uncover a more complete set of 'stylized facts' about growth and unemployment. Frequency domain analysis allows one to look at the relationship between growth and unemployment at *all frequencies.* This allows much more comprehensive analysis of where a possible relationship between growth and unemployment may lie, than is possible by using time domain analysis alone.

A very arbitrary split, for macroeconomic variables, might be that: low frequency movements are equivalent to movements in the equilibrium of the process; medium frequency movements equivalent to business cycle induced fluctuations and high frequency movements highlight seasonal trends.

The first step in the experiment, is to collect information about individual growth and unemployment series. This will be done by looking at the univariate spectra of the two economic variables and seeing if robust patterns show up, such as Granger's '*typical spectral shape*'. It will also involve relating the frequency domain evidence documented, to previous work done in the time domain.

Next, cross spectral analysis will be performed. The cross spectrum gives us two important summary statistics:

- *the phase spectrum*: this gives us the average value of the phase shift between the two series, growth and unemployment, at every frequency.
- *the coherency spectrum*: this gives us the correlation coefficient between growth and unemployment at every frequency.

These are very useful, as it allows us to compare the relationship between growth and unemployment at different horizons: equilibrium movements and business cycle movements.

This allows one to document how the correlations at various frequencies may compare with predictions of the growth and unemployment literature. This can be done for most of the G-7 countries over a very long time horizon.

Further, spectral analysis allows one to implement a different concept for the notion of equilibrium movements: equilibrium movements mainly show up as low frequency oscillations of a variable. The frequency domain can be used to apply a 'low pass filter' to growth and unemployment, to filter out seasonal and business cycle movements. An alternative would be to simply average the growth and unemployment rates over a particular sub-period and consider these as equilibrium rates. This is the approach taken in much of the literature, for example the Barro style growth regressions or the LNJ unemployment regressions. This paper also discusses the merits of these different methodologies.

Of course, a lot of these movements will be explained by important economic events that if not taken into account, could bias our judgement about the relationship. The main event I referring to is of course wars, which often see a reduction in growth and unemployment as labour is diverted to the war effort. There are other major events though, for example: the advent of North Sea Oil; the overthrow of political regimes like in Spain and the birth and destruction of nations. Such events will be taken into account when trying to discern the nature of the relationship between growth and unemployment.

The chapter will be structured as follows: section II summarizes the current wisdom on the relationship between growth and unemployment, in the time domain, while section III briefly summarizes the theory of frequency domain analysis and the methods used in this paper. Section IV describes the data. Section V carries out univariate spectral analysis of growth and unemployment, for the countries considered and compares the results to wisdom prevailing from the time domain. Section VI details cross-spectral analysis across the various countries. Section VII returns to the time domain by applying a low pass filter to growth and unemployment, to split the variables into equilibrium and business cycle movements, and discuss their equilibrium links across the countries in a historical perspective. Section VIII makes further use of the split into business cycle and equilibrium movements, by performing cross-correlation analysis and granger causality tests at the different frequencies. Section VIIII will conclude.

3.2 The bivariate relationship between growth and unemployment in the time domain

As mentioned earlier, we can think of the relationship between growth and unemployment can be roughly split into three components: low frequency movements are equivalent to movements in the equilibrium of the process; medium frequency movements equivalent to business cycle induced fluctuations and high frequency movements highlight seasonal trends. In the discussion below, I will focus on the equilibrium and business cycle relationships.

Over the business cycle, the relationship between output or productivity and unemployment is clear: we expect an inverse relationship. Two main reasons exist for this in relation to productivity: labour hoarding by firms in recessions and the importance of technological shocks in generating economic fluctuations, both of which deliver the procyclical behaviour of output per man-hour.. In relation to output, it is summarized by *Okun's Law.*

There has also been a growing theoretical literature detailing interactions between steady state growth and equilibrium unemployment. Search theoretic models illustrate how changes in steady state growth can affect the equilibrium unemployment rate. Two main effects are uncovered: *a capitalization effect* and *a creative destruction effect.* Endogenous growth models, with some kind of labour market friction, show how changes in equilibrium unemployment can affect the steady state growth rate. There are various mechanisms via which this can happen: *loss of skills; learning by doing; the cleansing effect* and *savings.*

A more detailed evaluation of the various models which link growth and unemployment will be carried out in the next chapter. The purpose of this chapter is to take an agnostic look at growth and unemployment and any linkages between them. For this purpose it is sufficient just to be aware that we should expect a relationship between growth and unemployment and that it may be very different at business cycle and long run frequencies.

One way of looking at the relationship between equilibrium growth and unemployment, is to plot a scatter of time averaged growth against unemployment. Bean and Pissarides perform such an exercise. A similar exercise is shown in figure 3.1. The figure plots the average growth rate of productivity against unemployment, for the OECD countries over the periods 1955-64, 1965-74 and 1975-84. There is mild evidence of a negative relationship between growth and unemployment, over the full sample, but this is primarily a consequence of the fact that the 1975-84 period was almost universally one of both lower productivity growth and higher unemployment than the two earlier periods. Individually, not one of the sub-periods shows a significant relationship[1].

[1] The results presented here are quantitatively slightly different to Bean and Pissarides (1993) as the sample differs slightly. The sample used here omits Greece, Iceland, Luxembourg and Portugal due to lack of data. The results are still qualitatively the same though.

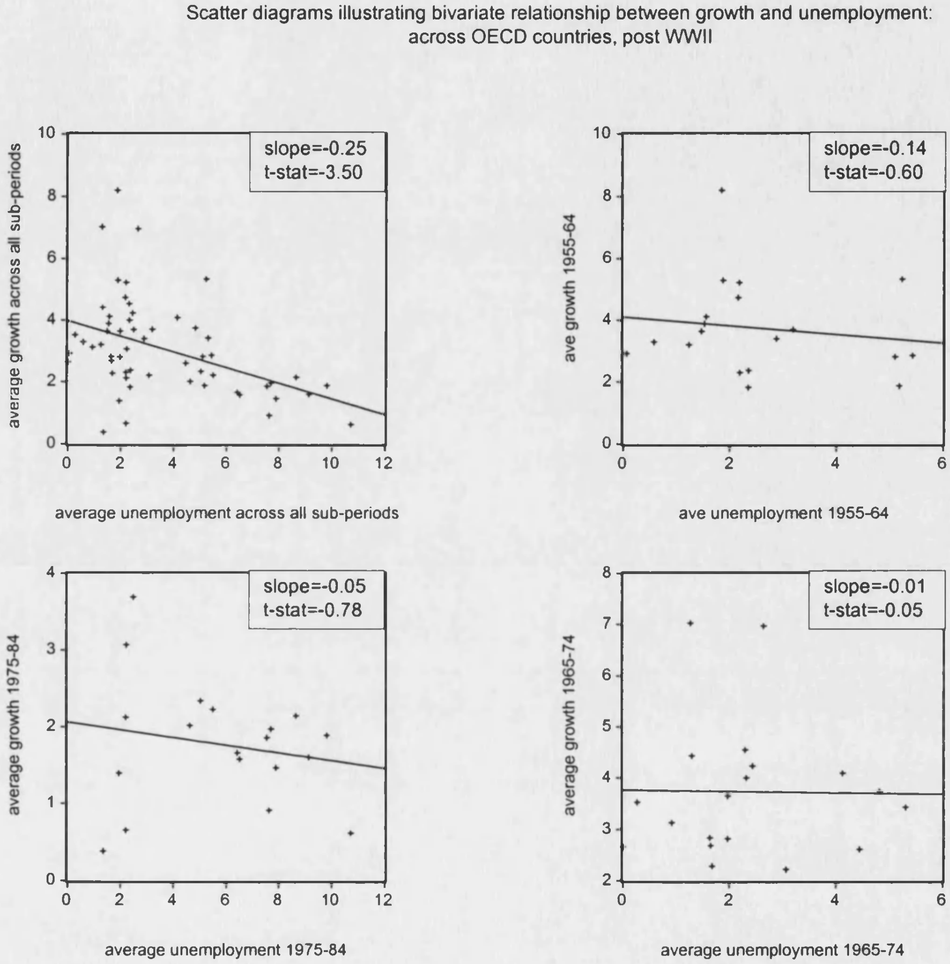

Figure 3.1: scatter of growth versus unemployment

Phelps and Zoega (1998) uncover results consistent with the negative relationship found in Bean and Pissarides. They look at a scatter of the change in equilibrium unemployment against the growth slowdown for OECD countries[2]. They find a positive relationship across a section of OECD countries, with the exception of Portugal, which has endured a severe growth slowdown but has mostly escaped the unemployment problem.

In figure 3.2 , we have performed a similar exercise to that of Bean-Pissarides, but for fewer countries with a longer time series for growth and unemployment. This avoids a problem common in much analysis of unemployment and growth post WWII: the importance of a trend due to the rise in unemployment from the 1970s onwards in Europe and the productivity slowdown in the 1970s, reducing the stationarity of the unemployment and growth series. Further it allows us to make more use of *within country variation* and less use of *cross country variation*. The figure plots the average growth rate of productivity for various countries over sub-periods: 1891-1910, 1911-1930, 1931-1950, 1951-1970, 1971-1990. For a pooled sample pre 1951 there is a positive and significant correlation between growth and unemployment, but a negative, and not significant one, post 1951. For the combined sample, little if any relationship can be discerned. Again for the post 1951 sample, the negative line is probably due to growth being higher and unemployment lower in the period 1971-1990 than in the period 1951-1970 for most of the countries considered.

The above scatter analysis is not suggestive of any robust relationship between equilibrium growth and unemployment.

There could be four reasons for this:

- There is no robust relationship between growth and unemployment.
- If there is a relationship, it maybe that cross-sectional analysis in the time domain is not detailed enough. More resolution may be needed if the relationship differs at different frequencies, as we have suggested earlier.

[2]The change in unemployment is $\frac{u_{86-95}}{u_{65-73}}$, and the growth slowdown is evaluated over the same two periods as the change in unemployment.

- There maybe an *identification problem.* As illustrated in the next chapter, when considering an efficiency wage model, depending on where the differences in unemployment come from, one can generate positive as well as negative correlation between g and u. If differences in unemployment come from differences in labour demand then it may generate a positive correlation between growth and unemployment. If they come from shifts in the shirking condition, i.e. differences in shirking behaviour and /or monitoring technologies, then this will generate a negative correlation between growth and unemployment.

- A relationship may show up if we control for the heterogeneity in institutional structures across countries.

  The next chapter will look at the issue of different institutional structures. This chapter will focus on trying to get a more detailed picture of the bivariate relationship between growth and unemployment. To do this frequency domain analysis will be used. This will allow us to evaluate the relationship between growth and unemployment at all frequencies. Below, I briefly outline the frequency domain approach.

3.3 The Theory of Spectral Analysis

In this section I will highlight the main intuition of spectral analysis and some of the tools relevant for this paper. For a more complete treatment, the reader is referred to Appendix A.

3.3.1 The equivalence of the frequency and time domains

Typical empirical work in macroeconomics is conducted in the *time domain.* For example, the value of a variable Y_t at date t, has often been described in terms of a sequence of innovations $\{\varepsilon_t\}_{t=-\infty}^{\infty}$ in models of the form

$$Y_t = \mu + \sum_{j=0}^{\infty} \psi_j \varepsilon_{t-j}$$

The focus of the time domain approach, is the implications of such a representation for the covariance between Y_t and Y_τ at distinct dates t and τ.

In this chapter, I will be also be using the analogue of this: the *frequency domain.* Typically, this approach describes the value of Y_t as a weighted sum of cosine and sine waves of varying frequencies,

$$Y_t = \mu + \int_0^{\pi} \alpha(\omega) \cos(\omega t)\ d\omega + \int_0^{\pi} \delta(\omega) \sin(\omega t)\ d\omega$$

the goal being to determine how important cycles of different frequencies are in accounting for the behaviour of Y. The frequency domain and the time domain are really two sides of the same coin: any covariance stationary process has both a time domain representation and a frequency domain representation[3]. The time series representation is *the autocovariance function*, and the frequency domain representation is *the power spectral density function*, or simply *the spectrum.* Any feature of the data that can described by one representation can equally well be described by the other representation.

3.3.2 The Spectrum

In the time domain, we evaluate the properties of an economic variable by looking at its *autoregressive* and *moving average* components. In some instances, the frequency domain representation, often *the spectrum*, can bring out facets of a data series which are not obvious from solely looking at the time domain. Below I briefly motivate the concept of the spectrum, before describing the important features of the unemployment and growth spectra plotted.

[3]It should be noted that the frequency domain representation can be extended to non stationary processes: see Priestley (1981).

A covariance stationary variable Y_t can be decomposed into an integral of periodic components:

$$Y_t = \mu + \int_0^{\pi} \alpha(\omega)\cos(\omega t)\ d\omega + \int_0^{\pi} \delta(\omega)\sin(\omega t)\ d\omega$$

where $\alpha(\omega)$ and $\beta(\omega)$ are uncorrelated random variables with mean zero and common variance $2f(\omega)$. $f(\omega)$ is the power spectrum. Appendix A shows how to derive the power spectrum as:

$$f(\omega) = \frac{1}{\pi}\sum_{k=-\infty}^{\infty} \gamma(k)e^{-i\omega k}$$

so that the spectrum is the *Fourier transform* of the autocovariance function, $\gamma(k)$.

Thus the variance can be decomposed as:

$$var(Y_t) = 2\int_0^{\pi} f(\omega)d\omega$$

So the power spectrum can be interpreted as the contribution to the variance of Y_t at frequency ω. This is important to remember when interpreting the spectra in section V.

Let us next consider some important examples of spectral shapes:

- If Y_t is white noise, then the spectrum is flat. This means that all cycles are equally important, which implies that the process is unforecastable.
- Now suppose Y_t is an AR(1) process with coefficient ρ, where $0<\rho<1$, i.e. it is *stationary.* The spectrum for this random variable has a peak in the neighbourhood $\omega = 0$ and is monotonically decreasing with $|\omega|$. Since the periodicity of a cycle with zero frequency is infinite, this stochastic process does not have an observable cycle.
- It Y_t has a unit root, then the spectrum would be unbounded at frequency zero. This is intuitive as a *non stationary* series has infinite variance.

3.3.3 Partitioning the Frequency Domain

As mentioned before, spectral analysis has one great advantage in studying the relationship between economic variables: it allows one to study their movements at *all* frequencies. One recent application of this advantage, has been in studying the relationship between prices and output. Conventional wisdom for decades has been that prices and output exhibit a positive correlation. Recently this has been called into question, with Cooley and Ohanian (1991) finding that this correlation is negative for the post-WWII period, in the US. Haan(1996) has used the spectral analysis to shed some light on this issue. He argues that the source of confusion is the focus on only one correlation coefficient and by doing this, losing out on the dynamic aspects of the comovement of variables. Haan uses spectral methods and finds that, for the post-WWII period, the comovement between GNP and prices is positive in the 'short run' and negative in the 'long run'. 'Short run' here, refers to cycles of period less than five years. Thus, by partitioning the frequency domain, one can sometimes uncover different comovements at different frequencies.

In studying growth and unemployment, a reasonable partitioning of the frequency domain may be into: equilibrium movements; business cycle movements and seasonal trends. In practice, there is strong evidence that such a partitioning could be made to work. NBER researchers, using the non spectral methods of Burns and Mitchell (1946), have isolated business cycle movements as lasting between 1.5-8 years. Englund, Persson and Svensson (1992) found that for Sweden, the business cycle was represented well in the frequency domain between 3-8 years. There seems to be convincing evidence that business cycles do not last longer than eight years and thus I take this as my demarcation frequency between business cycle movements and equilibrium movements. I will follow the NBER definition and argue that seasonal movements consist of cycles of less than 1.5 years. Given that the highest frequency that can be monitored with annual data is a cycle of two years, the data I utilize will only differentiate between equilibrium and business cycle movements. In practical terms, a cycle of eight years corresponds to a frequency of 0.25 in the spectral plots. This is because the *nyquist* frequency, or a period of 2 years, corresponds to a frequency of one and thus an eight year cycle will have a frequency a quarter of this.

3.3.4 Cross spectral analysis

Granger (1966) stated the opinion that cross spectral methods were likely to prove one of the most important tools of spectral analysis. It is premise which we utilize in this chapter, in using cross spectral methods to get an idea of the relationship between growth and unemployment, at all frequencies.

Cross spectrum analysis gives us two important summary statistics:

- *the phase spectrum*: this gives us the average value of the phase shift between the two series, growth and unemployment, at every frequency.
- *the coherency spectrum*: this gives us correlation coefficient between growth and unemployment at every frequency.

Both these statistics are recovered from the *cross spectrum.* For further details of this, see appendix A. The above statistics are very useful as they allow one to compare the relationship between growth and unemployment at different horizons: equilibrium and business cycle, given yearly data.

Below, I outline a few important types of relationship and their implications for the coherence and phase spectra:

- *Uncorrelated processes:* in this case, the coherence and phase will be zero for all frequencies.
- *Linear regression:* if $Y_t = aX_t + \varepsilon_t$, then the coherence will be one and the phase zero for all frequencies.
- *Linear regression with delay:* if $Y_t = aX_{t-d} + \varepsilon_t$, then the coherence spectrum is the same as for a normal linear regression, but the phase spectrum is different. The phase shift at frequency ω is $\Phi(\omega) = -\omega d$.

In other words, when there is a time delay, the phase spectrum is a linear function of frequency, with the slope representing the magnitude of the delay.

- *Fixed Angle Lag:* this is the case, when the phase shift is the same non zero value at all frequencies. Granger and Hatanka (1964) considered this to be a very important case, the reason being that the smaller the frequency the larger the time lag between corresponding components. They speculated that a lot of economic processes would have this feature.

3.3.5 Filtering

One of the aims of this chapter was to look at the relationship between equilibrium unemployment and growth. Previous attempts at this exercise have usually taken a simple average of growth and unemployment rates over a period of time and considered these equilibrium rates. One important issue to decide when using this technique, is the time period over which the average is taken.

A more sophisticated approach, is to put unemployment and growth through a Hodrick and Prescott (HP) filter. A HP filter optimally extracts a trend which is stochastic but moves smoothly over time and is uncorrelated with the cyclical component. The assumption that the trend is smooth is imposed by assuming that the sum of squares of the second differences of y_t is small. An estimate of the secular component is obtained by minimizing:

$$\min_{[y_t]_{t=1}^{T}} [\sum_{t=1}^{T} c_t^2 + \lambda \sum_{t=2}^{T}((y_{t+1} - y_t) - (y_t - y_{t-1}))]^2 \qquad \lambda > 0$$

where T is the sample size and λ is a parameter that penalizes the variability of the trend. As λ increases, the penalty imposed for large fluctuations in the secular component increases and the path for $\hat{y}_t$ becomes smoother. In fact, users of the HP filter can select λ a priori to isolate those cyclical fluctuations which belong to a specific frequency band.

The use of the frequency domain provides one with other possibilities. This paper proposes a different measure of equilibrium rates by making a note of the fact that most equilibrium movements of a variable are likely to be of low frequency. Higher frequency movements are likely to be due to business cycle or seasonal effects. This chapter proposes to put growth and unemployment through a 'low pass' filter and consider these equilibrium components.

A 'low pass' filter is considered a function $g(u)$ such that $|\Gamma(\omega)|^2$ has the form

$$|\Gamma(\omega)|^2 = \left\{ \begin{array}{ll} 1, & \text{for } |\omega| \leq \omega_0 \\ 0, & \text{for } |\omega| > \omega_0 \end{array} \right\},$$

$\Gamma(\omega)$ is called the *transfer function* or the Fourier transform of the filter, $g(u)$

In other words, a 'low pass' filter completely surpresses all components with frequencies higher than ω_0. Thus a critical factor in designing an economically meaningful 'low pass' filter is the cut off frequency ω_0. As mentioned in the section on partitioning the frequency domain, there is strong evidence that business cycles do not last more than eight years. Therefore, we choose ω_0 equivalent to a cycle of eight years, i.e. $\omega_0 = 0.25$, for the low pass filter used in this paper.

The filtering process is as follows: (a) transform the time series to the frequency domain by the Fourier transformation, (b) filter out all the unwanted components according to the transfer function of the filter, and (3) transform the remaining components back to the time domain by the inverse Fourier transform.. The result of these three operations is a the filtered process.

3.4 Data

The sample of countries considered includes: Australia, Canada, Germany, Sweden, the UK and the US. The limited size of this sample is purely data driven. Spectral analysis is a very data hungry progress. Various sources, for example Granger and Hatanka (1964) and Koopmans (1974), recommend upwards of 70 observations before reasonable estimates can be obtained. We would have liked to have carried out the analysis for the whole of the OECD, but for many of these countries only about 40 yearly post WWII observations are available. This is clearly insufficient to form reliable spectral representations. Four other countries we would have really liked to include were France, Italy, Spain and Portugal.. These countries would allow interesting comparisons to be made. Many argue that Italy and France share many similarities. Spain and Portugal form an even more striking combination. They have shared very similar recent histories in terms of the formation and break down of fascist regimes. They also share many similar institutional facets, yet there unemployment experiences have been vastly different, with the problem in Spain being much more acute. Blanchard and Jimeno (1995) make a comparative study of the two countries but only reach some very tentative conclusions. Maybe there is something in the growth-unemployment dynamic that may explain the countries different experiences.

For a detailed discussion of the data sources, please refer to appendix B. Some of the series are very long indeed. For all six countries growth figures were available from 1870 courtesy of Maddison (1994). In fact from the same source, equally long growth series were available for many other countries. Growth figures were not the constraint, unemployment figures were.

A problem with such long series, particularly with unemployment figures which go back to 1855 for the UK, is that the definitions have changed frequently. Further the measurement is likely to be much more reliable presently, than say 100 years ago. This may make the data very difficult to compare across time.

We believe this to be less of a problem than it potentially seems, due to the kind of econometric procedure used. The highest frequency spectral analysis allows us to observe is the *Nyquist frequency,* $\omega = \pi$. Given yearly data, this corresponds to a cycle every two years, i.e. not a very high frequency. Seasonal relationships between growth and unemployment will certainly not be observable with the given data set: yearly observations are just too infrequent for this. More importantly though, exact figures for growth and unemployment are probably not required to observe cycles of two years or longer. Approximate measures should suffice to recover movements of such periodicity. It is for this reason that we believe measurement error and changes in definition, though they undoubtedly exist, should not be such a big problem for the present analysis.

3.5 Univariate Spectral Analysis

3.5.1 Unemployment Spectra

Referring to figure 3.3, which plots estimates of the power spectrum for the unemployment rate in the countries considered, with 95% confidence bands[4]. Some of the underlying series are very long indeed. For example, data for the UK go back to 1855 and for the US they go back to 1890. Given the length of some of the unemployment series, we can be confident that the results are not the artifact of a particular period. Here I am particularly thinking of a lot of so called 'stylized facts', based on analysis that is just done for the post WWII period. For unemployment and growth this can be potentially misleading, due to the productivity slowdown and a marked upward trend in unemployment coinciding in this period.

The unemployment spectra are similar across the countries concerned, and show features consistent with the well known empirical regularity: Granger's *'typical spectral shape'*. Granger(1966) observed that most detrended macroeconomic variables exhibited a typical spectral shape. Estimated spectra look like a monotone decreasing function from low to high frequencies, with a pronounced peak in the neighbourhood of the zero frequency. The unemployment spectra, for all the countries, seem to follow this description very closely.

One feature to pick out, is the seeming lack of business cycle peak in the

[4]The spectra are estimated via the periodogram, smoothed using Daniel's flat window. For more details, refer to Appendix A.

unemployment spectra. We can define an economic cycle in the frequency domain as the occurrence of a peak in the spectral density of a series. In fact, if we look at the log spectrum of unemployment (see figure 3.4 which plots the log spectrum with 95% confidence intervals), to get more resolution at the high frequencies where the power is low, we can detect a small peak in all countries apart from Sweden around a frequency of 0.6, or a cycle of period around 3.5 years. Sargent (1979) in fact notices this phenomenon amongst most economic aggregates. They seem to have spectral densities resembling the typical spectral shape and do not display pronounced peaks at the range of frequencies associated with the business cycle. As Sargent rightly comments though, this does not mean that the series do not experience business cycles. One has to just take a quick look at the raw data plots of most economic aggregates to see this. In fact this suggests that the definition of business cycles in the frequency domain, based on cyclical peaks given earlier, is not very workable. Maybe using time domain definitions of business cycles may be more instructive.

The typical spectral shape, identified by Granger, implies that the weight of the components with very long periods are disproportionately large, i.e. that detrended aggregate times series display a very high degree of persistence. This is born out in Table 3.1, which documents the amount of the variance of unemployment and growth that is captured at lower than business cycle frequencies, i.e. cycles of over 8 years periodicity by our previous definition. In fact one could maybe consider a crude measure of persistence in the frequency domain to be just this statistic: persistence is the amount of unemployment explained by equilibrium movements. Between 83-95% of the variance of unemployment is explained at these frequencies, i.e. persistence is very high for *all* countries considered.

It may be instructive to compare this measure of persistence to those in the time domain. In the time domain, persistence has a different meaning. It is usually interpreted as how dependent current unemployment is on past unemployment. It is usually measured by the sum of coefficients on

Country	Unemployment	Growth
US	84%	36%
UK	86%	41%
Germany	83%	35%
Sweden	95%	32%
Australia	92%	28%
Canada	90%	39%

Table 3.1: **Variance:** contribution of below business cycle frequencies (greater than 8 years periodicity), to the explained variance of unemployment and growth, for the countries considered.

the autogressive components in an unemployment equation. But the closer this measure is to one, then the more of the variance of unemployment that will be explained by low frequency movements. Thus at some level, this time domain measure of persistence and the frequency domain measure are equivalent. Blanchard and Summers (1986) estimate unemployment, since 1900, in the UK and US as AR(1) processes and find coefficients of ρ, very close to but, less than one. They argue though, that an $ARMA(1,1)$ fits the unemployment series for these countries better. Alogoskoufis and Manning (1988) estimate $AR(2)$ processes for unemployment in a sample of sixteen OECD countries, since 1952. They find a root near the unit circle for European Community countries, with the US and the Nordic countries displaying much lower persistence. Phelps and Zoega (1998), use a Markov Switching Model to look at the level of persistence in the UK, over the period 1921-96. They find a raw persistence measure of 0.9, but a value of 0.65 once shifts in the mean of unemployment have been taken into account.

It seems that the raw measures of persistence, for the US and UK from Blanchard and Summers (1986) and Phelps and Zoega (1998), are consistent with the high degrees of persistence we see in the frequency domain. The evidence from Alogoskoufis and Manning (1998) for the US and Sweden is not consistent with our frequency domain measure of persistence. They argue the lower persistence in the US and Sweden is expected. This is due to less persistence in wage aspirations and less sluggishness in labour demand. In the US, it is argued that this is due to higher flexibility and in Sweden due to centralized wage bargaining. The difference, we believe, is due to the time horizons used. Alogoskoufis and Manning only look at unemployment post WWII. Our frequency domain measures are based on much longer series, as is the evidence of Blanchard and Summers and Phelps and Zoega. It may be the case that the persistence of unemployment reduced in the post WWII period, in both the US and Sweden.

A more sophisticated measure of persistence can be generated in the frequency domain, by considering a wider class of processes than is usually considered. By this, I mean allowing for the possibility of *long memory.*

A class of spectral density functions able to match Granger's typical spectral shape is given by

$$f(\theta) = dF(\theta) \;\sim\; g(\theta)\,\theta^{-2d}, \;\; as\;\theta \rightarrow 0^{+} \tag{3.1}$$

where " $\sim$ " indicates that the ratio of the left- and right-hand side tends to a bounded quantity, d is a non negative constant and $g(\theta)$ is a bounded function bounded away from zero in a neighbourhood of the origin. The parameter d represents the order of integration of the time series. If it is greater than zero, the time series exhibits *long memory* while it exhibits *weak memory* if the parameter is equal to 0. The parameter d measures the rate of divergence of the spectrum around zero frequency and thus it measures "how typical the spectral shape is". d is our measure of persistence: the higher the value of d, the higher is the weight of the components with very long periods and thus the higher is the persistence of the process.

A time domain representation of the time series X_t, $t \geq 0$, corresponding to equation 3.1 is given by the Wold representation

$$X_t = X_0 + \gamma\, t + \sum_{n=0}^{t} \phi_n\, \epsilon_{t-n}, \tag{3.2}$$

with Wold coefficients $\phi_n = \tilde{\phi}_n + d n^{d-1} + \mathrm{o}\left(\tilde{\phi}_n\right)$, where $\tilde{\phi}_n$ is a function converging to zero at a rate at least as quick as the exponential one ($\left|\tilde{\phi}_n\right| \leq \rho^n$,

$0 \leq \rho < 1$ as $n \uparrow \infty$), d is the order of integration of the time series, while $o\left(\tilde{\phi}_n\right)$ indicates a quantity of lower order than $\tilde{\phi}_n$, that is $\lim_{n \longrightarrow \infty} \frac{o(\tilde{\phi}_n)}{\tilde{\phi}_n} = 0$. The Wold coefficient ϕ_n gauges the fraction of the shock ϵ_{t-n}, n periods ahead, which has not yet been absorbed. Therefore, the rate of decaying of the Wold coefficients measures the persistence of the process.

A standard trend stationary process with $ARMA$ disturbance exhibits Wold coefficients ϕ_n's decaying at most at an exponential rate, that is a parameter of fractional integration d equal to zero. This weak memory property of $ARMA$ processes shows up, in frequency domain, under the form of a flat log spectral shape, around the zero frequency. A process with a unit root, exhibits Wold coefficients asymptotically approaching a constant that is $d = 1$. Thus its spectral shape is typical, yet particular as it exhibits a very specific rate of divergence around zero frequency. This set of considerations shows how standard $ARIMA$ processes cannot generate arbitrary spectral shapes, because they generate shapes with rates of divergence equal to either that of a unit root or a flat one.

Let us map the introduction of long memory into time domain concepts. If $0 < d < \frac{1}{2}$, then X_t has finite variance and still exhibits mean reversion. When $\frac{1}{2} < d < 1$, the process has infinite variance, but still exhibits mean reversion. The process is not covariance stationary, but less 'non stationary' than a unit root process. Further, the process now has mean reversion at a *hyperbolic rate*, i.e. lower than the *exponential rate* of trend stationary $ARMA$ processes. Finally when $d \geq 1$, the process has infinite variance and stops exhibiting mean reversion.

While formally testing for long memory in unemployment is beyond the scope of this paper, we can nevertheless informally discuss whether the results above and other time domain evidence is consistent with long memory[5]. Above, we showed that unemployment was very persistent. This could be

[5] A formal way of testing for long memory, or the value of d, is to perform semi parametric estimation of the OLS regression of the log of the estimated spectrum over the log-frequency, at around the zero frequency. Interested readers are referred to Michelacci and Zaffaroni (1997).

consistent with weak memory trend stationary $ARMA$ processes but with autoregressive coefficients summing close to one. But, they could also be consistent with long memory aswell. Phelps and Zoega (1998) use a Markov Switching Model on post WWII OECD unemployment, to show that for most countries, the data is consistent with infrequent mean shifts in unemployment, and not very high estimates of autoregressive persistence. They test that unemployment is stationary around a shifting mean against the alternative of a unit root process with a constant mean. The unit root hypothesis is resoundingly rejected. In light of the discussion above, this test could be misspecified.. It could be the case that unemployment exhibits long memory with $\frac{1}{2} < d < 1$. Thus unemployment would exhibit mean reversion at a hyperbolic rate, but would not be stationary. Standard unit root tests, like that employed by Phelps and Zoega, would exhibit low power with respect to this alternative (Diebold and Rudebusch 1991).

This alternative may not be so unreasonable. As Nickell (1998) argues, it is very unlikely that unemployment could display a unit root[6]. If this was the case, then unemployment would have no influence on wages. This would imply that there is nothing to anchor the unemployment rate. However, there is a lot of evidence that suggests unemployment does affect wages, see Bean (1994) for a survey. Bean indicates that the effect does vary widely across countries. The effect of unemployment on wages may be weak, but it does exist. Therefore, unemployment does have an anchor and it must display some mean reversion. This is evidenced by the fact that if we look at unemployment over a long enough time horizon, it is untrended (see LNJ 1991). This is not inconsistent with unemployment displaying long memory, in some cases, with $\frac{1}{2} < d < 1$. In this situation, unemployment would display mean reversion, but at a very slow hyperbolic rate, and would be non stationary. The tests performed in Phelps and Zoega could be confusing infrequent mean shifts, with just very slow mean reversion. This could maybe also explain

[6]Of course unemployment could never truly display a unit root, as it is bounded between zero and one. But it may, over certain periods of time, mimic the behaviour of a random walk.

the experience of Europe from the 1970s. Rather than illustrating *hysteresis effects*, or changes in the long run equilibrium unemployment rate, the experience may just be illustrating *long memory effects,* or extremely slow mean reversion. The above discussion suggests that it is an important next step to test formally for long memory in unemployment.

Does the typical spectral shape nature of unemployment imply that business cycle movements are not important in explaining unemployment? The below analysis suggests that if we only looked at the frequency domain, this would be the case. I will argue that this just highlights one of the limitations of spectral analysis and illustrates the need to look at the time domain as well, to understand fully the processes underlying economic variables.

One can think of unemployment as follows:

$$u_t = u_t^e + u_t^{bc} + u_t^s$$

where u_t^e, u_t^{bc}, and u_t^s are the: equilibrium; business cycle and seasonal elements of unemployment respectively. Focusing on the equilibrium and business cycle elements for the purpose of this exposition, we can deduce that the variance at frequency ω of u_t can be determined from the spectral decomposition

$$s_u(\omega) = var[u_t^e(\omega)] + var[u_t^{bc}(\omega)] + 2cov[u_t^e(\omega), u_t^{bc}(\omega)]$$

By definition, the direct contribution of u_t^{bc} to the variance of u_t for cycles of periodicity greater than eight years must be zero due to the our definition of business cycles. This implies that:

$$\begin{aligned} var[u_t^{bc}(\omega)] &= 0, \\ cov[u_t^e(\omega), u_t^{bc}(\omega)] &= 0 \text{ for } \omega = \omega^e \end{aligned}$$

where ω^e is the frequency equivalent of a periodicity of eight years or more.

Given that most of the power of the unemployment spectra is at frequencies below the business cycle, this would seem to imply that business cycle variations in unemployment really are not that important.

This would be an invalid conclusion: it fails to take into account the effect of business cycle variations in unemployment on the equilibrium level of unemployment. The frequency domain is not the best vehicle to study this correlation though. This is because the spectral representation theorem effectively decomposes a variable Y_t into a linear combination of sinusoidal terms, of varying frequency and mutually orthogonal (see appendix A). But one can think of periods where short run changes in the unemployment level have had an impact on the medium run NAIRU. An example of this is Europe over the 1970s and 1980s, where there was a strong correlation between the upward movement in the level of unemployment and estimates of the NAIRU. Various explanations for this were the effects of so called 'insiders' and long term unemployment. Bean (JEL 1994) provides a good survey of this literature. To analyze this particular economic mechanism, requires analysis in the time domain as well.

3.5.2 Growth Spectra

Figure 3.5 plots the growth spectra with 95% confidence bands for the countries considered. Once again the sample size is very long, with the data going back to 1871. The data is also very comparable across countries, as they are sourced from Maddison(1994) which uses *Geary-Khamis Dollars* to get growth data which can be compared across countries.

An interesting exercise is to compare the results here to those of King and Watson(1996). They find a pattern namely, '*the typical spectral shape of growth rates*'. This is naturally different to Granger's typical spectral shape, as it represents processes which are, in effect, first differences of the I(1) processes Granger was studying. 'The typical spectral shape of growth rates' broadly describes spectra which rise to a peak at a cycle length of about 5-10 years and then decline at very high frequencies. They find that for the US, post-WWII, growth spectrum, the peak occurs just inside the business cycle interval and this interval contains the bulk of the variance of output growth, in fact 58% exactly.

Country	Unemployment	Growth
US	∞	7.2
UK	∞	10
Germany	65	10
Sweden	∞	3.6
Australia	130	2.2
Canada	32.5	11.8

Table 3.2: **Peaks:** the figures represent the period of the cycle, in years, for which the corresponding spectra has a global peak

Referring to Table 3.1 it can be seen that growth spectra considered here illustrate the property that the bulk of the variance of output growth is contained in the business cycle interval. Only between 28-41% is contained in the low frequency interval. The US, the UK, Germany and Canada also illustrate a shape similar to that described by King and Watson. Table 3.2 documents the period for which the global peak of the spectra for each country occurs at. For the US, the UK and Germany this falls within the limits described by King and Watson, with Canada having a peak just outside these limits, at a cycle of 11.8 years. The spectra for Sweden and Australia do not follow 'the typical growth spectral shape' pattern. Sweden does have a large peak around the 10 year cycle, but has its global peak at the 3.6 year cycle. The spectrum for Australia is even more perverse. In this case, by far the biggest peak occurs at the higher end of the frequency range, namely 2.2 years.

The Australian spectrum provides an interesting case study as if one refers to the raw growth series plot in figure 3.6, it is noticeable how volatile growth was in Australia pre-1900, compared to other countries over the same period. This could maybe explain the importance of high frequencies in the Australian growth spectra. The growth spectrum for post- 1900 Australia illustrates this point. High frequencies are no longer important and the global peak occurs around the 10 year cycle. There is also a second important peak around the 4 year cycle though.

Thus, the evidence on 'the typical growth spectral shape' identified by King and Watson is mixed. Some countries bear out the expected shape but Sweden and Australia do not. Australia reverts to a shape close to 'the typical shape' if we exclude pre-1900 data. We could possibly justify omitting pre-1900 data on measurement error grounds. Early data is based on very incomplete sources and may not be that reliable. The reason why maybe King and Watson's result do not always hold in the spectra considered here, is that they only consider growth variables for the post-WWII period and for the US only. The data set here is much longer and considers a range of countries that may explain the idiosyncrasies registered.

Let us once more use the value of the variance of growth, explained by equilibrium movements, as a frequency domain measure of persistence. Unsurprisingly, it can easily be seen, by referring to Table 3.1, that the persistence of growth is much less than that of unemployment. In fact the values of persistence that we find in the frequency domain are remarkably consistent with those estimated in the time domain. Jones (1995a) performs various stationarity tests on the growth series of OECD countries. He finds that ADF tests strongly reject the null hypothesis of a unit root in growth rates, over the period 1900-87, and imply a first order autoregressive root that is typically less than 0.3. More specifically it is: 0.29 for Australia; 0.37 for Canada; 0.02 for Germany; 0.22 for Sweden; 0.24 for the UK and 0.25 for the US. Taking into account that these are only point estimates, and with the exception of Germany, they are very similar to the frequency domain persistence values of between 0.28-0.41. The rankings across countries may not be the same, but both measures are of similar orders of magnitude.

The estimated growth spectra merely confirm the intuition about growth rates from time domain experiments: growth is stationary and has very little persistence.

3.6 Cross Spectral Analysis

As mentioned earlier, many economists believe this to be the most important use of the frequency domain, as it allows one to document the relationship between two variables across the frequency distribution.

Cross spectral analysis gives us two important summary statistics:

- *the phase spectrum*: this gives us the average value of the phase shift between the two series, growth and unemployment, at every frequency.
- *the coherency spectrum*: this gives us the correlation coefficient between growth and unemployment at every frequency.

An example of the use of these concepts, has been at the NBER to try to isolate 'leading indicators' of business cycle movements, as an aid in the early recognition and prediction of cyclical movements. Essentially a good leading indicator displays a sizable phase lead at low business cycle frequencies over some important 'coincident' measures of the cycle, such as unemployment or GNP. Further, the indicator must also display a large coherence with those coincident measures. It should be noted though, that a good leading indicator does not necessarily help in predicting y_t any better than can be done by using past $y's$ alone. This is an important point to bear in mind when considering the analysis of unemployment and growth below.

Firstly, I will speculate as to what kind of features one may look for in the relationship between unemployment and growth. As mentioned in section 3.2, one may expect a different relationship at business cycle frequencies than at equilibrium frequencies. One possible line of thought, is that we should expect higher correlations at business cycle frequencies, due to common shocks to both growth and unemployment. Whereas at lower frequencies, growth will be led by technology but unemployment by demography. This is a contentious line of thought. We need to consider the feedback effects between growth and unemployment, namely: the capitalization effect; the creative destruction effect; loss of skill and learning by doing. The relative importance of these effects will determine the nature of relationship, at low frequencies, between unemployment and growth.

Referring to figures 3.7-3.9, which illustrate the coherence and phase plots for the countries considered. In the coherence plot, the dashed lines represent 95% confidence intervals, which are reasonably narrow[7]. The relative narrowness of the confidence intervals across countries is determined by two main factors: the number of observations and the size of the coherence estimate. The higher both are, the narrower the confidence intervals are. This explains why the US confidence interval seems very narrow, when compared to the Australian or Swedish bands. The first obvious point to make is that coherence spectra imply that there is significant non-zero correlation between growth and unemployment, for virtually all frequencies. Secondly Germany is the only country for which the coherence is higher at business cycle frequencies than at equilibrium frequencies. All the other countries have high coherences for cycles of 10-20 years periodicity. Further, all countries apart from Canada have high coherences at high frequencies, especially around the 2.5 year cycle. The US has a fairly stable coherence across all frequencies of around 0.8. Looking at its phase spectrum plot (figure 3.8) suggests that the relationship may of similar to a linear regression with delay: with unemployment leading growth.

Looking at both sets of phase plots suggests that, in general, unemployment leads growth. Further as Granger and Hatanka speculated, the phase plots in years show very clearly that the smaller the frequency, the longer the time lag. A note of caution should be mentioned when interpreting phase plots in terms of leads and lags. The phase plot is drawn on the $-\pi$ to π simplex to uniquely determine the phase shift at each frequency. But this leaves open to interpretation whether a lead could be a lag as well.. For example, a lead of $\frac{\pi}{2}$ could equally be interpreted as a lag of $\frac{3\pi}{2}$. Thus, I do

[7]The confidence intervals are computed using a procedure described in the appendix. It should be noted that the bands are probably more accurate for coherences above 0.4. This is because the distribution they are derived from is less of an approximation for higher coherences. See Enochson and Goodman (1965) for details.

not put too much emphasis on the results from the phase diagrams.

There does not seem to be strict demarcation in the relationship between equilibrium frequencies and business cycle frequencies. The high coherences mentioned earlier at low frequencies, apart from for Germany, extend to the low end of the business cycle frequency spectrum: namely, cycles of period 5-8 years. Given this and the problems outlined earlier, of using spectral peaks to identify business cycles, maybe we can follow Sargent (1979) and consider the following definition of business cycles: the business cycle is the phenomenon of a number of important economic aggregates being characterized by high pairwise coherences at low business cycle frequencies.

So, overall, the coherence plots are very suggestive that there is a relationship between growth and unemployment at equilibrium frequencies and at low business cycle frequencies. There does not seem to be a noticeable shift in the relationship, as we progress from equilibrium frequencies to business cycle frequencies as the theoretical considerations earlier may have suggested. The phase diagrams suggest that unemployment leads growth. This may imply that the feedback effects from unemployment to growth, i.e. loss of skills and learning by doing, are more important than the feedback effects from growth to unemployment, namely creative destruction and the capitalization effect. I would caution against this presumption, as the phase plots are difficult to interpret for the reasons mentioned earlier.

3.7 Back to the time domain: a low pass filter

In this section the growth and unemployment series, for the various countries considered, are passed through a 'low pass' filter, i.e. high frequency movements are filtered out. These filtered series are then considered equilibrium values. The logic runs as follows: filter out all frequencies due to the business cycle or above and one should be left with fluctuations due to changes in the equilibrium value of a variable. This paper follows: the NBER and Englund, Persson and Svensson (1992); and considers cycles of periodicity greater than eight years to be lower than any business cycle frequency on average.

An alternative would be to simply average the growth and unemployment rates over a particular sub-period and consider these as equilibrium rates. This is the approach taken in much of the literature, for example the Barro style growth regressions or the LNJ unemployment regressions. Of course the perfect method would be to produce measures of equilibrium growth and unemployment based on some economic model, for example the NAIRU as an estimate of equilibrium unemployment. It is a well documented fact though, that these measures are not very robust, being very sensitive to the models used.

Thus, as a second best solution, I consider spectral analysis as a good option. It is more sophisticated than a simple averaging procedure. This can be used to plot the same graph as Bean-Pissarides, but instead of merely having the averages of growth and unemployment, I will use filtered growth and unemployment rates to see if any relationship consequently shows up.

This has a major advantage over the simple averaging procedure used in much of the literature. The filtered series retains all the observations for individual countries. This is not the case if one uses the averaging procedure. For example, if you have a 100 observations and take 10 year averages, you are left with only 10 equilibrium observations, whereas the filtering method will retain the 100 observations. This allows one to plot the same scatter graphs as in section 3.2 but for individual countries, not *across* countries. This is a very important difference, as cross sectional variations in unemployment and growth, particularly across OECD countries, tend to be dominated by country specific fixed effects. If the relationship between growth and unemployment is very country specific, a simple look across a section of countries could be highly misleading. To really capture the relationship between unemployment and growth, we need to make use of *within country variation* as well as *cross country variation.* Utilizing a long panel within countries is the best way to achieve this. This allows one to get a truer picture of the relationship between growth and unemployment, as any variation in the relationship caused by different institutions in different countries is not included. Only changes in the institutional framework, within a country, over time, can distort the picture.

Referring to figures 3.10-3.15, we plot scatter diagrams for the filtered growth and unemployment series of the six countries considered and discuss their implications for the relationship between growth and unemployment.[8]

For Australia there is a slight negative relationship between filtered growth and unemployment across the pooled sample and the sub-periods. It is only significant for the pooled and post-WWII samples. A linear relationship does not fit very well and there is a much higher variance for both filtered growth and unemployment in the pre-WWII period.

Canada provides similar results to Australia, though only the pooled sample shows a significant relationship.

Germany shows little relationship for the pooled or pre-WWII sample. The post WWII sample shows a positive and significant relationship, though this is due to three outlying observations in the early 50s when most economies were seriously booming after recovering from WWII. If we ignore these outliers, then the relationship is more or less neutral. This raises a slight problem with the methodology used that needs to be highlighted.. The filter still includes cycles of approximately eight years or above[9]. The cycle caused by WWII for example, could fall into this category. In Germany there was a huge fall in output towards the end WWII and immediately afterwards. This was due to two reasons: the loss of the war and the wartime economy switching back to normal economic activities. This was followed by a huge boom in the early 1950s, which was also seen in many other countries. These two parts together could come across as a cycle of periodicity greater than eight years but of huge amplitude. I believe this to be the case with Germany, and so any outliers caused by this, must be treated with caution. Again there is

[8] The sample is split into pre WWII and post WWII periods. The pre WWII sample is from 1855-1950 where available and the post WWII period is from 1951-1992

[9] the reason why the filter can only approximate an ideal low pass filter of eight years or below is due to the problem of 'leakage'.

country	s.d. for filtered series			
	growth		unemployment	
	pre-WWII	post-WWII	pre-WWII	post-WWII
US	4.06	1.90	5.81	1.38
UK	2.37	0.75	2.97	2.57
Germany	4.69	3.38	5.94	2.64
Sweden	1.98	1.10	5.72	0.56
Australia	2.75	0.98	4.31	1.85
Canada	4.13	1.05	4.98	1.66

Table 3.3: **Standard Deviations:** S.Ds for filtered unemployment and growth.

a higher variance for both variables in the pre-WWII sample, particularly so for unemployment.

Sweden shows little relationship for the pooled or pre-WWII sample, like Germany. It shows a strong negative and significant relationship for the post WWII sample. Again the variance of filtered unemployment is much higher in the pre-WWI sample.

The UK shows little relationship in the pooled sample, a slightly positive but insignificant relationship in the pre-WWII sample and a strongly negative and significant relationship in the post-WWII sample. As noted before, the range of observations is much higher in the pre-WWII period.

The US has very similar results to the UK, but the fit is slightly worse for all periods

What general lessons can be drawn from the above observations? One expected finding is that the range and variance of both equilibrium growth and unemployment is higher in the pre than post-WWII period. This is reinforced by table 3.3, which documents the standard deviations of the filtered series in the pre-WWII and post-WWII periods.

This is unsurprising as some countries were quite early on in there industrial revolution. This period is often associated with more volatile growth and unemployment rates than when a country has matured. Secondly, there were major events in this period that would have effected even equilibrium growth and unemployment. These were events such as: WWI and WWII; the Great Depression, which was particularly severe in the US and the hyper-inflationary episodes in Germany. Measurement error could also possibly play a part. Early data is based on very incomplete sources and may not be that reliable. For example, in the UK, pre-1914 unemployment data is almost certainly excessively cyclical as it is based on union counts, whilst post-1918 is based on a registered unemployment benefit claimant count.

Only Canada and Australia show any kind of significant relationship in the pooled sample and in both cases it is negative. With the exception of Germany, all countries show a negative relationship in the post WWII period. It is particularly strong for the UK and Sweden. The positive relationship in the German case is probably due to outliers during the early 1950s. Further as mentioned in section 3.2, the negative relationship in the post WWII period may be due to the fact that the 1975-84 period was almost universally one of both lower productivity growth and higher unemployment than earlier in the post WWII period.

The above results suggest is difficult to have any strong sense of the relationship, between growth and unemployment, from the filtered growth and unemployment series scatter diagrams. There is some suggestion of a negative relationship, though for reasons mentioned above, this is not a strong conviction.

To a large degree these findings confirm the results reported in section 3.2. This is that the scatter diagrams show a negative relationship post WWII and little relationship across all sub-periods. The only difference occurs in the pre WWII sample, where the averaging method produces a positive and significant relationship between growth and unemployment. This is not replicated in the results from the filtering method. For reasons outlined at the beginning of this section though, the filtering method probably produces more reliable results. It may be the case that we need to take account of the differing institutions across countries more explicitly to get a better sense of this relationship. This exercise is carried out in the following chapters.

3.8 Time Domain Statistics

Splitting the frequency range into different components, by using a low pass filter, allows other interesting statistics to be developed in the time domain. In this section, I look at the cross correlations and granger causality tests, between the filtered growth and unemployment series.

3.8.1 Granger causality tests

An often remarked on phenomenon in economics, is that correlation does not necessarily imply causation. An example would be the positive correlation found between the death rate in the UK and the proportion of marriages solemnized in the Church of England. The Granger approach to the question whether X causes Y, is to see how much of the current Y can be explained by past values of Y and then to see whether adding lagged values of X can improve the explanation. Y is said to be Granger-caused by X, if X helps in the prediction of Y, or equivalently if the coefficients on the lagged Xs are statistically significant. It is important to note though, that the statement 'X Granger causes Y' does not imply that Y is the effect or the result of X. Granger causality measures precedence and information content, but does not by itself indicate causality in the more common use of the term.

We have performed Granger causality tests between our measures of equilibrium growth and unemployment: the filtered growth series (g_f) and the filtered unemployment series (u_f). The overwhelming finding is that the null hypothesis of non granger causality is rejected, in both directions[10]. In other words, we cannot reject the hypothesis that g_f granger causes u_f and that u_f granger causes g_f. I will comment more on these results in the next chapter, but even given the notoriously low power of granger causality tests, they suggest that growth and unemployment feedback into each other, at equilibrium

[10]The results of the tests are available on request. The tests were performed for a variety of lags to check for robustness, and at a significance level of 5%. In general, the test of growth not granger causing unemployment, was more significantly rejected than vice versa.

frequencies.

3.8.2 Cross correlations

The granger causality tests above suggest that we cannot rule out causality in both directions. Given this, looking at the cross correlation lag structure should provide us with important insights. Tables 3.4 and 3.5 document the cross correlations between filtered growth and filtered unemployment, for the various countries considered. With the exception of Sweden, the results are striking. Looking at the lag structure of $corr(u_f^{t+\tau}, g_f^t)$ for $\tau > 0$, we find that the cross correlations are nearly always negative for all the countries considered. For $corr(u_f^t, g_f^{t+\tau})$ with $\tau > 0$, we find at low lags that the correlation is positive and at higher lags it switches to being negative. The switching point occurs at lag lengths of 8-12 depending on the country. Again I will comment more on these results in the next chapter, when I relate them closely to the predictions of various models. They are very suggestive of the following mechanisms at work though:

- in the effect of growth on unemployment, capitalization dominates creative destruction (a negative $corr(u_f^{t+\tau}, g_f^t)$;
- in the effect of unemployment on growth, the cleansing effect is prevalent at lower lags of 0-8 years (a positive $corr(u_f^t, g_f^{t+\tau})$) , after which loss of skills and learning by doing effects dominate (a negative $corr(u_f^t, g_f^{t+\tau})$).

The exception of Sweden, maybe due to the emphasis that country has placed on using active labour market policies to sustain full employment, throughout its history. This may have counteracted the natural forces linking growth and unemployment. It should be noted, though, that 'the Swedish model' was perceived to have failed in the 1990s, when the combination of low growth and joining the ERM illustrated how active labour market policies were not effective as anti-cyclical devices. Active labour market spending ballooned and yet unemployment continued to increase.

The above insights will become clearer when we discuss the various models linking growth and unemployment, in the next chapter.

3.9 Conclusion

This chapter has used a combination of frequency domain and time domain methods to try and get a more detailed picture of the relationship between unemployment and growth. It has been argued that the time domain does not provide enough resolution about the relationship, especially if the relationship is different at equilibrium frequencies than at business cycle frequencies.

A variety of instruments are used, in the frequency domain, to recover some stylized facts about the relationship between unemployment and growth:

- Univariate analysis suggests that unemployment is a highly persistent process that may well show signs of long memory. They also confirm our prior belief that growth is highly stationary with little persistence.
- Cross spectral methods show a high degree of correlation between unemployment and growth at equilibrium and low business cycle frequencies, with no noticeable shift in the relationship as one progresses from equilibrium frequencies to business cycle frequencies.
- The relationship between filtered growth and unemployment gives a suggestion of a negative relationship, though this is not a strong conviction.

Mapping back into time domain, we find that granger causality tests cannot rule out steady state growth and equilibrium unemployment feeding back into each other. Further, cross correlation analysis is very suggestive that certain mechanisms are more important than others. This will become clear, when we review the various mechanisms linking growth and unemployment, in the following chapter. One finding will be that capitalization dominates creative destruction, in the effect of growth and unemployment.

It also seems that, in the impact of unemployment on growth: the cleansing effect is prevalent at medium run frequencies; with loss of skills and learning by doing dominating at long run frequencies.

Thus, the conclusion of this chapter is that bivariate analysis of growth and unemployment provides us with some highly pertinent stylized facts about: growth, unemployment and their mutual relationship. In isolation though, it is not enough to discriminate between the various mechanisms leading to a relationship between unemployment and growth. Only by more explicitly taking into account the differing institutions across countries, will that goal be achievable. An attempt at such is carried out in the following chapters.

3.10 Appendix A - The Theory of Spectral Analysis

This section reviews some of the important elements of spectral analysis utilized in this paper. Firstly I will describe the foundation of the frequency domain approach and it's relation to the time domain. This will be followed by a discussion of filtering procedures and cross spectral analysis, focusing on the coherence and phase concepts.

3.10.1 The Frequency Domain Approach to Time Series Analysis

Typical empirical work in macroeconomics is conducted in the *time domain.* For example, the value of a variable Y_t at date t, has often been described in terms of a sequence of innovations $\{\varepsilon_t\}_{t=-\infty}^{\infty}$ in models of the form

$$Y_t = \mu + \sum_{j=0}^{\infty} \psi_j \varepsilon_{t-j}$$

The focus of the time domain approach, will be the implications of such a representation for the covariance between Y_t and Y_τ at distinct dates t and τ.

In this chapter, I will be using the analogue of this: the *frequency domain.* Typically, this approach will describe the value of Y_t as a weighted sum of cosine and sine waves of varying frequencies,

$$Y_t = \mu + \int_0^{\pi} \alpha(\omega)\cos(\omega t)\ d\omega + \int_0^{\pi} \delta(\omega)\sin(\omega t)\ d\omega$$

the goal being to determine how important cycles of different frequencies are in accounting for the behaviour of Y. The frequency domain and the time domain are really two sides of the same coin: any covariance stationary process has both a time domain representation and a frequency domain representation. Any feature of the data that can described by one representation can equally well be described by the other representation. In this chapter, it is argued that the frequency domain is convenient for analyzing the link between growth and unemployment, as it allows one to look at the relationship at different frequencies: low, medium and high. It is further argued that these different frequencies each have an economic interpretation: low frequency readings as equilibrium movements; medium frequency as business cycle movements and high frequency as seasonal trends.

Representation

The Spectral Representation Theorem[11] says that any covariance-stationary process Y_t can be expressed as:

$$Y_t = \mu + \int_0^{\pi} [\alpha(\omega)\cos(\omega t) + \delta(\omega)\sin(\omega t)]d\omega \tag{3.3}$$

The random processes represented by $\alpha(\omega)$ and $\delta(\omega)$ have zero mean and the further property that for any frequencies $0 < \omega_1 < \omega_2 < \omega_3 < \omega_4 < \pi$, the variable $\int_{\omega_1}^{\omega_2} \alpha(\omega)d\omega$ is uncorrelated with $\int_{\omega_3}^{\omega_4} \alpha(\omega)d\omega$ and the variable $\int_{\omega_1}^{\omega_2} \delta(\omega)d\omega$ is uncorrelated with $\int_{\omega_3}^{\omega_4} \delta(\omega)d\omega$ while for any $0 < \omega_1 < \omega_2 < \pi$ and $0 < \omega_3 < \omega_4 < \pi$, the variable $\int_{\omega_1}^{\omega_2} \alpha(\omega)d\omega$ is uncorrelated with $\int_{\omega_3}^{\omega_4} \delta(\omega)d\omega$.

[11] In fact Priestley(1981) shows how this representation can be extended to non stationary linear processes.

The above representation, allows one intuitively to think of Y_t as a linear combination of sinusoidal terms, of varying frequency. The upper limit in the integral is π rather than ∞ as one cannot distinguish between variation at a corresponding frequency in the range $(0, \pi)$ and higher frequencies due to the periodicities of the cosine and sine functions. The frequency $\omega = \pi$ is called the *Nyquist frequency.*

The next important concept to introduce is the *(power) spectral distribution function* or $F(\omega)$. This arises from the *Wiener-Khintchine Theorem*, which as applied to real-valued processes says that, for any stationary stochastic process with autocovariance function $\gamma(k)$, there exists a monotonically increasing function $F(\omega)$ such that

$$\gamma(k) = \int_0^\pi \cos \omega k \; dF(\omega) \tag{3.4}$$

Equation 3.4 is called the spectral representation of the autocovariance function. The great use of this is that it can be shown that $F(\omega)$ has a direct statistical interpretation: it is the contribution to the variance of the series which is accounted for by frequencies in the range $(0, \omega)$.

For a purely indeterministic discrete stationary process, the spectral distribution function is a continuous (monotone bounded) function in $(0, \pi)$, and thus we can derive the *(power) spectral density function*, $f(\omega) = \frac{dF(\omega)}{d\omega}$. This is often referred to as the *spectrum.*

When $f(\omega)$ exists, equation 3.4 can be expressed in the form

$$\gamma(k) = \int_0^\pi \cos \omega k \; f(\omega) \; d\omega \tag{3.5}$$

Putting $k = 0$, we have

$$\gamma(0) = \sigma_x^2 = \int_0^\pi f(\omega) \; d\omega = F(\pi) \tag{3.6}$$

The physical meaning of the spectrum is that $f(\omega)d\omega$ represents the contribution to variance of components in the range $(\omega, \omega + d\omega)$. If a band contributes a large proportion of the total variance it may be considered important compared to a band which contributes a smaller amount to the variance. Equation 3.5 illustrates the point made at the beginning of this section, that the autocovariance function and the power spectral density function are equivalent ways of describing a stationary stochastic process: the time domain and frequency domain approaches are complementary.

Inverting equation 3.5 we get

$$f(\omega) = \frac{1}{\pi} \sum_{k=-\infty}^{\infty} \gamma(k) e^{-i\omega k} \tag{3.7}$$

so that the spectrum is the *Fourier transform* of the autocovariance function.

Estimation

Given a set of observations $\{y_t\}_{t=1}^{n}$, the spectrum , $f(\omega)$, is usually estimated through the *periodogram* $I(\omega)$, where

$$I(\omega) = \frac{1}{2\pi N} \left| \sum_{t=1}^{N} y_t e^{it\omega} \right|^2 . \tag{3.8}$$

This is because it can be shown that equation 3.8 reduces to

$$\frac{1}{\pi} \sum_{k=-(N-1)}^{N-1} c_k e^{-iwk} \tag{3.9}$$

where $c_k = \sum_{t=1}^{N-k} (y_t - \overline{y})(y_{t+k} - \overline{y})/N$, i.e. represents the sample estimate of $\gamma_{k,}$ and it is assumed that $c_k = 0$ for $|k| \geq N$. Thus the periodogram is the sample analogue of the theoretical spectrum.

It can be shown that the periodogram is an asymptotically unbiased estimator of the spectrum, but not a consistent one, as the variance of $I(\omega)$ does not tend to zero as N increases. This is not surprising given that the Fourier series representation 3.9 requires one to evaluate N parameters from N observations no matter how long the series. Thus to get a reasonable estimate of the spectrum, ways of *smoothing* the periodogram are used. By smoothing the spectrum one means that for each frequency, a weighted average of sample spectrum values for frequencies on either side of the frequency concerned are utilized. For a detailed discussion of various smoothing techniques the reader is referred to Koopmans (1974) and Priestley (1981). The *window* used for smoothing is *Daniel's flat window*. The results are robust to changes in the *bandwidth* of the window and the window itself.

3.10.2 Cross spectral analysis

Below I will discuss the concept of the *cross-spectrum*, in particular looking at the phase and coherence concepts.

By analogy with the univariate case (see equation 3.7), we will define the cross-spectrum of a discrete bivariate stationary process as the Fourier transform of the cross-covariance function, namely

$$f_{xy}(\omega) = \frac{1}{\pi}\left[\sum_{k=-\infty}^{\infty} \gamma_{xy}(k)e^{-iwk}\right]$$

over the range $0 < \omega < \pi$ where $\gamma_{xy}(k) = Cov(X_t, Y_{t+k})$.

Note that cross-spectrum is a complex function unlike the auto-spectrum as $\gamma_{xy}(k)$ is not an even function. Thus we can write $f_{xy}(\omega)$ in one of two ways

$$f_{xy}(\omega) = c(\omega) - iq(\omega)$$

or

$$f_{xy}(\omega) = \alpha_{xy}(\omega)e^{i\Phi_{xy}(w)}$$

where

$$\alpha_{xy}(\omega) = \sqrt{[c^2(\omega) + q^2(\omega)]}$$

is the *cross-amplitude spectrum,*

$$\Phi_{xy}(\omega) = \tan^{-1}\left[\frac{-q(\omega)}{c(\omega)}\right]$$

is the *phase spectrum,* and

$$C(\omega) = \sqrt[+]{\frac{\alpha^2_{xy}(\omega)}{f_x(\omega)\ f_y(\omega)}}$$

is know as the *coherency spectrum*, where $f_x(\omega)$ and $f_y(\omega)$ are the power spectra for the individual processes.

Further, it can be shown that

$$0 \leq C(\omega) \leq 1$$

The phase spectrum measures the phase difference between corresponding frequencies of the processes. When on variable is leading the other, $\frac{\Phi(\omega)}{\omega}$ measures the extent of the time lag. The coherency spectrum is equivalent to the square of the correlation coefficient between corresponding frequencies of the processes.

Thus the coherence can be used to measure the degree to which the two series are related and the phase may be interpreted in terms of time lags.

Estimation

Estimation is analogous to the univariate case. A smoothed version of the *cross periodogram* is estimated, from which it is easy to recover estimates of the phase and coherency spectrum.

3.10.3 Filtering

Let $Y(t)$ be the unfiltered series and $X(t)$ the filtered series. The filtering process can be represented as

$$X(t) = \int_{-\infty}^{\infty} g(u)\ Y(t-u)\ du.$$

Further, let

$$\Gamma(\omega) = \int_{-\infty}^{\infty} g(u) e^{-iwu}\ du.$$

where $\Gamma(\omega)$ is called the *transfer function* of the system and is simply the Fourier transformation of the filter $g(u)$.

The spectral representation for $Y(t)$ is[12]

$$Y(t) = \int_{-\infty}^{\infty} e^{i\omega t}\, dz_y(\omega)$$

where $z_y(\omega)$ is a complex random process with uncorrelated increments so that

$$\begin{aligned} E[dz_y(\omega)\ \overline{dz_y(\omega)}] &= 0, \qquad \omega \neq \lambda \\ &= dF_y(\omega),\ \omega = \lambda \end{aligned}$$

So, the spectral representation of $X(t)$ is

$$\begin{aligned} X(t) &= \int_{-\infty}^{\infty} g(u) \left\{ \int_{-\infty}^{\infty} e^{iw(t-u)} dz_y(\omega) \right\} du \\ &= \int_{-\infty}^{\infty} e^{i\omega t}\, \Gamma(\omega) dz_y(\omega) \\ &= \int_{-\infty}^{\infty} e^{i\omega t}\, dz_x(\omega) \end{aligned}$$

where $dz_x(\omega) = \Gamma(\omega) dz_y(\omega)$

Thus a 'low pass' filter is considered a function $g(u)$ such that $|\Gamma(\omega)|^2$ has the form

$$|\Gamma(\omega)|^2 = \left\{ \begin{array}{l} 1, \text{ for } |\omega| \leq \omega_0 \\ 0, \text{ for } |\omega| > \omega_0 \end{array} \right\},$$

In other words, a 'low pass' filter completely surpresses all components with frequencies higher than ω_0. Thus a critical factor in designing an economically meaningful 'low pass' filter is the cut off frequency ω_0.

3.10.4 Confidence Intervals

The above estimation procedures derive point estimates of: the spectrum, cross-spectrum, phase spectrum and the coherency spectrum respectively. Below I state various results which can be used to derive appropriate confidence intervals. The discussion below is based on Koopmans (1974), which the reader is referred to for a more comprehensive treatment of the issue.

[12] In this sub-section I have written the spectral representations in complex number form, for ease of exposition. They are simply generalisations of equation 3.3 to the complex numbers space.

The Power Spectrum

There is a general result that states under reasonable conditions[13], then the distribution of

$$\frac{r\,\widehat{f}(\omega)}{f(w)} \sim \chi_r^2$$

where $\widehat{f}(\omega)$ is a smoothed periodogram estimator and r is the equivalent degrees of freedom, which for the Daniel window used in the paper is twice the number of observations.

This result can be used to calculate $100(1-\alpha)\%$ confidence intervals for the spectrum.

Let

$$P(\chi_r^2 \leq a) = \alpha/2, \qquad P(\chi_r^2 \leq b) = 1 - (\frac{\alpha}{2})$$

then the $100(1-\alpha)\%$ confidence interval for the spectrum, $f(\omega)$ is

$$\frac{r\,\widehat{f}(\omega)}{b} \leq f(\omega) \leq \frac{r\,\widehat{f}(\omega)}{a}.$$

The $100(1-\alpha)\%$ confidence interval for the log spectrum, $\log(f(w)$ is

$$\log(\frac{b}{a})$$

i.e. is of constant width over the frequency range.

The Coherence Spectrum

For the coherence spectrum, Enochson and Goodman (1965) have shown that for $n > 20$, the random variable

$$\varphi = \tanh^{-1}\left(\widehat{C}(\omega)\right)$$

is approximately normally distributed with mean and variance

$$\begin{aligned} E(\varphi) &= \tanh^{-1}(C(\omega)) + \left(\frac{1}{2(n-1)}\right) \\ Var(\varphi) &= \left(\frac{1}{2(n-1)}\right) \end{aligned}$$

[13] these conditions are that M and N are large, where these represent the truncation point in the smoothed periodogram estimator and the sample size respectively.

In these expressions, $2n$ denotes the equivalent degrees of freedom of the estimator $\widehat{f}(\omega)$ and $\widehat{C}(\omega)$ is the sample coherence. If $u_{\frac{\alpha}{2}}$ is the upper $\frac{\alpha}{2}$ cutoff point for the standard normal distribution, then after some manipulation, it can be shown that the $100(1-\alpha)\%$ confidence interval is

$$\underline{C(\omega)} \leq C(\omega) \leq \overline{C(\omega)}$$

where

$$\begin{aligned}
\underline{C(\omega)} &= \tanh\left\{\tanh^{-1}\left(\widehat{C}(\omega)\right) - u_{\frac{\alpha}{2}}\left(2(n-1)^{-\frac{1}{2}} - 2(n-1)^{-1}\right)\right\}, \\
\overline{C(\omega)} &= \tanh\left\{\tanh^{-1}\left(\widehat{C}(\omega)\right) + u_{\frac{\alpha}{2}}\left(2(n-1)^{-\frac{1}{2}} - 2(n-1)^{-1}\right)\right\},
\end{aligned}$$

Easier to implement is a test of the hypothesis $C(\omega) = 0$ vs $C(\omega) > 0$. As if $C(\omega) = 0$, then

$$(n-1)\left(\widehat{C}(\omega)\right)^2 / [1 - \left(\widehat{C}(\omega)\right)^2] = F_{2,2(n-1)}$$

The Phase Spectrum

For the phase spectrum, Hannan (1970) has shown that a $100(1-\alpha)\%$ confidence interval for $\Phi(\omega)$ is the set of all values of the parameter satisfying the inequality

$$\left|\sin\left(\widehat{\Phi}(\omega) - \Phi(\omega)\right)\right| \leq \left\{\frac{1-\widehat{C}(\omega)^2}{\widehat{C}(\omega)^2(2n-2)}\right\}^{\frac{1}{2}} t_{2n-2}\left(\frac{\alpha}{2}\right), \qquad \omega \neq 0, \pi, \quad (3.10)$$

where $t_{2n-2}(\frac{\alpha}{2})$ is the upper $\frac{\alpha}{2}$ cutoff point of the t distribution with $2n-2$ degrees of freedom.

One can solve for the angle Φ^* for which equation 3.10 holds with equality. Then, the confidence interval is

$$\widehat{\Phi}(\omega) - \Phi^* \leq \Phi(\omega) \leq \widehat{\Phi}(\omega) + \Phi^*$$

3.11 Appendix B - Data

The growth figures are from Maddison (1994). He uses the Geary-Khamis approach to ensure comparisons are transitive across countries. It is based on the twin concepts of purchasing power parity of currencies and international average prices of commodities.

The unemployment figures come from a variety of sources, which are listed below for each country.

- *UK* - Until 1971, the figures refer to registered unemployed at local unemployment offices or careers offices on one day in each month, capable of and available for work. After 1971, the series is based on records of claimants at unemployment benefit offices. It therefore excludes unemployed people not claiming benefit, but includes the severely disabled unemployed not included in previous figures. For 1921-1938 includes persons temporarily stopped. 1855-1899: C.H. Feinstein (1976), Table 57. 1900-1983: T. Liesner (1989), Table UK.10.

- *US* - 1890-1987. It includes those not working during the survey week but who are available and currently looking for work. The sample consists of about 60,000 households selected to represent the total population aged 16 years and over. From January 1967 the lower age was raised from 14 to 16 years and the figures were revised back to 1947. Source T. Liesner (1989).

- *Sweden* - 1920-1987. OECD data used from 1950. Earlier data are taken from League of Nations and United Nations sources. Agricultural workers are excluded up to 1939. For 1920-28 the figures refer to trade unionists only.

- *Germany* (1867-1938 and 1948-1987); *Australia* (1900-1987); *Canada* (1921-1987). Source: T. Liesner (1989).

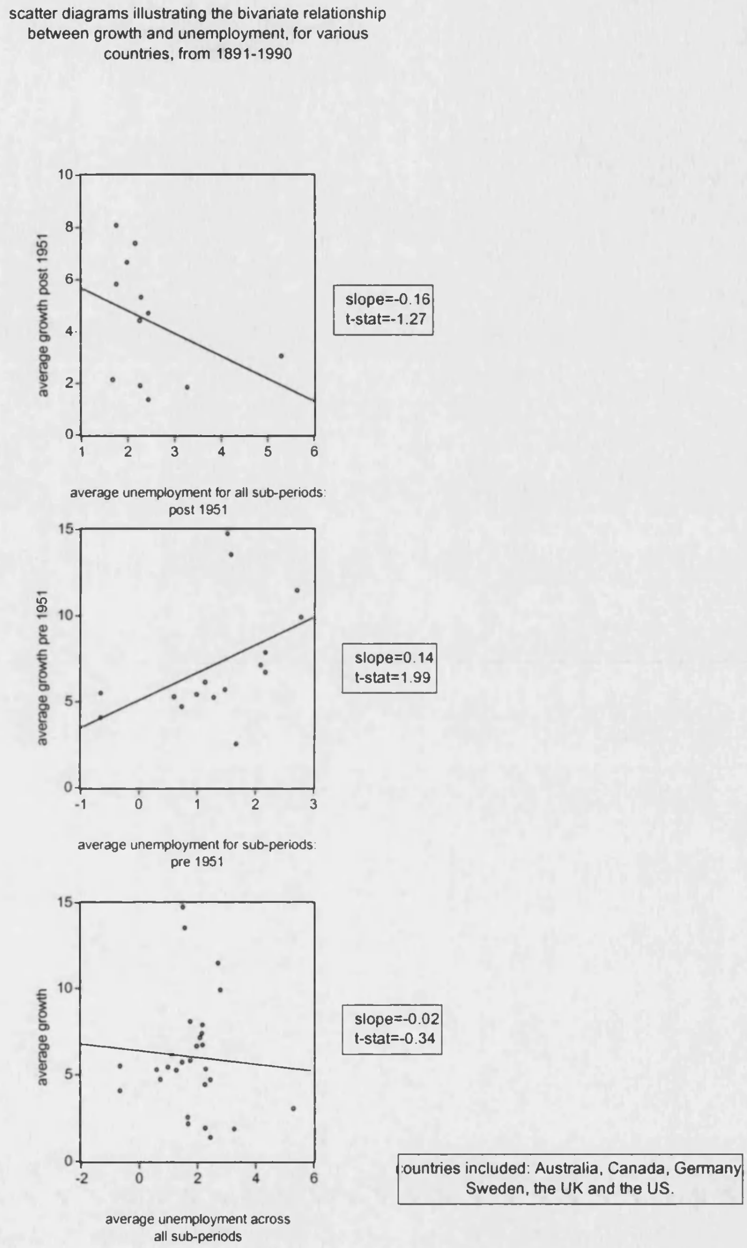

Figure 3.2: scatter of growth versus unemployment (version 2)

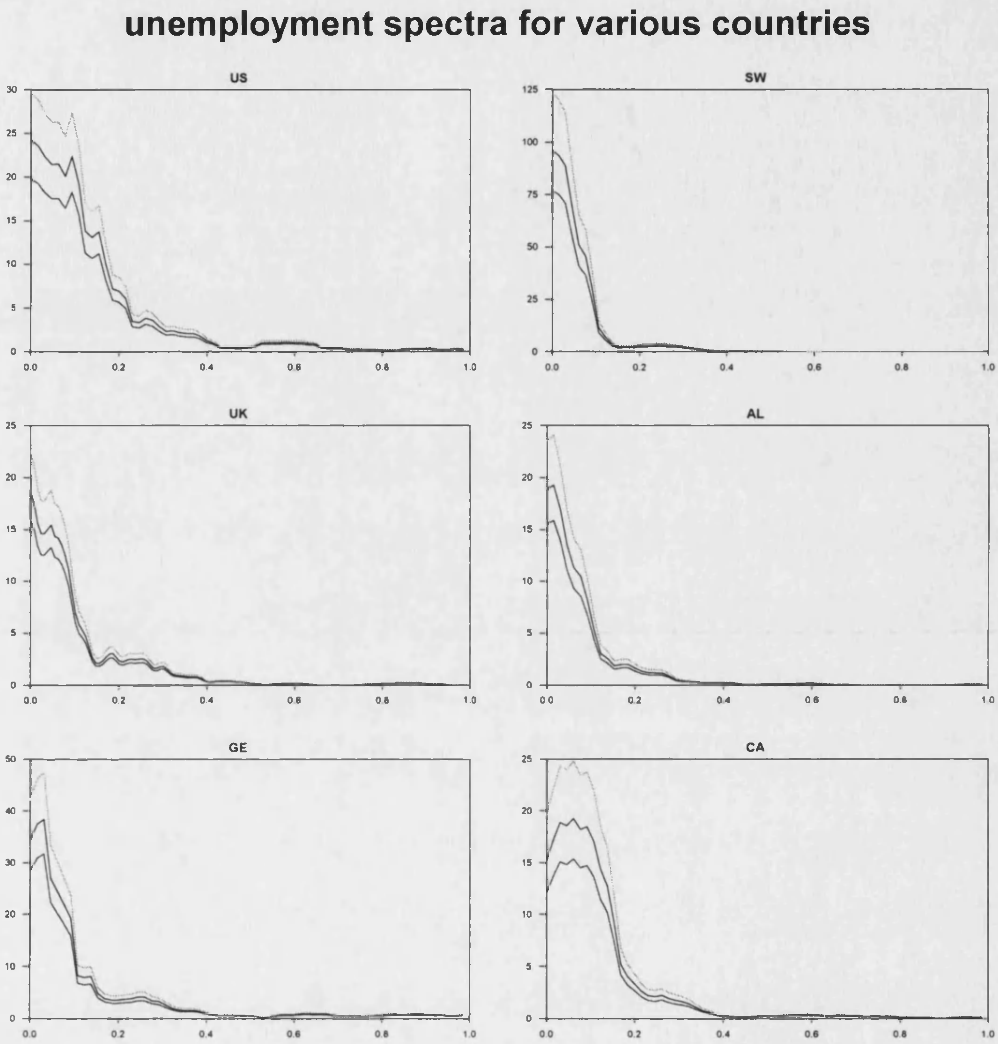

Figure 3.3: unemployment spectra

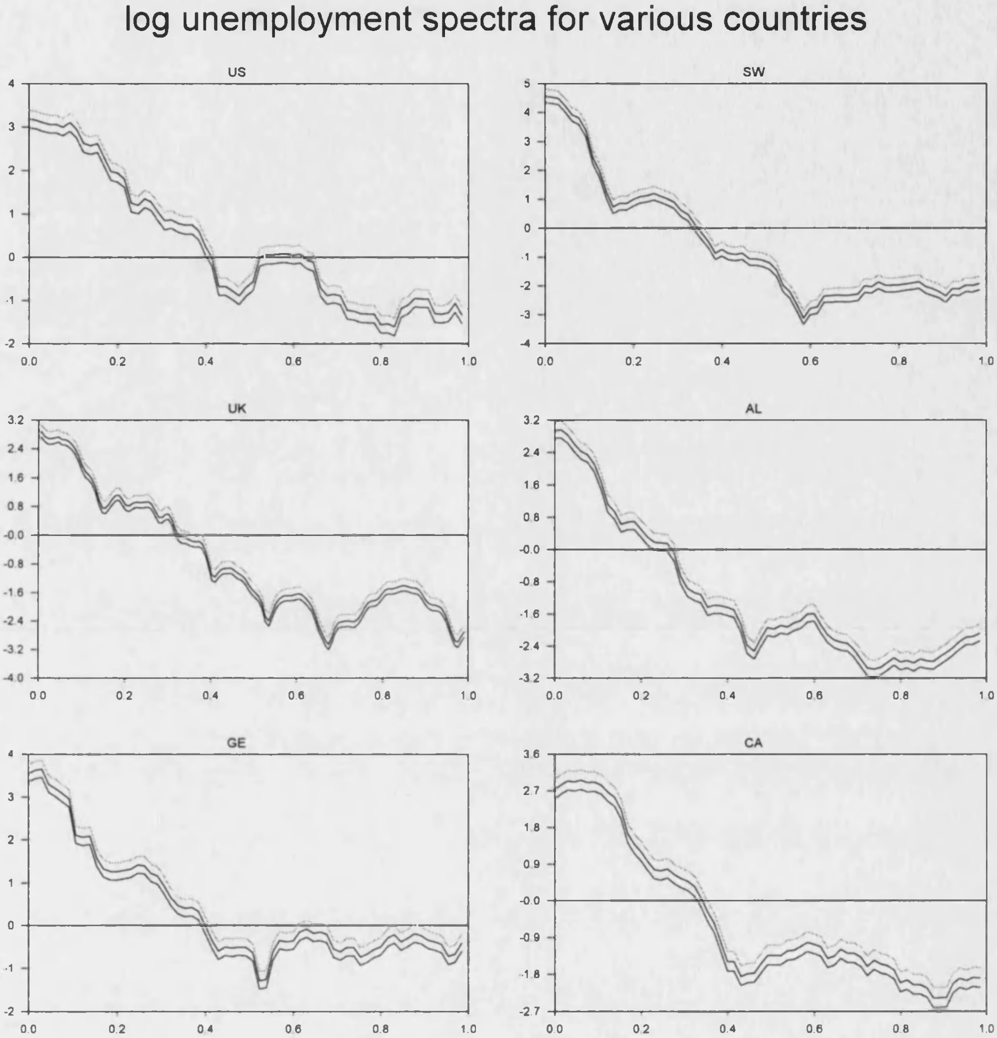

Figure 3.4: log spectra of unemployment

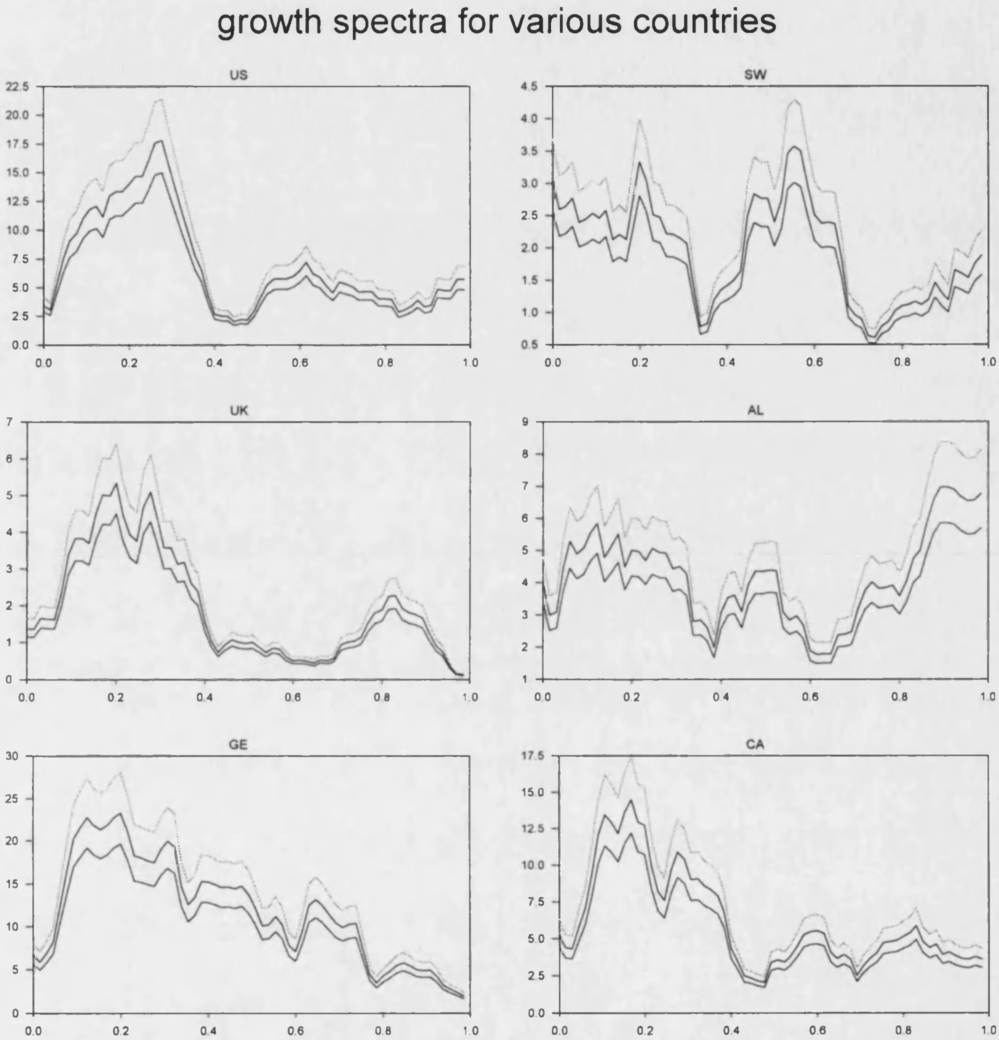

Figure 3.1: Figure 3.5: growth spectra

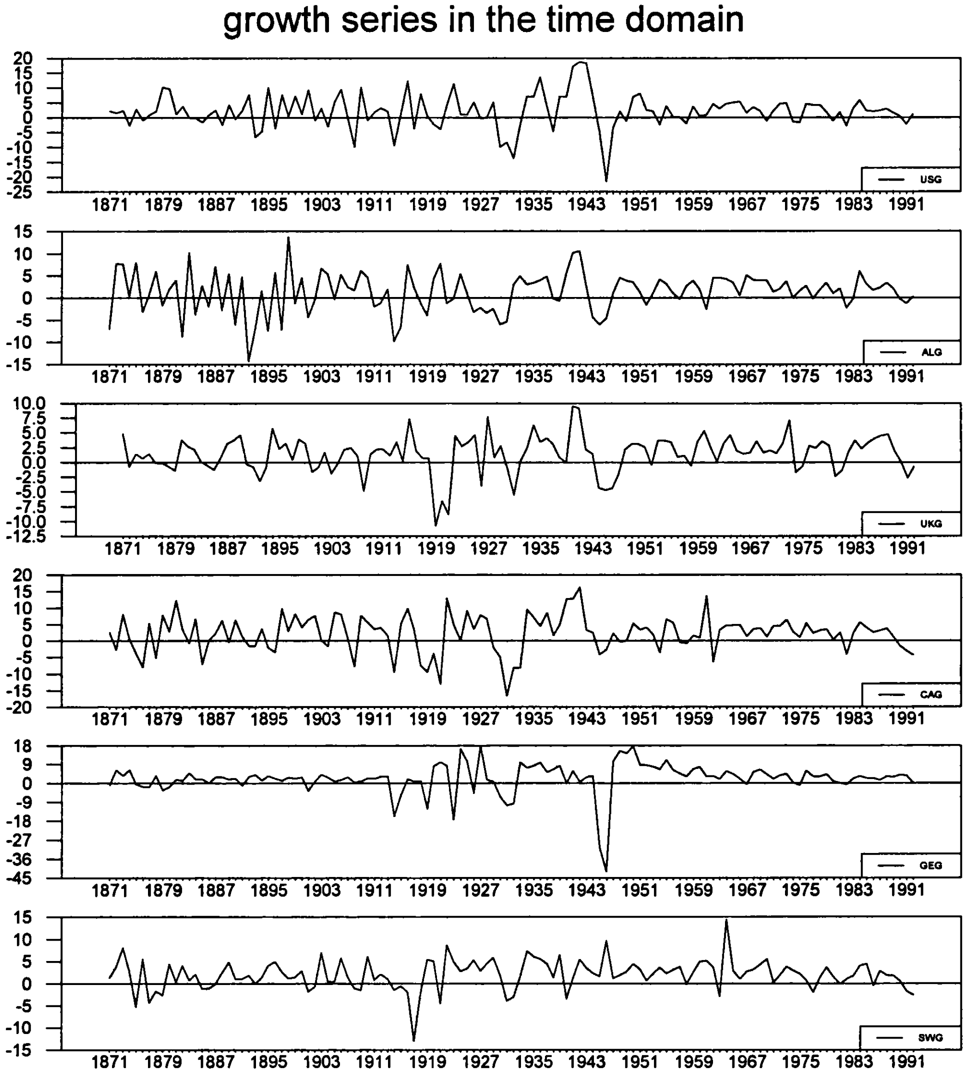

Figure 3.2: Figure 3.6: historical growth series

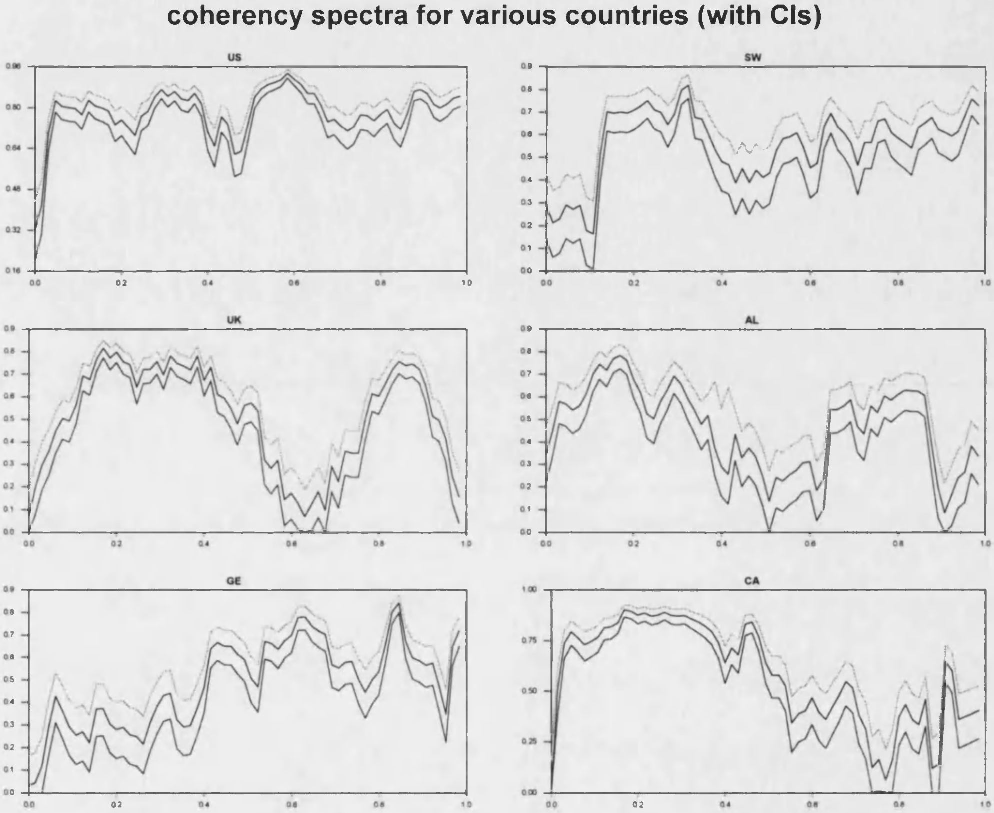

Figure 3.7: coherency spectra

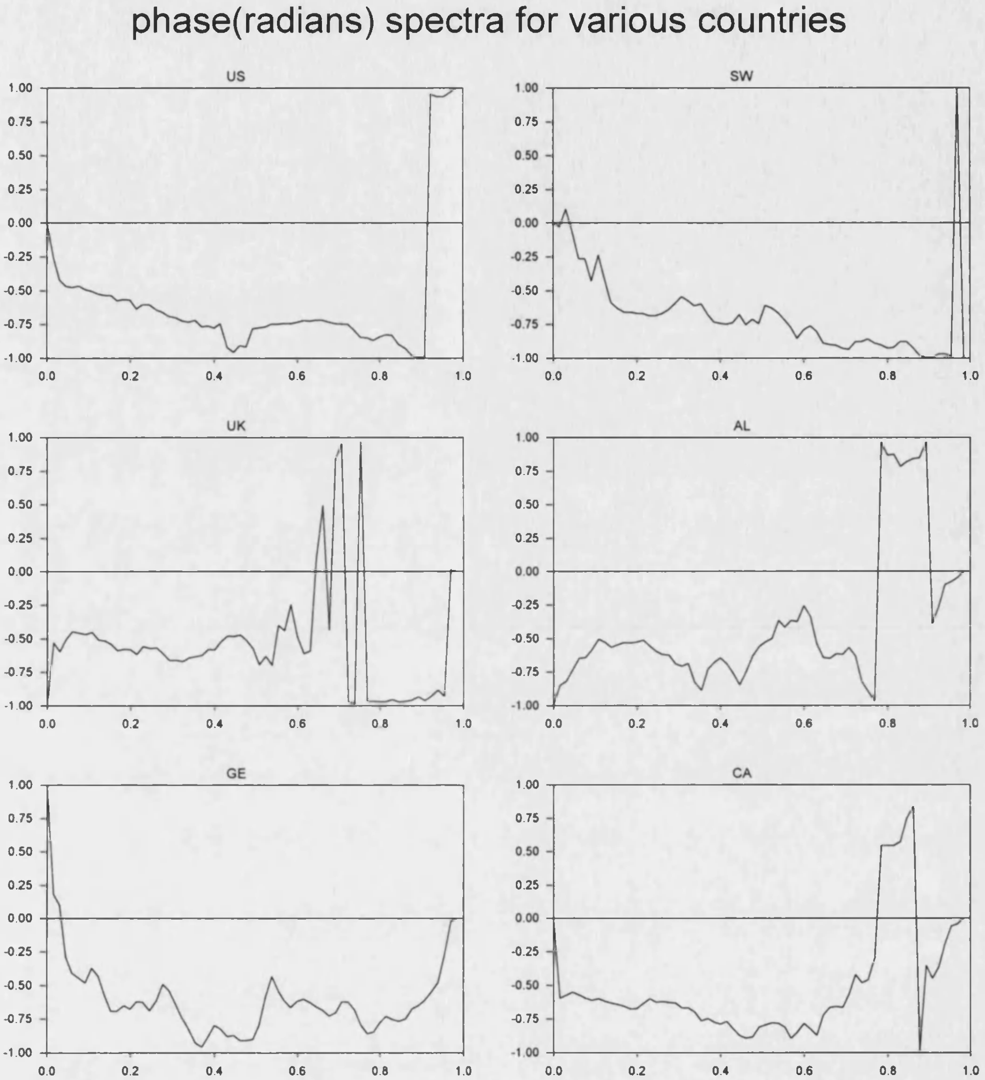

Figure 3.8: phase(radians) spectra

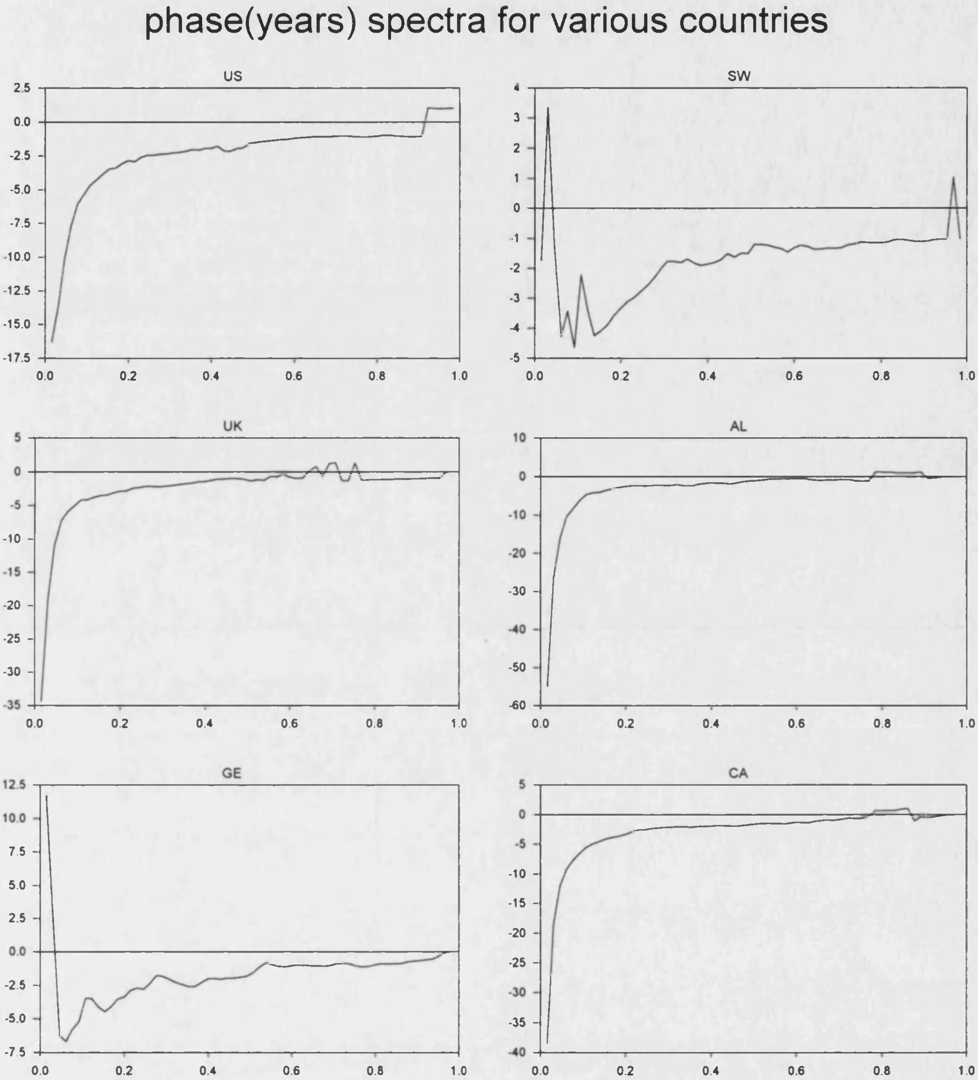

Figure 3.9: phase(years) spectra

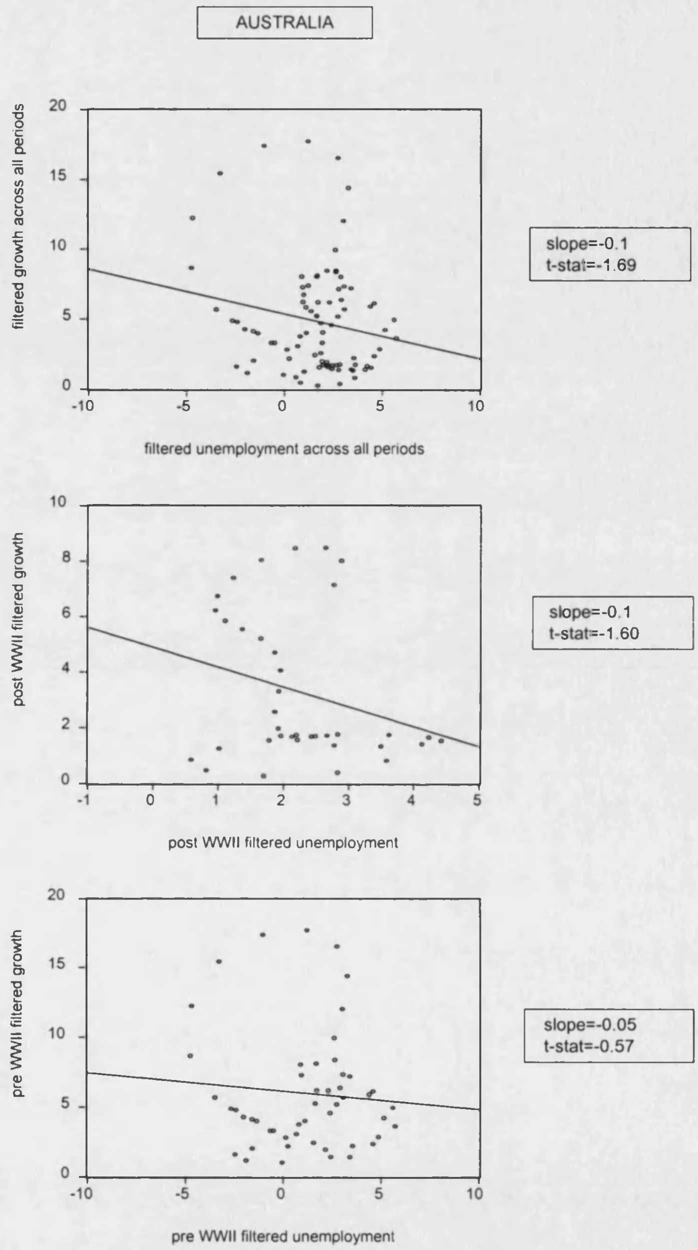

Figure 3.10: scatter graphs for Australia

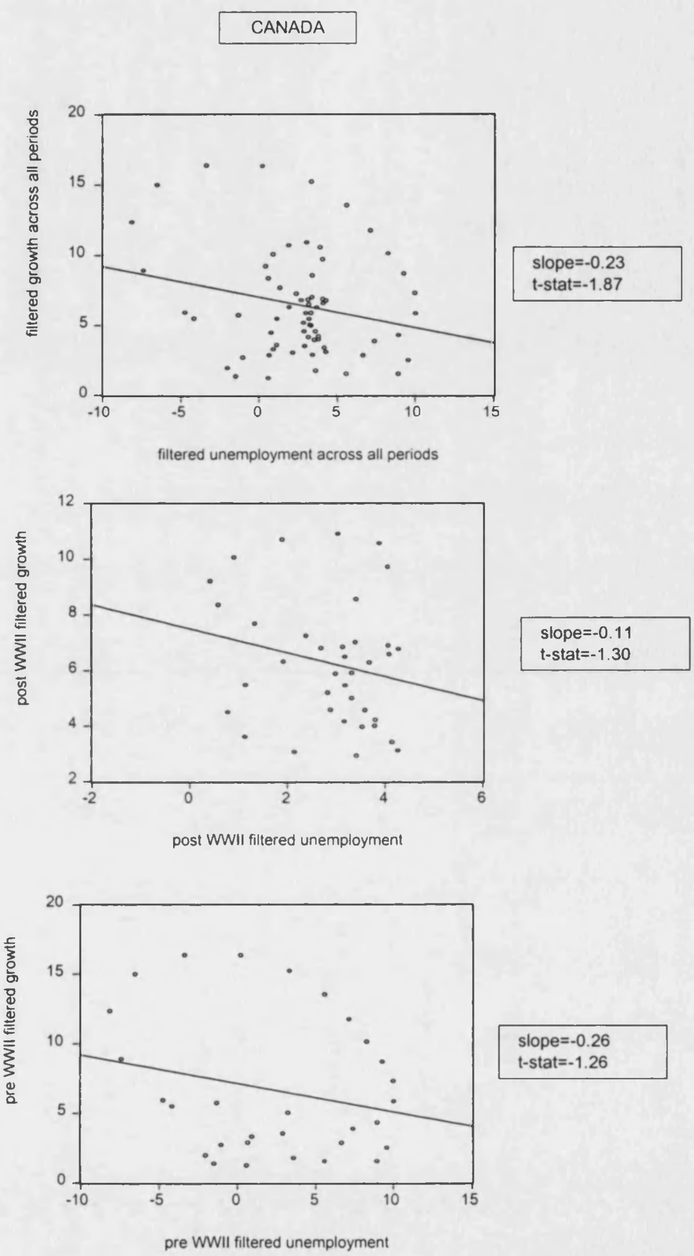

Figure 3.11: scatter graphs for Canada

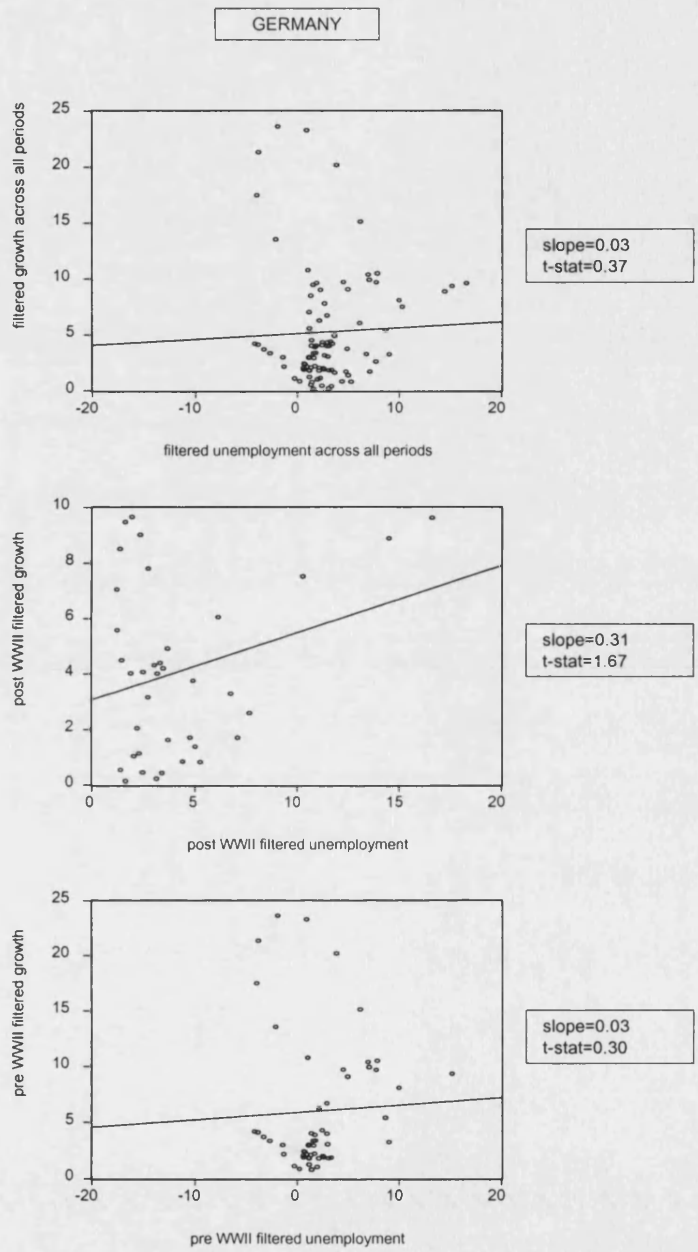

Figure 3.12: scatter graphs for Germany

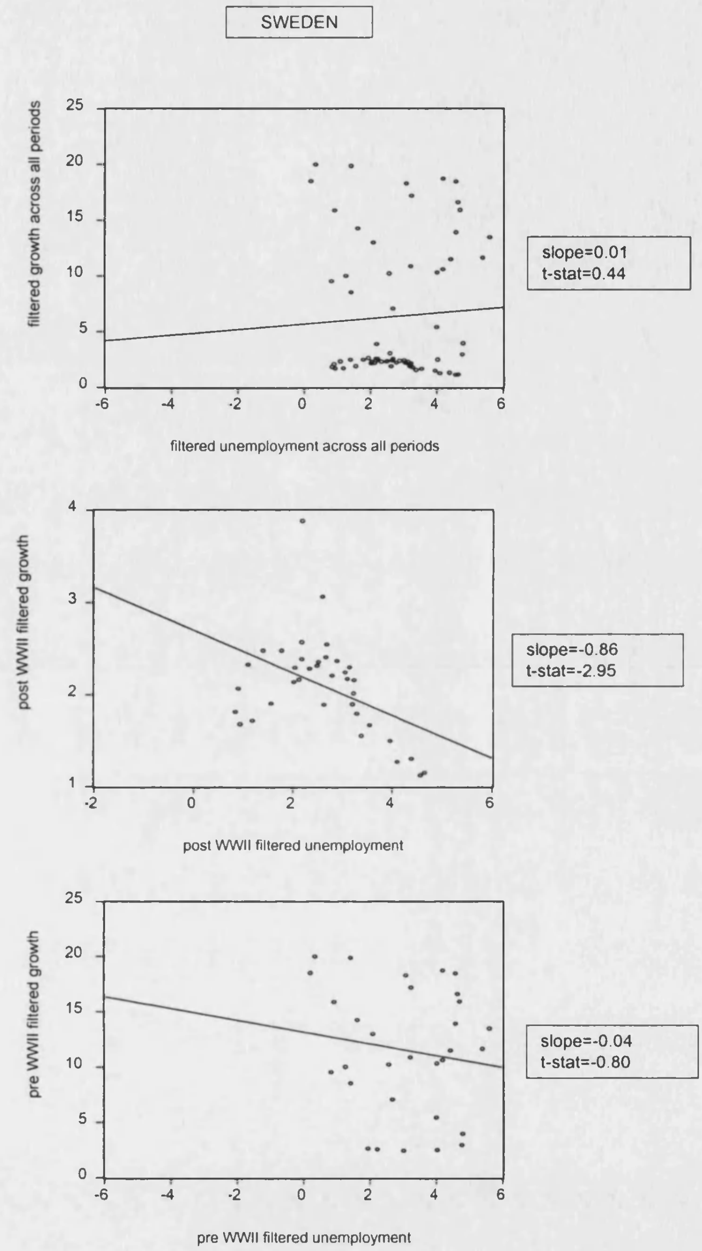

Figure 3.13: scatter graphs for Sweden

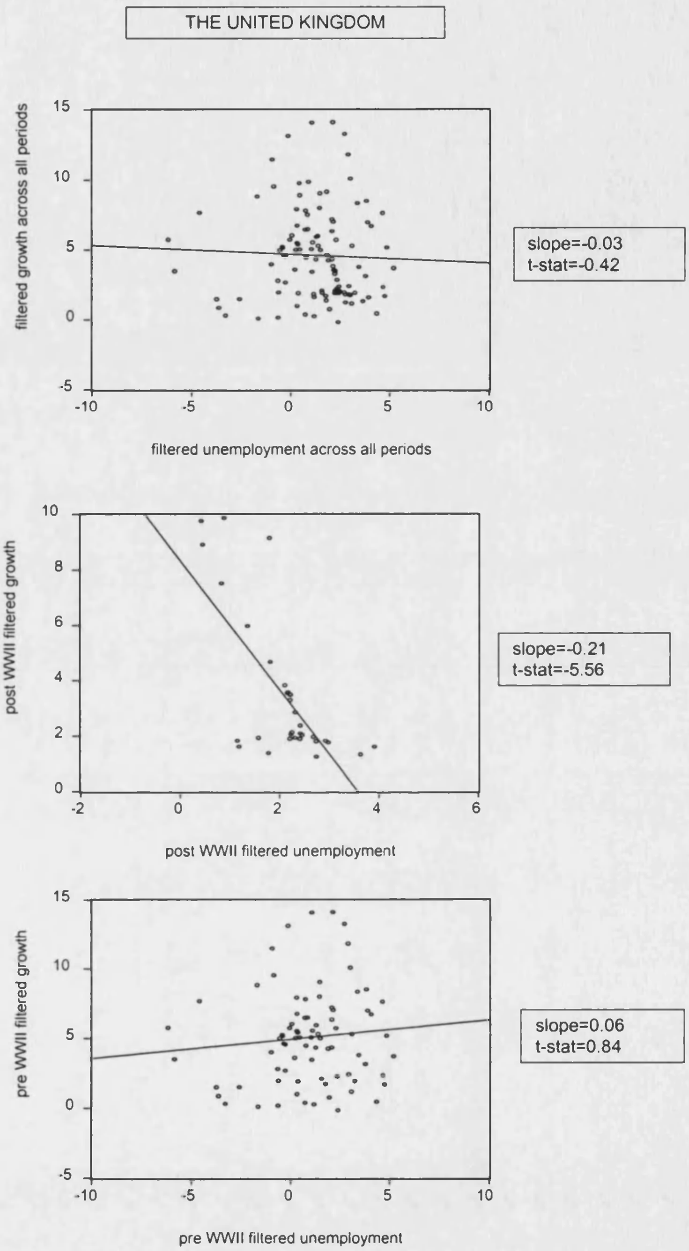

Figure 3.14: scatter graphs for the United Kingdom

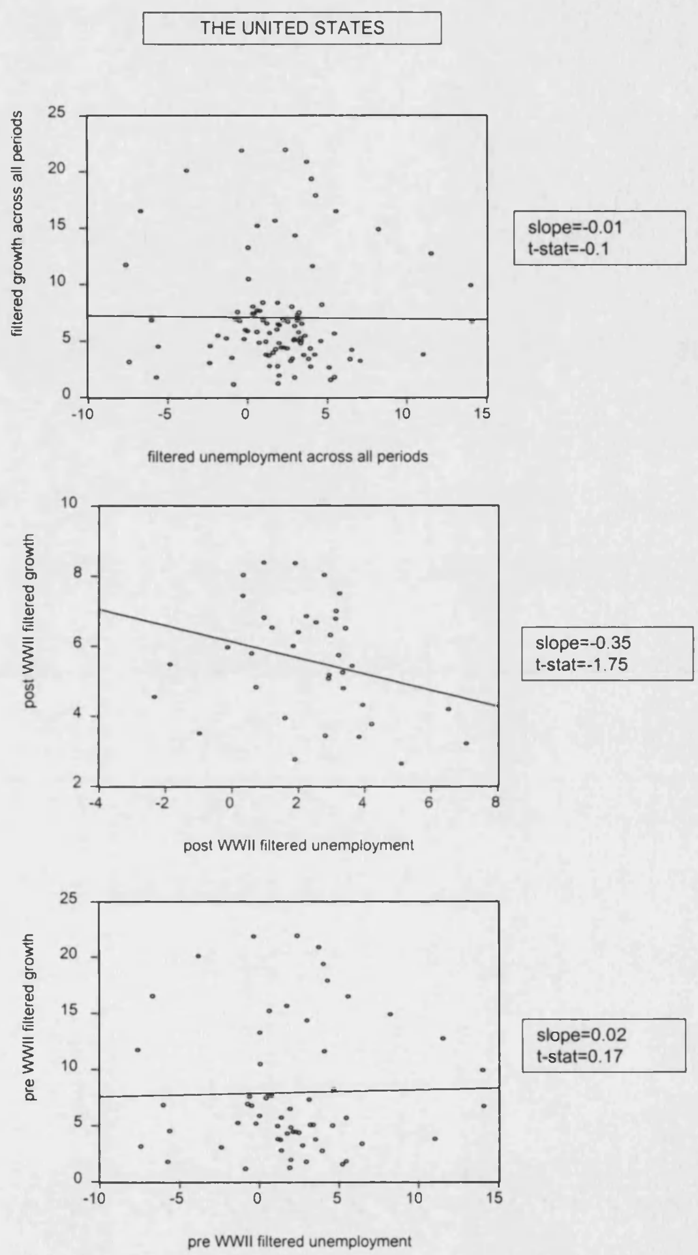

Figure 3.15: scatter graphs for the United States

	US	UK	Germany	Sweden	Australia	Canada
lags						
0	-0.0084	-0.0504	0.0348	0.0344	-0.1976	-0.2402
1	-0.2548	-0.2386	-0.0589	-0.0510	-0.3678	-0.4484
2	-0.4233	-0.3534	-0.1284	-0.0834	-0.4907	-0.5677
3	-0.4850	-0.3703	-0.1608	-0.0650	-0.5434	-0.5795
4	-0.4497	-0.3013	-0.1574	-0.0154	-0.5270	-0.4975
5	-0.3568	-0.1875	-0.1327	0.0386	-0.4624	-0.3606
6	-0.2550	-0.0810	-0.1076	0.0748	-0.3781	-0.2167
7	-0.1804	-0.0231	-0.0991	0.0827	-0.2975	-0.1036
8	-0.1434	-0.0301	-0.1134	0.0650	-0.2310	-0.0379
9	-0.1307	-0.0908	-0.1450	0.0338	-0.1770	-0.0134
10	-0.1177	-0.1727	-0.1816	0.0029	-0.1292	-0.0103
11	-0.0858	-0.2436	-0.2112	-0.0181	-0.0852	-0.0084
12	-0.0327	-0.2806	-0.2285	-0.0262	-0.0513	0.0028
13	0.0266	-0.2783	-0.2362	-0.0248	-0.0394	0.0221
14	0.0698	-0.2467	-0.2442	-0.0197	-0.0596	0.0409
15	0.0796	-0.2026	-0.2541	-0.0159	-0.1117	0.0516

Table 3.4: **Cross Correlations:** Correlations are for growth leading unemployment.

	US	UK	Germany	Sweden	Australia	Canada
lags						
0	-0.0084	-0.0504	0.0348	0.0344	-0.1976	-0.2402
1	0.2581	0.1655	0.1307	0.1545	-0.0181	0.0130
2	0.4741	0.3322	0.2109	0.2517	0.1272	0.2569
3	0.5914	0.4038	0.2656	0.3033	0.2101	0.4470
4	0.6002	0.3743	0.2947	0.2901	0.2276	0.5587
5	0.5276	0.2717	0.3024	0.2095	0.1992	0.5892
6	0.4212	0.1418	0.2885	0.0832	0.1540	0.5509
7	0.3236	0.0287	0.2441	-0.0467	0.1148	0.4624
8	0.2541	-0.0439	0.1564	-0.1316	0.0871	0.3412
9	0.2040	-0.0773	0.0197	-0.1372	0.0601	0.2014
10	0.1480	-0.0912	-0.1522	-0.0592	0.0160	0.0556
11	0.0638	-0.1096	-0.3226	0.0736	-0.0550	-0.0819
12	-0.0510	-0.1452	-0.4405	0.2100	-0.1454	-0.1945
13	-0.1741	-0.1897	-0.4610	0.2990	-0.2305	-0.2662
14	-0.2681	-0.2188	-0.3670	0.3104	-0.2787	-0.2874
15	-0.2997	-0.2080	-0.1807	0.2472	-0.2676	-0.2594

Table 3.5: **Cross Correlations:** Correlations are for unemployment leading growth.

Chapter 4

An Evaluation of the Theoretical Links between Steady State Growth and Equilibrium Unemployment

4.1 Introduction

The aim of this chapter is to document the theoretical links between steady state growth and equilibrium unemployment and evaluate them given the bivariate evidence accumulated in the previous chapter. The previous chapter analyzed the general bivariate link between growth and unemployment and argued that one needed to take into account the various institutional differences across countries, to get a complete picture. The task of the present chapter is to provide the theoretical framework to perform such analysis.

How does technological progress affect the equilibrium unemployment rate? This question has preoccupied policy makers and workers since at least the industrial revolution. Workers often worry that the kind innovation we see, for example when Ford car plants became automated in the 1920s, will destroy their jobs. Schumpeter (1942) came up with the notion of 'creative destruction' which he described as follows (page 83):

'The fundamental impulse that keeps the capitalist engine in motion comes from the new consumers' goods, the new methods of production or transportation, the new markets....[the process] incessantly revolutionizes from within, incessantly destroying the old one, incessantly creating a new one. This process of Creative Destruction is the essential fact about capitalism'

Policy makers have since struggled to articulate the meaning of this for the real economy. New technology destroys jobs but also creates new ones. The key question for the policy maker is which force dominates: destruction or creation? If destruction dominates, then it implies that there is a trade off between steady state growth and unemployment. Many economists, for example Gordon (1995), have argued that we need to appeal to a growth-unemployment trade off to explain the contrasting performances of the USA and Europe, since the early 1970s. The USA has had a more marked productivity slowdown than Europe, but it has had a much lower mean unemployment rate.

Formal economic models have only recently been able to generate relationships between unemployment and growth. Previously, according to neoclassical growth theory, equilibrium productivity growth was purely determined by the exogenous rate of labour-augmenting technical progress. Further, a well documented stylized fact is that the unemployment rate is untrended in the long run (LNJ 1991). This was seen as evidence that growth cannot have a great effect on the equilibrium unemployment rate. This lack of relationship between growth and unemployment no longer holds if we allow the growth rate to be endogenous, as recent models do (see Romer 1986, 1990 and Lucas 1988), and consider unemployment in a search theoretic framework (see Pissarides 1990 and Mortensen and Pissarides 1998). Endogenous growth models suggest that factors which affect the rate of innovation or human capital accumulation will affect the equilibrium growth rate. Search theoretic models suggest that any factor that affects the rate of job destruction, or the discounted future returns from posting a vacancy and hence job creation, will affect the unemployment rate.

These linkages suggest how growth can influence unemployment and vice versa. If unemployment is associated with loss of skills (see Pissarides 1992), then an increase in the unemployment rate can reduce the accumulation of human capital and thus lead to a reduction of the equilibrium growth rate. Also, an increase in unemployment *ceteris paribus* will lead to a fall in employment. This could reduce the amount of learning by doing, if this is prevalent, and provide another mechanism for lower human capital accumulation and thus lower equilibrium growth. Further, if there are strong complementarities between the skills of the workforce and the returns to technical innovation, lower learning by doing could indirectly reduce the rents available to an innovator and thus reduce equilibrium growth, via a fall in technical progress. One final mechanism, though certainly not the least important, is saving. High unemployment may have a negative effect on future growth by reducing the pool of savings available for investment, be it in physical or human capital, or in knowledge-creating activities.

The Economist (February 11, 1995) summarized the conventional view of how steady state growth impacts on unemployment. When new technology arrives, old jobs are destroyed with beneficial effects on labour productivity and new ones are created, because of increased aggregate demand due to higher incomes that an increase in the growth rate brings. Search theoretic models can illustrate both effects (see Aghion and Howitt 1994 and Mortensen and Pissarides 1998). The *creative destruction effect* is when productivity growth occurs through the destruction of low productivity jobs and their replacement by new high productivity ones elsewhere in the economy, thus increasing the inflow rate into unemployment. The *capitalization effect* is where an increase in the growth rate increases the present discounted value of the profits from creating a new job slot, leading firms to open more vacancies increasing the rate of job creation and thus ultimately reduce unemployment.

The overall effect on unemployment will depend on the balance of these two effects. Mortensen and Pissarides (1998) conjecture as to what may determine the importance of these two effects. There are two main factors to consider here: the extent to which technical progress is embodied and the size of *renovation costs.* The intuition is simple, if technical progress is disembodied, so that labour productivity in existing jobs grows at the exogenous rate of technical progress, then there is no creative destruction effect, as there is no need to destroy jobs to take advantage of the technical progress. If technical progress is embodied in new capital, productivity in existing jobs does not grow. Growth can come about either through job destruction and creation of a new more productive job or through 'restructuring' without job destruction. Now if renovation costs are too high, then restructuring an existing job will not be an option. This will imply that the capitalization effect will disappear, as an increase in growth will not increase the discounted returns of opening a job slot because the job cannot adapt to technical progress.

For ease of exposition, I split the analysis into two sections a) exogenous growth and b) endogenous growth. In the first section, we use the Aghion & Howitt (1994) model to illustrate the various linkages between unemployment and growth, namely: the capitalization effect and the creative destruction effect. We discuss in detail how robust these effects are and also review other models in this class. We could have also used the more general stochastic search theoretic model of Mortensen and Pissarides (1998) to show the capitalization and creative destruction effects. We chose the Aghion and Howitt model as it allows a more transparent treatment of the linkages from unemployment to growth, which come into play when we go on to the endogenous growth influences. This does not mean it is any more realistic. The purpose of the chapter is not to provide the most realistic model, but one that can allow a useful discussion of the important effects.

When we move on to the endogenous growth influences, the set of linkages becomes much richer as a) unemployment can now *feedback* into growth and b) institutions have a more pervasive effect. We review the important predictions, that models in this class have, for the link between growth and unemployment.

The chapter will be structured as follows: section II documents the interrelationships between growth and unemployment in a model of exogenous growth, namely the *capitalization* and *creative destruction* effects. Section III considers the richer set of interactions once we allow growth to be endogenous and Section IV summarizes the main findings of the various models and evaluates them given the bivariate evidence documented in the previous chapter. Section V concludes.

4.2 Exogenous Growth

In this section, we firstly outline the important elements of the Aghion and Howitt model (1994). Next, we discuss extensions to the model, in particular: an endogenous interest rate and intersectoral complementarity. Finally we review the more general search theoretic model of Mortensen and Pissarides(1998).

4.2.1 The Aghion and Howitt model

The economy comprises of a continuum of agents, infinitely-lived, and indexed from 0 to 1. Each individual is endowed with a flow of one unit of labour services and a stock of X units of human capital. All individuals share the same linear preferences over lifetime consumption:

$$U(c) = E_0 \int_0^\infty c_t \cdot e^{-rt} dt,$$

where $r > 0$ is the subjective rate of time preference, and c_t is the individual's consumption of a final good at time t. There is no disutility of work and human capital has no consumption use.

There is a continuum of firms in the economy, whose total mass is endogenously determined in a steady-state equilibrium. Firms are also infinitely lived. Each firm is really a *research facility* for producing new knowledge. Let D_t be the sunk cost of setting-up a research facility at date t.

Once its research cost D_t has been sunk, each firm generates a stream of *innovations,* or new technological vintages, according to a Poisson process with parameter λ.

New ideas need to be embodied into new machines in order to be implemented. Let C_t be the fixed cost that must be paid by a firm implementing a new innovation at date t or the *implementation cost.*

The output flow of any production unit at any time s is:

$$y_t = A_t \cdot \psi(x_s - a)$$

where a (> 0) is the minimum human capital input representing overhead costs. Ψ is a regular neoclassical production function and $A_t = A_0 \cdot e^{gt}$ is the unit's productivity parameter. In order to keep present values finite, assume $g < r$.

An innovation that occurs in any given firm at time t will open access to the leading technology A_t as of that date. Thus, provided the firm incurs the implementation cost C_t, it will be able to establish a production unit of vintage t.

The source of unemployment in the model is labour reallocation across firms. Any production unit has to incur a fixed overhead cost in human capital whose price in terms of final consumption rises at the economy-wide rate of growth. A production unit whose technology is fixed eventually becomes unable to produce enough to cover its fixed cost, at which point the job is destroyed, forcing the worker into unemployment until matched with a new machine.

The labour market is modelled via a matching function (see Pissarides 1990):

$$m = m(1, v)$$

where m is the aggregate flow of new workers and is a function of the total labour force, as we allow for on the job search, and the total mass of vacancies in the economy, v. For simplicity we assume that the matching function is *deterministic*, though Aghion and Howitt (1998) show that the results easily extend to the case of *stochastic* matching.

Let $\frac{1}{q}$ be the amount of time a firm needs to spend searching for an appropriate worker-machine match after it has experienced an innovation. Let $\frac{1}{p}$ be the time spent searching by a worker before being successfully matched with a machine. Then:

$$\frac{1}{q(v)} = \frac{v}{m(1,v)}$$

and

$$\frac{1}{p(v)} = \frac{1}{m(1,v)}$$

Let p and q have the usual interpretation as in Pissarides (1990) and follow the standard search theoretic assumptions. Let S be the duration of a match, then equilibrium unemployment is determined by the condition that the flow into unemployment is equal to the flow from it, i.e.

$$(1-u)\frac{1}{S} = p(v)$$

$\Rightarrow$

$$u = 1 - S \cdot p(v) \tag{4.1}$$

This is the *unemployment equation,* which holding S constant, can also be regarded as a Beveridge Curve showing unemployment as a decreasing function of vacancies.

Now we need to determine S in equilibrium. Suppose at time t, a firm is hit by a technological innovation that opens up access to the leading vintage, namely A_t. The firm then searches for a suitably skilled worker. Hence at date $t_0 = t + \frac{1}{q}$, a match is made to form a new production unit. The surplus flow generated by this production unit at any date $\tau \geq t_0$ is:

$$\max_{x \geq a}\{A_t \cdot \psi(x-a) - P_\tau \cdot x\} = A_t \cdot \Pi(\frac{P_t}{A_t}), \tag{4.2}$$

where Π is decreasing in its price argument.

Since A_t remains constant while P_τ grows at the same rate as the economy in the steady- state: $P_\tau = P_0 \cdot e^{g\tau}$, the unit will produce less and less as P_τ

grows, until it becomes unprofitable at date $t_0 + S$. At that date the ratio of $\frac{P_T}{A_t}$ reaches the shut down value $P^{\max} = \Pi^{-1}(0)$.

$\Rightarrow$

$$\frac{P_{t_0}}{A_t}e^{gs} = P^{\max}$$

or equivalently

$$: S = \frac{\Gamma}{g} \text{ where } \Gamma = \ln(P^{\max}) - \ln(\frac{P_{t_0}}{A_t}) > 0$$

Intuitively, the faster the price of human capital grows, the sooner will production units hit the zero-profit bound $P^{\max}$. Hence the inverse relationship between the growth rate g and the duration of the match S. This is the cause of the *direct creative destruction effect* of growth on unemployment. Rewriting equation 4.1 illustrates this:

$$u = 1 - \frac{\Gamma p(v)}{g} \tag{4.3}$$

Thus, holding Γ and v constant, an increased growth rate g directly raises the job-destruction rate, thereby increasing the unemployment rate. There could be further indirect effects through the vacancy channel. To illustrate this, we need to consider a free entry condition for firms.

The fixed cost of entry at date t is $D_t = d \cdot A_t$. The expected net benefit of entry, which also grows at the steady rate g, can be expressed as:

$$W_t = W \cdot A_t = E_{\theta \geq 0}[(V_{t+\theta} + W_{t+\theta})e^{-r\theta}],$$

where $t + \theta$ is the arrival date of the first innovation experienced by the firm that enters at date t and $V_{t+\theta} = V \cdot A_{t+\theta}$ is the present values of the profit stream accruing from that innovation. With some manipulation, we can arrive at:

$$W = \frac{\lambda V}{r - g}$$

where λ is the poisson arrival rate of innovations at a firm and hence $\lambda \cdot V_t$ is the instantaneous expected income from having created a firm. So we have a free entry condition:

$$d = \frac{\lambda V}{r-g} \tag{4.4}$$

Next we need to derive an expression for V. An innovation at t will not begin to produce output until $t_0 = t + \frac{1}{q(v)}$ when the appropriate worker has been found. At that time, the implementation cost $C_t = c \cdot A_t$ must be paid by the firm to initiate the new match. From that time until $t + \frac{1}{q(v)} + S$ the match will generate a flow of surplus given by equation 4.2, of which we assume the firm can bargain for the constant fraction β[1]. Hence using the fact that:

$$\frac{P_{t_0+s}}{A_t} = P^{\max} \cdot e^{gs-\Gamma} \text{ for all } s \leq \frac{\Gamma}{g} = S,$$

we have:

$$V = e^{\frac{-r}{q(v)}}\{\beta \int_0^{\frac{\Gamma}{g}} e^{-rs}\Pi(P^{\max} \cdot e^{gs-\Gamma})ds - c\} \tag{4.5}$$

From (4.4) and (4.5) we have a final expression of our free entry condition:

$$d = \frac{\lambda}{r-g} e^{-\frac{r}{q(v)}}\{\beta \int_0^{\frac{\Gamma}{g}} e^{-rs}\Pi(P^{\max} \cdot e^{gs-\Gamma})ds - c\} \tag{4.6}$$

The free entry condition illustrates the *capitalization effect* and the *indirect creative destruction effect*[2].

The capitalization effect occurs as if g increases and the rate of interest is exogenous, then the net discount rate $(r - g)$ at which firms capitalize their expected income falls, and this in turn increases the present benefit of entry. This will increase the equilibrium level of vacancies v and hence decrease equilibrium unemployment, as shown by equation 4.3.

This effect is present partly because the interest rate is *exogenous*. Suppose we endogenize the interest rate by choosing an iso-elastic utility function instead:

$$u(c) = E_0 \int_0^{\infty} e^{-\rho t} \frac{c_t^{1-s}}{1-s} dt; \; s > 0$$

[1]Standard nash bargaining intuition is used here, see Pissarides(1990).

[2]To fully specify the model, we need an equilibirum condition on the market for human capital. See Aghion and Howitt (1994) for further details.

Then it can be easily shown that $(r-g)$ increases as g increases if $s > 1$, as in steady state equilibrium with consumption growing at rate g,

$$r = \rho + sg$$

In other words, the capitalization effect is reversed if the elasticity of marginal utility is greater than unity. The intuition for this is the following: the instantaneous utility function $\frac{c_t^{1-s}}{1-s}$ has a constant elasticity of marginal utility equal to $-s$. It is a standard result that the elasticity of intertemporal substitution is the reciprocal of this. Thus if s is high, we have a low elasticity of intertemporal substitution. A change in the growth rate will change the optimal consumption path. If the elasticity of intertemporal substitution is low, this will require a large change in the interest rate to bring the consumer back onto its optimal consumption path. Eriksson (1995) generalizes this result in an optimizing ramsey model. If ζ is the capital tax rate, then the condition for the capitalization effect to be reversed is: $s > 1 - \zeta$, which Eriksson argues is not unreasonable, see Blundell(1988), Hall (1988) and Paterson and Pesaran (1992).

The free entry condition also implies an indirect creative destruction effect. An increase in the growth rate also reduces the life-time of production units, and induces a faster decline of profits during this lifetime, since the price of the human capital input also grows at a faster rate. This will reduce V and therefore tends to reduce the firm's incentive to enter and create a stream of vacancies. This effect reinforces the direct creative destruction effect and will thus increase unemployment.

Even the indirect creative destruction effect is not robust though. So far we have assumed that the goods produced by the various sectors of the economy were *perfect substitutes*, so that the price of each good would equal unity. What happens if we reduce the degree of substitutability between goods of different vintages? Aghion and Howitt (1998) analyze this question in detail, I merely summarize the intuition below. Without perfect substitutability, an increase in the growth rate will generate a continual increase in demand for existing plants output as well as a continual increase in the cost of operating a plant. This will raise the output price of any intermediate plant. Thus, because the costs and revenues of an intermediate plant increase in response to an increase in the growth rate, the overall effect on V is not obvious. If the degree of intersectoral complementarity is high enough, then regardless of the capitalization effect, revenues could increase enough so that V increases and the indirect creative destruction effect is overturned.

4.2.2 The Mortensen and Pissarides model

The more general search theoretic model of Mortensen and Pissarides (1998) provides a more complete explanation of which is more important: capitalization or creative destruction. Let us abstract from the issues of an endogenous interest rate and the possibility of intersectoral complementarity. The key insight of this paper is in its treatment of technical progress. Once a job is created, the employer has three choices at any future date: continue to produce with the technology embodied in the job when it was created; pay a fixed renovation cost to update its technology and continue producing with the same worker; or close the job down and exit production. In the model of Aghion and Howitt, described above, employers never update by assumption, so the useful life of a job is always shorter when the rate technological progress is higher. In the model of Mortensen and Pissarides (1998) the cost of renovating the technology or the *renovation cost* determines which of the capitalization and creative destruction effect is more important.

If renovation costs are too high, then restructuring an existing job will not be an option. This will imply that the capitalization effect will disappear, as an increase in growth will not increase the discounted returns of opening a job slot, because the job cannot adapt to technical progress. In contrast, at the other extreme of zero renovation costs, or continuous updating of technology, there is no required destruction of jobs to implement new technology and hence no creative destruction effect. Job creation is thus positively affected by technological progress because of the capitalization effect of growth on expected profits.

It should be noted that the capitalization effect in this model is subtly different to that of Aghion and Howitt (1994). In the Aghion and Howitt model above, the capitalization effect is due to the set-up costs D_t. This can be seen by looking at equation 4.4. If there are no set-up costs, then the free entry condition becomes:

$$V = 0 \tag{4.7}$$

In other words there is no capitalization effect. It should be fairly clear that some cost is required, in any search based model, to generate a capitalization effect as otherwise the free entry condition will just revert to equation 4.7. Or in other words, to when the value of posting a vacancy reaches zero. This effect returns in the model of Mortensen and Pissarides, in the form of a cost of posting vacancies. It may be argued that this is easier to justify than a general research facility set up cost. The intuition for the effect in Mortensen and Pissarides is simple: consider again the case of exogenous interest rates where an increase in g reduces $(r - g)$. In other words, at a faster rate of technological progress all future income flows are discounted at a lower rate. Because the cost of creating a vacancy is borne now, whereas profits from it accrue in the future, the lower discount rate increases job creation.

Mortensen and Pissarides show that there is a critical renovation cost such that faster growth decreases unemployment, when the actual cost of updating a job's technology is below the critical value and increases unemployment when the actual cost is above the critical value.

The above discussion shows that there is no consensus about the size of the capitalization and creative destruction effects. All we can say is that theory is capable of delivering an effect of steady state growth on equilibrium unemployment. Next, we endogenize the growth rate to allow for a richer set of interactions.

4.3 Endogenous Growth

In the previous section, we considered growth in the standard neoclassical sense, i.e. equilibrium productivity growth is purely determined by the exogenous rate of labour-augmenting technical progress. Now, we allow for this process to be endogenous. This allows for a lot of *indirect* interactions between growth and unemployment and for unemployment to *feedback* into growth.

It seems rather obvious that changes in unemployment can affect equilibrium growth. Economic theory though, has only recently been able to model this. Endogenous growth models suggest that factors which affect the rate of innovation, or human capital accumulation, will affect the equilibrium growth rate (see Barro and Salai-Martin 1995 for survey). If unemployment is associated with *loss of skills* (see Pissarides 1992), then an increase in the unemployment rate can reduce the accumulation of human capital and thus lead to a reduction of the equilibrium growth rate. Also, an increase in unemployment, *ceteris paribus,* will lead to a fall in employment. This could reduce the amount of *learning by doing,* if this is prevalent, and provide another mechanism for lower human capital accumulation and thus lower equilibrium growth. Of course, these effects could be ameliorated if human capital accumulation also occurs formally through schooling or formal training. Employment today could reduce the amount of time potentially devoted to human capital accumulation.

A further route which has the opposite effect, is the *'cleansing effect'* of recessions. It has been recently suggested that recessions may be periods when there is a great deal of unrecorded investment-like activity taking place. Aghion and Saint-Paul (1991) argue that recessions allow quicker 'organizational change' than booms and that deeper recessions will encourage further restructuring. This would imply an increase in unemployment leading to an increase in growth.

One final mechanism, though certainly not the least important, is saving. High unemployment may have a negative effect on future growth by reducing the pool of savings available for investment, be it in physical or human capital, or in knowledge-creating activities.

Below, I briefly outline a model illustrating the negative impact unemployment can have on growth, due to loss of skills, before considering the implications of this in the model of Aghion and Howitt above. Next, I will discuss the implications of the savings nexus for the interactions between growth and unemployment. This discussion will be framed around the overlapping generations models of Bean and Pissarides (1993) and Daveri and Tabellini (1997). Finally I will review other classes of models that may generate a relationship between growth and unemployment.

4.3.1 Skills

Consider the following model: workers may be in two states, employed (E) or unemployed (U). The flow transition probability from U to E is ε; the flow transition probability from E to U is γ. A worker's human capital evolves according to:

$$\frac{dh}{dt} = -\delta h \text{ if he is unemployed, and:}$$

$$\frac{dh}{dt} = \phi h \text{ if he is employed}$$

Total production is proportional to the employed's aggregate human capital. Defining H_e and H_u as the employed's and unemployed's human capital respectively, it can be seen that the system will evolve according to:

$$\frac{dH_e}{dt} = (\phi - \gamma)H_e + \gamma H_u$$

$$\frac{dH_u}{dt} = -(\delta + \varepsilon)H_u + \varepsilon H_e$$

In the long run steady state, both H_e and H_u will grow at the same rate, which will be the highest eigenvalue of the system. Hence the growth rate of the economy is determined by:

$$g = \frac{-(\gamma + \varepsilon) + \sqrt{(\gamma + \varepsilon)^2 + 4(\phi\varepsilon - \delta\gamma) + \delta\phi}}{2}$$

It can be seen that g increases in ε and decreases in γ. At the same time, equilibrium unemployment will be:

$$u = \frac{\gamma}{\gamma + \varepsilon}$$

Thus it can be seen that the flow that increases unemployment, will also cause a fall in the rate of human capital accumulation and hence a fall in the steady state growth rate. A similar kind of logic can be applied to the problem of learning by doing.

Next, let us look at the impact of these feedback effects, in the model of Aghion and Howitt. Consider the following specification for growth:

$$g = g_0 + b(1-u), \qquad \text{where } g_0, b, b' > 0$$

Here the term $b(1-u)$ can be interpreted as a *learning by doing* term that is external to the firm. Or we can think of $-bu$ as a *loss of skill effect.* If we reverse the sign of b then $-bu$ can be perceived as a *cleansing type effect.* Let us stick with the case of $b > 0$ for the moment.

This feedback effect, changes the free-entry condition in the basic Aghion and Howitt model. This condition now becomes:

$$d = \frac{\lambda e^{-\frac{r}{q(v)}}}{r - g_0 - b(1-u)}\{\beta \int_0^{\frac{\Gamma}{g_0}} e^{-rs+b(1-u)s}\Pi(P^{\max} \cdot e^{g_0 s - \Gamma})ds - c\} \tag{4.8}$$

The replacement of g by g_0 in the integrand comes from the fact that a production units productivity-adjusted price for land now grows at rate g_0 not g. The new factor $e^{b(1-u)s}$ in the integrand appears because learning by doing causes the productivity of each match to rise by a rate $b(1-u)$ thereby enhancing the value of each innovation. The unemployment equation becomes:

$$u = 1 - \frac{\Gamma p(v)}{g_0}$$

because the length of each match is now $\frac{\Gamma}{g_0}$ instead of $\frac{\Gamma}{g}$.

What is the impact of this change. Perhaps the easiest way to think about it is that the feedback effect from unemployment to growth creates a *macroeconomic complementarity.* Cooper and John (1988) analyzed the impact of introducing such effects. It can lead to a *multiplier effect* and if strong enough, *multiple equilibria.* An increase in the exogenous part g_0 will have the same capitalization and creative destruction effects without learning by doing, but they will be quantitatively larger due to the feedback from unemployment to growth. This is the multiplier effect. Multiple equilibria can be constructed as follows. Consider the case where the capitalization effect dominates the creative destruction effect. In a low-level equilibrium, high unemployment inhibits growth by slowing down learning by doing, and slow learning keeps unemployment high by making it unprofitable to create a lot of vacancies. In a high-level equilibrium, low unemployment stimulates growth through learning by doing, and the prospect of fast learning provides the incentive for firms to create enough vacancies to keep unemployment low. The same logic can be applied to the loss of skills mechanism.

If we have a cleansing effect, then we can still get multiple equilibria, but there properties will be very different. With cleansing predominant, we could generate a low growth-low unemployment and a high-growth-high unemployment set of equilibria, when the creative destruction effect dominates the capitalization effect.

4.3.2 Saving

This mechanism is the focus of overlapping generations models, such as Bean and Pissarides (1993) and Daveri and Tabellini (1997). Once we endognize growth, then savings should be an important determinant of not only the level of GDP/capita, but of the steady state rate of growth. The endogenous growth theory literature (see Barro and Salai-Martin 1995) suggests various ways of affecting steady state growth, such as: human capital accumulation and research and development to increase the chances of innovating and implementing those innovations. This requires some kind of financial investment, which in turn necessitates savings.

Overlapping Generations Models (OLGs) are a good vehicle for generating a savings mechanism. This is due to the life-cycle motivated savings of the young. In these models, only the young work and they must save for when they are old and retired. I will briefly motivate and discuss some of the main results coming out of this literature. For further details of the models, interested readers are referred to Bean and Pissarides (1993) and Daveri and Tabellini (1997).

The Bean and Pissarides model

Bean and Pissarides (1993) use an overlapping generations model with two additional features. First, firm's technology exhibits decreasing returns with respect to their own capital but the aggregate technology is linear in aggregate capital. This is a fairly standard way of generating endogenous growth, via a physical capital externality. Second, there are labour market frictions, modelled by a matching function, which generate a positive natural rate of unemployment. These features generate interactions between growth and unemployment. The key equation in this model is:

$$g = \frac{K_{t+1}}{K_t} - 1 = \frac{s(N_t)}{K_t} - 1 \tag{4.9}$$

Here the steady state growth rate, which equals the rate of capital growth is simply function of the level of savings[3]. Bean and Pissarides presume the level of savings is positively related to the employment level, an assumption we will discuss in detail a bit later. This key relationship is the cause of the interactions between unemployment and growth, in this model. This mechanism can lead to some *indirect* interactions between unemployment and growth, or in other words, changes in institutional variables that lead to changes in both growth and unemployment.

Consider a reduction in hiring costs, it will increase employment as firms

[3]Implicitly in this formulation is the assumption of complete depreciation after a single period. This assumption is not important and non depreciating capital can be easily introduced into the model, without changing anything of substance.

have higher profits from a job match[4]. According to equation 4.9 this will increase savings and thus increase growth. An increase in income taxes, on the other hand, will have the opposite effect. A balanced budget condition is assumed, i.e. that an increase in taxes is used to finance an increase in government spending. An increase in the tax rate, increases the opportunity cost of working and thus wages in a Nash bargain in this model. This leads to lower employment which will reduce savings and thus growth.

One of the more interesting results of Bean and Pissarides is of the effects of a change in the savings rate, s. The basic model has a very classical feature that a reduction in the savings rate, or an increase in the propensity to consume, will lower savings and thus growth, but leave unemployment untouched. Bean and Pissarides augment this model by introducing some Keynesian features, namely an imperfectly competitive consumption goods sector. In this augmented model, an increase in the propensity to consume not only raises consumption, but also raises employment and output because of the effect the deeper market has on competition and the price mark-up. If this effect is strong enough then total savings and investment will also rise. The only problem with this later Keynesian result is that it is driven by the assumption that setup costs are denominated in terms of consumption goods, so a fall in the mark-up due to increased competition also lowers set-up costs.

Finally, let us consider the effect of an increase in the relative bargaining strength of workers[5]. Unemployment will rise as wages will increase, due to the increased bargaining strength of workers. This will reduce savings. On the other hand, increased bargaining strength shifts income from entrepreneurs to workers. Since workers do all the saving in this model, savings will increase because of this. Thus, the effect on savings is ambiguous

[4] Of course, in a more general search model, the effect on employment would be ambiguous. Job creation would increase as it will become more profitable for firms to post a vacancy. But job destruction could increase as it is now cheaper to find a new job-worker match. In this model, the latter effect does not exist. Employment is purely determined by job creation in this two period OLG model, as all matches end automatically after one period.

[5] This increases the amount of surplus workers receive in the nash bargaining solution.

and so the effect on growth is also ambiguous.

This last effect probably highlights better the importance of the life cycle savings of workers in generating most of the important results of this model. If work was uniformly spread over one's lifetime, then most of the effects discussed above would disappear, as they rely on a life-cycle savings mechanism. A life cycle savings mechanism may not be unreasonable as most individuals are required to save for retirement. It can be argued that an OLG model is simply capturing this phenomenon in a simple way. Further, most saving in the industrialized world occurs through the medium of pension funds. Still, it is not comfortable to have a model in which all the main effects rely on a life cycle savings mechanism. Below, we discuss the Daveri and Tabellini OLG model, which provides another channel by which growth and unemployment can interact.

The Daveri and Tabellini model

Daveri and Tabellini present an OLG model where equilibrium unemployment is caused by monopolistic trade unions. Assume competitive firms hire labour and capital up to the point where the respective perceived marginal product equals the relevant input price. Further assume a balanced budget condition holds. Under a union bargaining solution, equilibrium employment is given by:

$$l^* = \left[\frac{(1-\alpha)^2(1-\tau^l)}{\sigma}\right]$$

where τ^l is the labour income tax rate, $\cdot\sigma$ is the replacement ratio and α is the technology coefficient from a production function of the following kind:

$$y = \phi(k)l^{1-\alpha} \tag{4.10}$$

where y is the level of output normalized by the labour force, l is the employment rate and k is the capital at the beginning of the period normalized by the labour force.

The key growth equation is given below:

$$1+g^*(k) \equiv \frac{k'}{k} = F[\phi_k(k)l^{*1-\alpha}(1-\tau^k)]\{1+l^*\frac{\alpha}{1-\alpha}\}\sigma l^{*1-\alpha}\frac{\phi(k)}{k} \quad (4.11)$$

Where $F\,[]$ is the savings rate and is a function of underlying preferences[6] and τ^k is a tax on capital.

As expected in this class of models, for any given capital stock, equilibrium growth is higher the greater is the employment rate. Here though, the effect of employment on growth occurs though two distinct channels. First, by observation of the production function, equation 4.10, it can be seen that higher employment increases the marginal product of capital, as captured by the term $\phi_k(k)l^{*1-\alpha}$ in equation 4.11, and this in turn induces more savings by the young. Second, higher employment increases the average income of young individuals, which in a life-cycle model leads to more savings. This is captured by the term $l^{*1-\alpha}\frac{\phi(k)}{k}$ in equation 4.11. Only the second effect is captured in the Bean-Pissarides model. This is because they choose to model preferences as Cobb-Douglas:

$$U = C_1^{1-s}C_2^s$$

where C_1 and C_2 represent consumption in the first and second periods respectively.

With Cobb-Douglas preferences, as above, this implies a constant savings rate,s. Thus the first effect is abstracted out of consideration from the Bean-Pissarides model. Daveri and Tabellini argue that the first channel is very robust and intuitive. Higher employment implies a lower capital-labour ratio, and hence a more productive capital stock. This in turn fosters investment and stimulates growth. Even this mechanism can be challenged on empirical grounds though. Essentially this result requires that the interest rate has a positive impact on savings. Liebfritz et al (1997) presents a summary of 14 recent single country studies of this relationship. There are four with a

[6] Daveri and Tabellini assume that the sustitution effect outweighs the income effect and thus the savings rate is an increasing function of the interest rate.

positive effect, four with a negative effect, two with some positive and some negative effects and four with no effect. So it is not clear how strong this mechanism is in practice.

Let us take a more explicit form of the production function, equation 4.10. Let $\phi(k) = Ak$, so that we have an endogenous growth model and $\phi_k(k) = A = \frac{\phi(k)}{k}$[7]. The corresponding growth rate is:

$$1 + g^*(k) \equiv \frac{k'}{k} = F[Al^{*1-\alpha}(1 - \tau^k)]\{1 + l^* \frac{\alpha}{1-\alpha}\}\sigma l^{*1-\alpha} A \qquad (4.12)$$

Here growth is permanently affected by employment. As employment is reduced, the marginal product of capita falls. Firms scale down investment, but the marginal product of capital is not affected by this lower investment rate. Hence the growth affect is permanent. Obviously if we have a standard neoclassical, diminishing returns to each input, production technology, this would not be the case. Because as firms scaled down investment, the marginal product of capital would rise as $\phi\,()$ would be concave. This would continue until the growth effect had vanished and the economy is back to lower steady state level of output.

Thus the model of Daveri and Tabellini can generate effects of employment of growth even if growth is exogenously determined. But for these effects to be *permanent,* growth needs to be endogenously determined. This model shows how the replacement rate, σ, and labour taxes, τ^l, can have important effects on growth by changing employment.

4.3.3 Other Channels and Models

So far we have looked at a very narrow range of models for generating linkages between growth and unemployment. Once we endogenize growth there are many other classes of models which can also generate interactions between growth and unemployment. We review these other models in this section.

[7]This is the same functional form as in Bean and Pissarides (1993), based on Romer (1986).

Optimizing Ramsey Models

Eriksson (1997) uses a classical Ramsey optimizing growth model with a search theoretic labour market to see if there is a trade-off between employment and growth. We discussed earlier how, in this model, the capitalization effect can be overturned if the elasticity of intertemporal substitution was low enough[8]. Eriksson also endogenizes the growth rate in his model to allow unemployment to feedback into growth. The growth rate is endogenized by assuming that perpetual growth is made possible by a positive technological externality, working through the presence of the average capital stock ($\overline{K}$) in the individual firm's production function:

$$F = A\overline{K}^{v} K_i^{\alpha} N_i^{1-\alpha}$$

where $\alpha + v = 1$[9].

Let us look at some of the effects in this model. An increase in the capital tax rate will reduce the incentive to save. This will cause the growth rate to fall. For a firm considering how many vacancies to put out, this means that the cost of vacancies will grow slower. Thus some of the recruiting activities are pushed into the future i.e. $\frac{V}{U}$ or θ, *labour market tightness,* falls. Thus employment will fall, through the matching function. This will further reduce growth, due to the same effect as in Daveri and Tabellini, namely the marginal product of investment falls as N falls.

An increase in the bargaining strength of workers, or an increase in unemployment benefit, increases the amount of surplus workers can extract in a nash bargain. This makes the revenue accruing to a firm for a successful match fall. This makes the firm less prone to put out vacancies. Thus θ and N decrease. This leads to a fall in growth for reasons mentioned above. The effect on growth of a change in the bargaining strength of workers is different to that of Bean and Pissarides, who find an ambiguous effect. This is be-

[8]This would imply (r-g) rises as g increases.

[9]This is the same production function as in Daveri and Tabellini (1997) and Bean and Pissarides (1993), based on Romer (1986)..

cause the life cycle saving mechanism of workers is not present in Eriksson's optimizing Ramsey model.

An increase in the cost of posting vacancies or hiring costs will lead to similar effects in this model. This effect is not robust though, as was mentioned when discussing a similar effect in the Bean-Pissarides model. This is because in Eriksson's model, the job separation rate is *exogenous*. An increase in the cost of vacancies will lead to less vacancies being created and hence less job creation. But if we allow for an *endogenous* job separation rate, this could fall in response to this effect. This is because if it is more expensive to match new jobs with workers, firms may be less willing to destroy old jobs. Thus the total effect on unemployment and hence growth will be ambiguous.

Frictions caused by Education Costs

Falkinger and Zweimuller (1997) present an endogenous growth model in which workers have to be educated to get employed. Unemployment is not caused by matching frictions, or real wage rigidity, but by the fact that only workers who satisfy a certain skill requirement can find employment. Getting the necessary education requires resources which are provided via perfect capital markets. They find that increased innovation costs, or decreasing profits, lead to a decrease in the growth rate but an ambiguous effect on employment. On the one side, less growth and less innovation lead to lower life-time income of workers, so that less people can afford education. On the other side, less growth and innovation imply a lower interest rate, which makes it easier to finance education.

The effects of profits on unemployment is different from most models, due to the interactions of the interest rate and education and thus onto employment in this model. Let us take the example of the Bean and Pissarides model. As Caballero (1993) noted while commenting on the Bean-Pissarides model, one of the implications of its Keynesian extension is that sectors with higher degrees of imperfect competition should show a greater negative correlation between growth and unemployment in response to an increase in the propensity to consume. But higher degrees of imperfect competition are generally associated with higher profits. Thus lower profits, when interacted with the marginal propensity to consume should be associated with lower growth and higher unemployment.

Efficiency Wage Considerations

Finally, another class of models that can generate correlations between growth and unemployment are endogenous growth models, with the labour market modelled according to efficiency wage considerations. In fact Saint-Paul (1991) shows how, when we consider the general equilibrium of an efficiency wage model, the correlation between growth and unemployment may be positive or negative. Following Saint-Paul, consider the following endogenous growth model:

$$Y = AK^{\alpha}(He)^{1-\alpha}$$

$$\dot{K} = \beta Y$$

$$\dot{H} = \gamma Y$$

$$e = e(\frac{w}{\omega p}, u), \qquad e_1^{'} > 0,\ e_2^{'} > 0,\ e(1, \cdot) = 0,\ e(\cdot, 0) = 0$$

Where H is human capital, K is physical capital, e effort, $\frac{w}{p}$ the real wage, ω the alternative wage (which grows at the same rate as the economy) and u unemployment.

Consider the balanced growth path of the economy with a constant effort. Let g be the growth rate. This implies:

$$\frac{\dot{Y}}{Y} = g = \alpha\beta\frac{Y}{K} + (1-\alpha)\gamma\frac{Y}{H} \tag{4.13}$$

Along a balanced growth path, all variables grow at the same rate, implying:

$$\frac{H}{K} = \frac{\dot{H}}{\dot{K}} = \frac{\gamma}{\beta}$$

$$\Longrightarrow \qquad \frac{Y}{K} = A(\frac{\gamma e}{\beta})^{1-\alpha}$$

$$\frac{Y}{H} = A(\frac{\beta}{\gamma})^{\alpha} e^{1-\alpha}$$

Substituting into (4.13), this yields a growth rate increasing in e:

$$g = A\beta^{\alpha}(\gamma e)^{1-\alpha}$$

Further assume $e(x,u) = (x-1)^{\delta}u^{\rho}$. Then the Solow condition[10] can be written as:

$$\frac{w}{p} = x\omega = \frac{\omega}{1-\delta}$$

This determines a constant, exogenous real wage premium. This generates an upward sloping SC locus in the (u,e) plane. The equation for SC is:

$$e = (\frac{\delta}{1-\delta})^{\delta}u^{\rho}$$

Now, if N is total employment, and L the total labour force, labour demand will be determined by the equalization of the marginal product of labour and the wage:

$$\frac{eH}{N}(1-\alpha)(\frac{K}{He})^{\alpha} = \frac{\omega}{1-\delta}$$

Assuming $\omega = \frac{H}{L}$, i.e. that the alternative wage is proportional to human capital per capita, and noting that in equilibrium $\frac{K}{H} = \frac{\dot{K}}{\dot{H}} = \frac{\beta}{\gamma}$, this defines a downward sloping locus LD in the (u,e) plane, with the following equation:

$$(\frac{\beta}{\gamma})^{\alpha}e^{1-\alpha} = \frac{(1-u)}{(1-\alpha)(1-\delta)}$$

[10] $e_1(x,u) * x = e(x,u)$

It is clear that depending on where the differences in unemployment come from, the model can generate positive as well as negative correlation between g, i.e. e, and u. If differences in unemployment come from differences in labour demand, it may generate a positive correlation between growth and unemployment. If they come from shifts in SC, i.e. differences in shirking behaviour and /or monitoring technologies, t this will generate a negative correlation between growth and unemployment.

4.4 A summary and evaluation of the models

So far we have documented the theoretical links between steady state growth and equilibrium unemployment. Since we can identify many channels linking growth and unemployment, it is difficult to gauge the theoretical robustness of the effect of growth on unemployment or vice versa.

When we consider the case of exogenous growth, we discover two effects of growth on unemployment: the capitalization effect and the creative destruction effect. Neither is particularly robust, as is evidenced by the introduction of an endogenous interest rate and of complementarities amongst goods.

We follow by allowing growth to be endogenous and this introduces a *feedback effect* from unemployment to growth. Loss of skill, learning by doing and the saving mechanism would predict that this effect should be negative. But if we allow for the possible cleansing effect of recessions, the sign of this effect could be reversed. This feedback effect leads to a macroeconomic complementarity, and the possibility of multiplier effects and multiple equilibria.

Introducing endogenous growth also allows institutions to *indirectly effect* growth and unemployment. Most of models discussed allow institutional changes, such as changes to: taxes, hiring costs, the replacement rate and the bargaining power of workers to affect growth by first impacting on unemployment. But Eriksson (1995) shows how by considering the importance of *labour market tightness,* these indirect effects can impact firstly on growth and thus onto unemployment.

The next step is to try to discriminate between the various models, on the basis of empirical evidence. We do this below by using the evidence of Jones (1995a) and the bivariate evidence documented in the previous chapter. According to endogenous growth theory, permanent changes in certain policy variables have permanent effects on the rate of economic growth. As Jones (1995a) noted, growth rates of GDP per capita show little or no persistent increase, in the post WWII era, for OECD countries. In fact, for some of the countries, there is a significant negative trend for the post WWII period. Thus, the determinants of long-run growth in these countries either must not exhibit persistent increases, or must exhibit offsetting movements.

Jones (1995a) uses these facts to develop a sharp criticism of AK-style growth models. It is important to outline this criticism, as AK-style models are at the core of the OLG models and the optimizing Ramsey models outlined in section 4.3. The mechanism underlying the AK models, is that increased savings leads to increased investment and more capital accumulation. Due to a physical capital externality, this leads to increased growth. It can easily be shown that a simple AK-style model will have the following relationship between steady state growth and investment:

$$g_y = -\delta + Ai$$

where δ is the rate of depreciation and i the investment rate in physical capital[11].

So, steady state growth is a positive affine transformation of the investment rate for physical capital. In this class of models then, the dynamics of growth rates should be similar to the dynamics of investment rates. An increase in the investment rate, perhaps due to an increase in the capital subsidy, will be matched by an increase in the steady state growth rate. Investment rates for many of the advanced OECD countries exhibit a strong positive trend in the postwar period. Moreover, this trend is strengthened if one follows De Long and Summers (1991) and Jones (1994), and focuses

[11] For example, the growth equation (equation 9) in the model of Bean and Pissarides is exactly this, but with a rate of depreciation equal to one.

on producer durables investment. These have increased by about 3%, from just over 4% of GDP to 7% for: France, Germany, the UK and the US. In Japan, the rise is even larger, from about 3.5% to 9%. Despite these large movements in investment rates, growth rates have fallen, if anything, in the postwar period.

Could there be variables which could counter balance this effect? It is difficult to think of any. Two possibilities are human capital investment and openness. Yet, both of these are also trended upwards in the postwar period. This suggests that the AK models do not provide a good description of the driving forces behind growth in developed countries. It also suggests that models based on a savings mechanism are probably not the right vehicles to evaluate the growth-unemployment dynamic. This rules out the OLG models and optimizing Ramsey models for generating a *permanent* growth-unemployment dynamic. As the analysis of the Daveri and Tabellini model showed earlier, we can still generate a *temporary* growth-unemployment dynamic with a standard neo-classical production function, once we drop the AK-style production function. In fact Jones (1995a) estimates that a permanent increase in the investment rate affects growth only over the relative short horizon of 8-10 years. This could be consistent with a temporary growth-unemployment dynamic caused by a savings mechanism, as suggested by Daveri and Tabellini (1997).

We can draw some even stronger conclusions by using the bivariate evidence documented in the previous chapter. The granger causality tests could not rule out causality running in both directions. Yet we have also documented that unemployment is: highly persistent, shows mean reversion, but may or may not be stationary. Whereas growth is highly stationary and has very little persistence. Further, the coherence diagrams suggested a relationship between growth and unemployment at equilibrium frequencies and at low business cycle frequencies. Given the above evidence that growth illustrates little persistence but unemployment a lot, it may be the case that at low business cycle frequencies the relationship is due to unemployment effects impacting on growth. This could be due to: the effect of savings; cleansing type effects; loss of skills and learning by doing. At lower equilibrium frequencies, the relationship maybe due to growth impacting on unemployment, through capitalization and creative destruction effects.

The cross correlations analyzed in the previous chapter allow us to explore this hypothesis further. Looking at the lag structure of the correlation for growth leading unemployment, we found that the cross correlations were nearly always negative for all the countries considered. This would be consistent with capitalization dominating creative destruction, as increased growth leads to lower unemployment in this scenario.

For the correlation of unemployment leading growth, we found at low lags that the correlation was positive and at higher lags it switched to being negative. The switching point occurred at lag lengths of 8-12 depending on the country. The only mechanism, which we discussed in section 4.3, that can generate a positive correlation of unemployment leading growth, that we see at shorter lag lengths, is a cleansing type effect. This is because an increase in unemployment will allow quicker organizational change and this would increase future growth, i.e. lead to positive correlation between unemployment and growth. Now the prevailing literature generally associates this effect with recessions, i.e. it is the *business cycle* component of unemployment leading to a change in the *structural* growth rate. Here we have a link between the filtered unemployment and filtered growth, i.e. our measures of *structural* unemployment and *structural* growth. Thus the cleansing type effect we have identified here, is slightly different to that in the prevailing literature. But there is no reason why a cleansing effect cannot occur in response to an increase in structural unemployment. In fact many authors argue that the deeper the recession, the stronger the effect is (Aghion and Saint-Paul (1991)) and it is very likely given the persistence we see in unemployment, that a deep recession will have structural effects aswell.

What can explain the negative correlation between unemployment and growth we see at longer lags? Section 4.3 suggests three suspects: loss of skills, learning by doing and savings, each of which can deliver a negative correlation between unemployment and growth. The savings mechanism works as follows: an increase in unemployment reduces savings, which in turn reduces investment and thus causes growth to fall. An increase in unemployment can also cause an increase in the atrophy of skill; and, ceteris paribus, lead to a fall in the employment rate, which in turn could reduce learning by doing. Both effects will reduce the skills base of the labour force and thus reduce growth. We can probably rule out the effects of savings, as Jones's evidence suggests that the effects of savings, working through investment, do not last longer than 8-10 years. Yet, the negative correlation only kicks in at lags higher than 8 years. That suggests that loss of skills or learning by doing maybe the dominant effects, of unemployment on growth, at longer horizons.

4.5 Conclusions

This chapter has documented numerous mechanisms that link growth and unemployment. Some of the effects uncovered were more theoretically robust than others. The bivariate evidence linking growth and unemployment, discussed in the previous chapter, has been useful in helping discriminate between the various models. In particular, when combined with the Jones (1995) critique of AK models, we derive some pertinent results. It seems that at longer horizons, the relationship between growth and unemployment is be dominated by growth affecting unemployment, rather than vice versa. This is because growth is highly stationary with low levels of persistence, whereas unemployment is a highly persistent process. Further, cross correlations suggest that capitalization effects are more important than creative destruction effects. At medium run horizons, a cleansing type effect seems to be very pervasive.

To sharpen our judgements further, we must extend our empirical evidence beyond looking only at the evolutions of growth and unemployment.

In the next chapter, we introduce other variables, capturing the effect of *institutions.* This will allow us to check whether the bivariate correlations discussed here, are robust to the introduction of other factors; and test some of the *indirect* mechanisms linking growth and unemployment analyzed in this chapter.

Chapter 5

A Multi-Variate Evaluation of the Mechanisms Linking Growth and Unemployment

5.1 Introduction

In previous chapters, we have documented empirical evidence on the bivariate link between growth and unemployment and the theoretical mechanisms linking the two. But bivariate correlations can sometimes be misleading if the correlation is caused by other underlying factors. It could be the case that when we allow for the impact of other factors, namely institutions, these bivariate correlations could be overturned.

For example, suppose a reduction in labour taxes leads to a reduction in the surplus that workers could appropriate from innovators. This could lead to an increase in the incentives to innovate, an increase in R&D and an increase in growth. At the same time and for the same reasons, it may also lead to a reduction in unemployment. If we just looked at the bivariate correlation of growth and unemployment, it would be negative and maybe we would conclude a capitalization type effect we in operation. This would be the wrong conclusion as what is driving the negative correlation are changes in labour taxes. This could be perfectly consistent with the *direct effect* of growth on unemployment being positive, i.e. consistent with creative destruction dominating capitalization. To solve this problem, we explicitly control for the effects of institutional changes in this chapter.

We have noted previously that both theoretical considerations and the bivariate evidence suggest that growth and unemployment feedback into each other. This implies that both are *endogenous variables* and thus the standard practice of estimating a single growth or unemployment equation, to recover the effects of growth on unemployment and vice versa, is liable to suffer from the problem of *simultaneity bias.* To tackle this problem, we will estimate a system, including a growth and unemployment equation. This will be estimated across a panel of OECD countries to test the various hypotheses suggested by the growth-unemployment literature.

We noted, in the previous chapter, the importance of Jones' (1995a) critique of AK models of growth. In this chapter we try to discriminate between the mechanisms causing a link between growth and unemployment further, by testing Schumpeterian R&D growth models directly, and the importance they place on creative destruction. The Schumpeterian approach has some interesting implications that affect not just unemployment and growth. The main propagation mechanism of the Schumpeterian approach is innovation. One intuitive prediction is that R&D expenditure should be highly correlated with growth, as higher R&D should increase the probability of innovations. This can be tested by looking at the correlation between R&D expenditure and steady state growth, over a panel of OECD countries. Also, if creative destruction is important, then this should show up in a high correlation between growth and job destruction. We use Davis and Haltiwanger and Schuh's (1994) data on US job creation and job destruction to test this link.

The chapter is structured as follows: section II analyses the link between growth and R&D, while section III lays out the empirical methodology underlying a system including an unemployment and a growth equation and discusses the data. Section IV documents the results of estimating the system. Section V looks at the correlations of growth, job creation and job destruction, and section VI concludes.

5.2 The Link between Growth and R&D

The bivariate evidence in the previous chapter suggested that the capitalization effect dominates the creative destruction effect. This result could prove to be misleading, once we control for movements in other factors, as we try to do later. Also, on some level, looking at the relationship between growth and unemployment is a rather indirect way of trying to recover Schumpeterian forces. The main propagation mechanism of the Schumpeterian approach is innovation. Thus, one would expect that R&D should be highly correlated with growth, as higher R&D should increase the probability of innovations. This can be tested by looking at the correlation between growth and R&D. This has been a source of intense debate recently, with the issue really being what measure of R&D should be used.(see Jones 1995b and Aghion and Howitt 1998). Below I will try to clarify the relevant issues and present some new evidence.

5.2.1 Theoretical considerations

Jones (1995b) made a highly influential critique of R&D models of growth based on Schumpeterian notions. His argument was as follows. There has been a substantial increase in R&D levels in the post WWII period that might have been expected to raise growth. Yet, as we have mentioned in Chapter 4, growth rates have certainly not risen in this period, if anything they have fallen. This suggests that Schumpeterian forces cannot be the main driving force of growth. The following reduced form of the Romer (1990) model of endogenous technical change, illustrates the point. The aggregate flow of output is:

$$Y = K^{\alpha}(AL_1)^{1-\alpha},$$

and the rate of growth of technical knowledge A is proportional to the current flow of research labour L_2:

$$\frac{\dot{A}}{A} = \delta L_2$$

Total labour supply is constant and can be freely allocated between research and manufacturing:

$$L = L_1 + L_2$$

Thus, in the steady state, the rate of growth of output should be proportional to the steady-state share s^* of the total labour force devoted to R&D:

$$g_y = g_A = \delta L_2 = \delta s^* L$$

But as Jones documents, $L_2 = s^* L$ has increased substantially since the 1950s in all OECD countries, while growth of output per capita has not. He uses this to suggest decreasing returns in the production of new knowledge, the argument being as more knowledge is been accumulated, the harder it becomes to extend, as the easy innovations are made first. To accommodate decreasing returns, Jones proposes a slightly different innovation process:

$$\frac{\dot{A}}{A} = \delta L_2^{\lambda} A^{\gamma-1} \tag{5.1}$$

with $\gamma < 1$, and $\lambda \leq 1$. It is easy to show in this case that growth is no longer endogenous, as it becomes proportional to the rate of population growth (n), namely:

$$g = \frac{\lambda n}{1-\gamma}$$

Aghion and Howitt (1998) argue that there is a way of rescuing Schumpeterian type endogenous growth models that is consistent with the facts. They consider a Schumpeterian model with capital accumulation. The key facet is the innovation process, which is:

$$\phi_t = \lambda \phi(\frac{R_t}{A_t^{\max}});\ 0 < \lambda,\ \phi' > 0,\ \phi'' < 0,\ \phi(0) = 0; \tag{5.2}$$

where ϕ_t is the Poisson arrival rate of innovations in a sector to which R_t units of final output have been put into R&D. $A_t^{\max}$ is the maximal value of the productivity parameters A_{it} in the economy at date t, and λ is a parameter indicating the productivity of R&D. ϕ exhibits decreasing returns to scale, which is the result of a research congestion. The $A_t^{\max}$ parameter captures the force of increasing complexity; as technology advances the resource cost of further advances increases proportionally.

Growth in the leading edge parameter $A_t^{\max}$ occurs as a result of the knowledge spillovers produced by innovations. At any moment of time, the leading-edge technology is available to any successful innovator, and this publicly available knowledge grows at a rate proportional to the aggregate rate of innovations. The factor of proportionality, which is a measure of the marginal aggregate impact of each innovation on the stock of public knowledge, is assumed to equal $\frac{\sigma}{Q_t} > 0$. σ is the size of the innovation and Q_t is a measure of how many different intermediate products exist at time t. The factor of proportionality is normalized by Q_t, to allow for the fact that as the economy develops an increasing number of specialized products, an innovation of given size will have a smaller impact on the aggregate economy. This yields a rate of technical progress of:

$$g_t = \frac{\dot{A}_t^{\max}}{A_t^{\max}} = \frac{\sigma}{Q_t}\lambda\phi(n_t) \tag{5.3}$$

where $n_t = \frac{R_t}{A_t^{\max}}$.

Aghion and Howitt show how structural parameters that affect the incentives to innovate and accumulate capital can still effect the steady state growth rate, i.e. growth is still endogenous. The reason why the result is different to that of Jones, is both capital and labour are used in R&D under the Aghion and Howitt innovation process (equation 5.2) , as opposed to just labour in the Jones specification[1] (equation 5.1). The Aghion and Howitt model predicts that we should look at the relationship between steady state

[1] Input R_t includes capital and labour. For details of the model, see Aghion and Howitt (1998) ch.12.

growth and $\frac{R\&D}{GDP}$ rather than the number of scientists as predicted by a Romer type model. This is because of the complexity normalization $n_t = \frac{R_t}{A_t^{\max}}$ and the spillover normalization $\frac{\sigma}{Q_t}$. A simple rise in absolute R&D expenditure would not cause an increase in growth due to these two effects. In the next section, we empirically test the validity of this argument.

5.2.2 Empirical evidence

If we are going to see a relationship between $\frac{R\&D}{GDP}$ and steady state growth, then it should be apparent for the US. This is because the US has been the frontier economy when it comes to innovation, for most of the last century. Thus we first plot a scatter of moving averaged $\frac{R\&D}{GDP}$ against a measure of steady state growth. $\frac{R\&D}{GDP}$ is averaged over the five years immediately preceding the growth observation. For example we would pair the filtered growth measure for 1980 with the averaged $\frac{R\&D}{GDP}$ over 1975-79. This is so any relationship documented does not merely reflect *correlation*, but could potentially reflect *causality*. It is very easy to imagine growth causing $\frac{R\&D}{GDP}$. We can think of some effect very similar to the *capitalization effect* of growth on unemployment. An increase in growth could increase the present discounted value of a future innovation and this will lead to an increase in $\frac{R\&D}{GDP}$, just as the capitalization effect leads to an increase in vacancies[2]. We filter out causality running in this direction, by timing the R&D to happen before the growth takes place[3]. The measure we use is the filtered growth measure, as described in chapter 3 and based on Maddison's (1994) historical data. In other words, growth once cycles of frequency eight years or less have been filtered out. This allows us to use the full set of annual data, from 1958 onwards. The limitation is the data on R&D, which come from

[2]In fact, although Jones (1995) uses a decreasing returns to R&D innovation process to generate an exogenous growth rate, he still finds a positive correlation between the share of labour employed by the R&D sector and steady state growth. The causality runs from growth to the R&D though.

[3]We also perform granger causality tests, and these do rule out causality in both directions, but the results are sensitive to the number of lags used.

the NSF(1996). Referring to figure 5.1, we can see a positive and significant correlation between filtered growth and , though there seems to a substantial tail of observations spread along $\frac{R\&D}{GDP} \approx 2.8\%$.

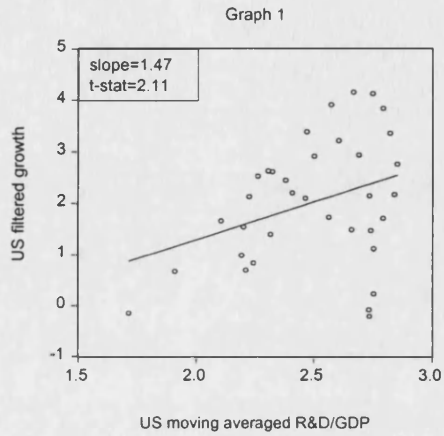

Figure 5.1: scatter of growth vs R&D for the US

Next, we see if this relationship still holds when we allow for some cross sectional variation, i.e. include other OECD countries. Here, we use a panel of two observations: time averaged for 1970-79 and 1980-89. The $\frac{R\&D}{GDP}$ is from the OECD (1995) and is the limiting factor in the size of the sample. The growth data are once again from Maddison(1994). Figure 5.2 plots a scatter of $\frac{R\&D}{GDP}$ against time averaged growth for the pooled OECD sample. There is clearly little relationship that can be discerned from it.

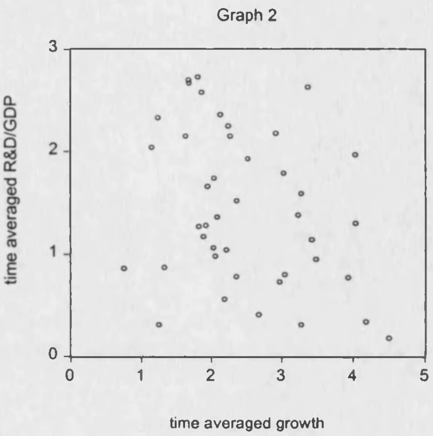

Figure 5.2: scatter of growth vs R&D for a pooled OECD sample

This could be because there is little relationship, or because of the predominance of country-specific effects. To test whether the latter hypothesis is true, we run a simple panel data version of equation 5.3, namely:

$$g_{it} = \alpha_i + d_1(\frac{r\&d}{gdp})_{it} + d_2 hu_{it} + d_3 lgdp_{it} + \varepsilon_{it} \tag{5.4}$$

where α_i is a fixed effect, hu and $lgdp$ are used as state variables to capture initial conditions and possible convergence effects, as suggested by Barro and Sala-i-Martin[4]. For a detailed discussion of the data, see section 5.3.2 and the data appendix. No other environmental variables are included, as if these Schumpeterian models are to believed, such variables are important precisely because of their effect on $\frac{R\&D}{GDP}$. The results are reported below[5]:

$\hat{d_1}$= 0.24 (0.65) $\hat{d_2}$= 0.17 (1.29) $\hat{d_3}$= -4.29 (-5.73)

We use a procedure that produces robust statistics to heteroscadasticity. We use man_{it}, which is a state variable representing the initial level of manufacturing output in any sub-period, as an instrument for gdp_{it} to counter any

[4]These are respectively a measure of the stock of human capital and the level of log GDP, both measured during the initial year of the corresponding sub-period.

[5]the t-ratios are in brackets

lagged endogenous variable or measurement error problems[6]. As can be seen from the results, the coefficient on $(\frac{r\&d}{gdp})$, although having the right sign is nowhere near significant. This suggests that for countries not on the technological frontier, R&D is not an important determinant of steady state growth. An immediately obvious problem with the above regression, is that we have not dealt at all with the potential endogeneity of $(\frac{r\&d}{gdp})$. We mentioned earlier how it is easy to conceptualize growth affecting R&D expenditure. It is difficult to solve for the potential endogeneity bias in this equation, as if we use $(\frac{r\&d}{gdp})_{t-1}$ as an instrument for $(\frac{r\&d}{gdp})$, then we no longer have a panel of data, but merely a cross section. Thus we would no longer be able to take account of the country specific effects, which is the whole point of doing this exercise. The endogeneity bias may not be so bad though, if we make the reasonable assumption that since $\frac{r\&d}{gdp}$ tends to be a very smooth and slow moving variable, it is a fairly exogenous variable. The problem lies partly in trying to estimate the *structural relationship*, equation 5.3, directly. In the next section, when we estimate a system involving growth and unemployment, we will come back to this problem again and consider a *reduced form* of equation 5.3, by substituting out the $(\frac{r\&d}{gdp})$ variable.

5.3 Growth and Unemployment Revisited

5.3.1 Empirical Methodology

The previous chapter suggested that, at least theoretically, steady state growth and unemployment feedback into each other. We argued that growth impacted on unemployment through capitalization and creative destruction effects; and that unemployment affected growth through: loss of skills; learning by doing; cleansing effects and savings. Further, Granger Causality tests could not reject the hypothesis of causality in both directions. This suggests that to consistently identify the effects of growth on unemployment and vice

[6] See the later section on growth and unemployment for a more detailed discussion of this issue.

versa, we need to take into account the potential for simultaneity bias caused by unemployment and growth both being endogenous. We attempt to solve this problem by estimating a system of unemployment and growth equations, across a panel of OECD countries. The data are discussed in more detail in the next section, but a panel is used, as it allows us to utilize variation in *time* and *cross section.* Cross-sectional variations in unemployment and growth are dominated by fixed effects at the country level. This is not surprising, as institutions only change slowly over time. For example, as Nickell (1997) notes, labour market legislation differs markedly across countries and such legislation did not change much after the late 1960s or early 1970s. Using a panel of observations allows one to take account explicitly of these fixed effects.

Unemployment

In considering factors affecting equilibrium unemployment, we draw on the analysis of Layard, Nickell and Jackman (1991) and Layard and Nickell (1997). Layard and Nickell (1997) show that from a very general model of the labour market, which allows for: insider influences on wages; outsider influences on wages, working through the 'threat points' in a nash bargain and the problems of matching workers to employers and searching behaviour, we can derive the following general equation for equilibrium unemployment:

$$u = f(\underset{+}{s}, \underset{-}{c}, \underset{+}{b}, \underset{+}{\beta}) \tag{5.5}$$

In other words, equilibrium unemployment is a decreasing function in any factor which: reduces the exogenous separation rate out of unemployment, s; increases search effectiveness of the unemployed, c; lowers the benefit replacement ratio, b, or lowers the strength of worker in the wage bargain, β. Most of the subsequent discussion of the effect of labour market institutions comes under these four headings, with the exception of taxes. We would expect labour taxes to either have no effect or a positive effect on unemployment, depending on whether higher taxes are passed on to higher gross wages. Daveri and Tabellini (1997) suggest that this is the case for Europe and thus we should expect labour taxes to have a positive and significant effect on unemployment for European countries[7]. We saw in the previous chapter how they derive an overlapping generations model, with union bargaining, that leads to unemployment positively depending on labour taxes. Phelps(1994) and Pissarides (1996) also argue that taxes have an important impact on labour costs in wage bargains because of important non-labour income effects. These effects arise because while labour costs are subject to both payroll and income taxes, non-labour income is subject only to income taxes.

Taking into account the additional growth effect documented in the previous chapter, consider the following empirical specification for an *equilibrium unemployment equation*:

$$u_{it} = \alpha_i + b_1 g_{it} + b_2 t_{it}^l + b_3 \sigma_{it} + b_4 \pi_{it} + b_5 u_{it-1} + \varepsilon_{it} \tag{5.6}$$

where: u_{it} is the equilibrium unemployment rate in country i at time t; g is the steady state growth rate of GDP per capita; t^l labour taxes; σ the replacement rate; π the change in inflation and α_i represents a fixed effect for each country.

Apart from the growth variable, this specification draws on the cross country unemployment analysis of Layard Nickell and Jackman (LNJ 1991) and Layard and Nickell (1997). The fixed effect and σ pick up arguments in equation (5.5). An increase in the replacement rate would be expected to have a positive effect on equilibrium unemployment for two reasons. First, if the real value of benefits are higher, this could lead to reduced search amongst the unemployed and thus reduce transition rates into employment. Second, by increasing the value of a workers outside option, it could lead to higher wages negotiated in any given bargaining process. The LNJ style regressions, also include other variables that affect the arguments of equation (5.5), such as: benefit duration; employment protection; union and employer

[7]Daveri and Tabellini's definition of Europe, refers to Continental Europe and thus does not include Scandinavian countries and the UK.

co-ordination. To the extent that these labour institutional variables have not changed much since the late 1960s (Nickell 1997) a lot of their impact will be picked up by the fixed effects.

The main focus is on the sign of b_1. If $b_1 < 0$, it suggests that capitalization dominates creative destruction, which would be consistent with the bivariate evidence presented in the previous chapter. If the opposite is true, it would suggest that creative destruction is the dominant force.

The change in inflation variable is included to allow for a short to medium term trade off between unemployment and inflation. A lagged unemployment variable is included to take account of the very high persistence in unemployment, as documented in chapter 3.

The country specific effect is entered as a 'fixed' rather than a 'random' effect. This if for two reasons: first, the sample is of only 18 OECD countries and thus methodologically, fixed effects specific to each country may be a better interpretation of the facts than effects drawn randomly from some underlying distribution (Baltagi 1997). Second, and more importantly, for the random effects model to be consistent, the random effects must be uncorrelated with the exogenous variables included in the model. This is unlikely to be the case in either an unemployment or growth equation. The country specific effects partly cover omitted variables correlated with the exogenous variables. In the unemployment equation, we may expect omitted variables representing difficult to measure, or observe, elements of the wage bargaining process to be correlated with labour taxes and/or the replacement rate. Ilsam (1995) applies similar logic to argue for fixed effects in growth equations.

Growth

In the previous section, we made an attempt to directly estimate the structural growth relationship, derived from the model of Aghion and Howitt (1998 ch12.). Here, we consider estimating a reduced form of this equation, by factoring out the $\frac{r\&d}{gdp}$ variable. The reasoning goes as follows. In Schumpeterian models of growth, such as Aghion and Howitt (1998 ch12), the incentive to innovate is the monopoly rents induced by implementing a vertical product innovation. Any feature that reduces the value of innovation will reduce R&D intensity and hence through equation 5.3 will reduce steady state growth. Thus any institutional feature that increases the ability of workers to capture the monopoly rents by increasing wages, i.e. reduces the surplus available to a potential innovator, will reduce growth in these types of models. So, any institution that increases the outside option or insider power of workers, could reduce growth. Thus labour market legislation, for example on employment protection or benefit durations, could effect growth directly *and* through the unemployment variable. Consider an R&D function like the following:

$$\frac{r\&d}{gdp} = F(t^l, \sigma, bd, coord, uc, ep, x)$$

where bd are benefit durations, $coord$ is a measure of union and employer co-ordination, ep is a measure of employment protection, uc is union coverage[8] and x is a vector of omitted variables. Referring to the unemployment equation (5.6), we could consider as an approximation to the above:

$$(\frac{r\&d}{gdp})_{it} = \gamma_i + u_{it} + \nu_{it}$$

where the effect of these institutional variables is captured by an unemployment term u_{it} and a fixed effect. As we noted earlier, labour market legislation has not changed much since the late 1960s (Nickell 1997) and so a fixed effect may capture a large part of its effect which does not work through the unemployment rate. Although this is a far from perfect specification for R&D, it will capture some of its effect and more importantly, it will capture a lot of the effects relevant to the Schumpeterian approach.

By substituting out $(\frac{r\&d}{gdp})_{it}$ from equation 5.4 we arrive at the following reduced form *equilibrium growth equation:*

$$g_{it} = \gamma_i + c_1 u_{it} + c_2 hu_{it} + c_3 lgdp_{it} + \omega_{it} \tag{5.7}$$

[8] For a more detailed description of the variables see the data appendix and Layard and Nickell (1997).

where: hu is the stock of human capital; $lgdp$ is the initial level of log GDP in the sub-period and γ_i is a fixed effect.

Apart from the unemployment term and the addition of fixed effects, this specification is similar to a simple Barro style growth regression (Barro and Sala-i-Martin 1995). The unemployment term, apart from capturing any effects working through innovation, will also capture effects working through loss of skills, learning by doing, savings and cleansing effects, as documented in chapter 4. Following Barro and Sala-i-Martin, we use an empirical framework of conditional convergence, that relates real per capita growth to the initial level of state variables and environmental variables. In the specification above the state variables are hu and $lgdp$. We augment the above specification by adding some environmental variables that might be important for the OECD. To test the importance of physical capital externalities, we add a term reflecting investment, namely $(\frac{I}{gdp})$. We also introduce a terms of trade variable, tot, since OECD economies tend to be fairly open and there has been much time series variation in terms of trade measures. Barro and Sala-i-Martin (1995) control for many more environmental variables, such as: the black market premium on foreign exchange and measures of political instability. Since we are focussing on highly developed OECD countries, most of these variables, though they will differ across these sample countries, will not show much time series variation. Thus there effects will mainly be washed up by the fixed effect. The specification we test, is the following:

$$g_{it} = \gamma_i + c_1 u_{it} + c_2 hu_{it} + c_3 lgdp_{it} + c_4 tot_{it} + c_5 (\frac{I}{gdp})_{it} + \omega_{it} \qquad (5.8)$$

Once again, the main focus is on c_1, the coefficient on the unemployment variable. If it is positive, it suggests that cleansing type effects are prevalent. If, on the other hand, it is negative, this would be consistent with: loss of skills, learning by doing or savings effects. We would expect c_3 to be negative as it represents the standard absolute convergence coefficient. The sign of c_2 is a bit more complex. Standard neo-classical Ramsey models would predict $c_2 < 0$ due to diminishing returns to reproducible factors. But if we allow for endogenous growth and externalities to human capital, an increase in hu could increase growth. tot is a variable measuring the change in the price of exports relative to imports and thus we should expect $c_4 > 0$. Finally we would expect $c_5 \geq 0$. If physical capital externalities are prominent, then this term will be significantly positive. Though as Jones (1995a) argued, the evidence for physical capital externalities is not strong (see the discussion in chapter 4). It will be interesting to see if his critique is born out in an insignificant c_5.

5.3.2 Data

The data is for a panel of 18 OECD countries during the period 1960-1989. The reason why the sample is restricted to only 18 OECD countries is data availability. In particular, certain variables were unavailable for: Greece, Luxembourg, New Zealand and Portugal. We will discuss a few pertinent points below, but all the data sources are listed in the Data Appendix.

Since we are interested in equilibrium movements in growth and unemployment, we remove the effect of the cycle by averaging each variable over a five-year period. In previous chapters, we have argued that there is compelling evidence that business cycles do not last beyond eight years. Given this why have we used a five year averaging procedure? We use it for two reasons. Firstly it is standard in the literature to use periods averaging 5-6 years (see: Barro and Sala-i- Martin 1995, Islam 1995, Layard and Nickell 1997, and Daveri and Tabellini 1997 to name a few) and thus it makes the results easier to compare if we use the same averaging procedure. Secondly, if we increase the sub periods to averages over eight years then we lose two observations. Given that at least one observation is lost to create lags, this would result in only three usable observations. We believed it was more important to keep a higher number of time series observations that were easier to compare to the previous literature in this area.

The growth rates are recovered from Maddison (1994) which uses Geary-Khamis dollars to normalize GDP across countries. The unemployment variable is the standardized unemployment rate according to OECD definitions. For labour taxes, we use the tax wedge. Following LNJ (1991) this includes payroll taxes, income taxes and consumption taxes. Taxation on labour typically operates via the wedge between the real cost of a worker to an employer and the real consumption wage of the worker[9]. For the replacement rate, we use an aggregate gross measure as produced by the OECD, following Daveri and Tabellini (1997), since we want to separate out the effect of labour taxes from unemployment benefits. Many would argue that changes in labour taxes mainly work through the replacement ratio. This is because in most OECD countries benefits are exempt from income taxes. Thus if we increase income taxes, *ceteris paribus*, labour taxes increase and the net replacement ratio rises. We want to separate out this effect from the direct effect of an increase in labour taxes on gross wages and hence on unemployment. Thus we include both labour taxes and the *gross* replacement rate.

The human capital variable deserves special mention, as measures of human capital have often been a weak spot in growth regressions. Previous work (for example Daveri and Tabellini 1997) has often used a secondary enrollment ratio measure. This really is not a particularly useful measure, as it is not related to the stock of human capital amongst the current working age population. Barro and Lee (1993) have made important progress in this respect. Based on census data and other information, they have constructed a human capital variable which gives the average schooling years in the total population over age 25. This is a stock measure and is what we use as our human capital variable in the growth equation. The terms to trade variable measures the growth rate of export prices minus those of import prices.

[9]Of course this measure is far from perfect, for example some income taxes fall on capital income and some consumption taxes are paid by individuals who are out of the labour force (see LNJ for more details).

5.4 Estimation and Results

There are various methods available to estimate regressions with panel data. Since we are applying the fixed effects model, we consider two options: the least squares dummy variables (LSDV) estimator with instruments; and the first difference estimator with instruments. Both methods are designed to solve the problem of country specific effects. The LSDV estimator is biased when lagged dependent variables are present (Nickell 1981), which is a problem in both the unemployment and growth equation, more so in the former case, as will be discussed below [10].

5.4.1 The Unemployment Equation

Consider the unemployment specification, equation 5.6. Even if growth was exogenous in this equation, the regression coefficients would be biased due to the presence of the lagged dependent variable (Nickell 1981). Further this bias is likely to be large as it depends on the size of T, or the number of time series observations and not N the number of cross sectional observations. In our sample, there are 4-5 time series observations depending on the number of lags used. This is very small and thus the biases from the LSDV estimator are likely to be large.

One solution is to first difference equation 5.6, so we have:

$$\Delta u_{it} = b_1 \Delta g_{it} + b_2 \Delta t_{it}^l + b_3 \Delta \sigma_{it} + b_4 \Delta \pi_{it} + b_5 \Delta u_{it-1} + \Delta \varepsilon_{it} \tag{5.9}$$

The fixed effect has disappeared and we can now use instrumental variables to solve for the problem of the lagged dependent variable and the endogeneity of Δg_{it}.

[10] A seemingly more sophisticated method to solve the problem of lagged endogenous variables, than first differencing and using instruments, is to first difference and use the General Methods of Moments (GMM) estimator. This essentially chooses the optimal instrument matrix utilising all possible lags. This technique is not reported in this section as the GMM estimator suffers large biases when the cross section is small (Arellano and Bond 1991 and 1998). In our sample the cross section is small, being only 18 countries. We did try using GMM estimators, but found the results were not consistent with other techniques, suggesting large small sample biases.

The results from using a variety of instrument sets are reported in Table 5.1. In all specifications we include a set of time dummies. All equations are estimated using a one step IV estimator which has test statistics robust to heteroscadasticity[11]. In the basic specification we use u_{it-2} to instrument Δu_{it-1}, as suggested by Anderson and Hsiao (1981). Based on a differenced version of the equilibrium growth equation (5.8) we instrument out Δg_{it} with Δhu_{it}, Δtot_{it}, $\Delta(\frac{I}{gdp})_{it}$, and $\Delta lgdp_{it}$. We further use Δman_{it} and man_{it-1} as instruments for $\Delta lgdp_{it}$ to avoid a potential lagged dependent variable problem in the growth specification (see equation 5.7) and to reduce potential measurement error problems. We discuss these issues in more detail later, when we estimate the growth equation.

For this basic specification, we find that the effect of growth on unemployment is negative and not significant. The effects of labour taxes and the replacement ratio are found to be positive, as expected, but not significant.. Daveri and Tabellini find that labour taxes have a positive and significant effect for continental Europe in their analysis. This maybe because they allow for a different effect of taxes in continental Europe, Scandinavia and the Anglo-Saxon economies; or because they use different taxation data, focussing on effective as opposed to statutory rates. We do not pursue that line of thought in this paper. A change in inflation has a negative and significant effect on unemployment, suggesting a short/medium run trade off between unemployment and inflation. The lagged unemployment variable has a positive and significant effect, supporting the notion that unemployment is a highly persistent process. Unfortunately the hypothesis of no second order serial correlation is rejected at the 5% level, suggesting that the estimates

[11] The estimations were carried out using Dynamic Panel Data (DPD), by Arellano and Bond. Tests for serial correlation are reported. These are for first order serial correlation in levels equations and second order serial correlation in first differences equations. In first differences equations, the one step estimator is consistent up to first order serial correlation, but is inconsistent if second order serial correlation is detected and lagged dependent variables are present. A Sargan statistic is presented to test the overidentifying IV restrictions. This is based on the two step estimator in DPD, and is only reported when the two step procedure has been possible. Arellano and Bond (1991) discuss in more detail the above testing procedures.

from the basic specification could be inconsistent.

Next, we take into account the possible endogeneity of changes in inflation. If unemployment changes, this could lead to a change in wage pressure and hence a change in inflation. Since the sub-periods are five year averages and we are looking at the change in inflation, which is not a persistent process, the lag of this variable is not necessarily a good instrument, as it is not highly correlated with the contemporaneous change in inflation. Thus, we instead use the contemporaneous rate of change of the supply of money ($d2ml$) as an instrument for inflation. This is based on a monetarist interpretation of inflation, that is some ways, inflation is linked to narrow money via the 'Quantity Theory of Money'. Although M1 will be endogenous to some degree, it should be more exogenous than π, to the extent that the central bank controls the stock of narrow money. To the extent that narrow money is an important factor in inflation and the central bank has control over it, this should be a good instrument. Thus to estimate equation 5.9, we use all the instruments in the basic specification plus $d3ml$.

For this specification, we find that b_1 is negative and significant at the 10% level, but just under significance at the 5% level. Taxes and the replacement rate are still not significant, but now lagged unemployment is no longer significant, though it has the expected sign. The size of the inflation effect is very large though and just significant at the 10% level. The size of the effect is surprising, Layard and Nickell (1997), also find a negative and significant inflation effect, though at -0.21, it is about a sixth of the effect discovered here. Though they do not instrument inflation, and as we can see from the results in the first specification, when inflation is not instrumented, the effect is more significant, but of significantly lower absolute value. The serial correlation test suggests no problems and the Sargan overidentifying statistic suggests that the instruments are valid.

Next we take account of spurious results due to the possible endogeneity of tax rates and unemployment benefits. For example suppose that there is a large, negative aggregate demand shock that raises unemployment. This could cause an increase in labour taxes to pay for increased unemployment benefits. These variables are unlikely to be as endogenous as the change in inflation variable as they are statutory rates. They are set by government and do not react naturally to a change in unemployment as say inflation, which is determined as a natural economic outcome.

In the third specification, following Andersen and Hsiao (1981) and Daveri and Tabellini (1997) we augment the instrument set by using rr_{it-2} and tl_{it-2} as further instruments. We use the second lag of these variables only as instruments rather than Δrr_{it-1} and Δtl_{it-1}as well, as Daveri and Tabellini do, to avoid potential correlation with the error term, $\Delta\varepsilon_{it-1}$caused by the presence of the Δu_{it-1} term as a right hand side regressor. We find that b_1 is still negative, but no longer significant. This is due to a substantial increase in the standard error of the coefficient, as the absolute value of the coefficient increases. The increase in the size of the standard error is not surprising, given that we are using more instruments. A couple of surprising results are the negative, though not significant sign on the replacement rate. Daveri and Tabellini (1997) find a similar problem when they instrument out the replacement rate. Also the inflation effect is even larger now, approximately ten times the size of the effect in Layard and Nickell (1997). This is slightly worrying as the inflation effect is now the most important impact by far. Layard and Nickell also find it to be one of the most important variables, but not to the extent we find it here. Further, the magnitude and significance of the lagged unemployment effect completely collapses. This maybe be due to two things: a) the choice of instruments for the replacement rate and the tax rate may be capturing the effect of lagged unemployment as they are second lags of their respective variables; b) by using five year averages of the unemployment rate in the estimations, we may also be reducing the persistence in unemployment when compared to looking at annual rates, by removing a large portion of the cyclical effect.

5.4.2 The Growth Equation

Consider the growth relationship, equation 5.7. Aside from the endogeneity of unemployment and potential endogeneity of the investment share, there is a potential lagged dependent variable problem with the *lgdp* variable. This is not as serious a problem as in the unemployment equation, as *lgdp* is not strictly a lagged dependent variable. It as an initial levels term, whereas, the dependent variable is a differenced term. One solution to this potential problem, rather than first differencing, is to try to find a suitable instrument for *lgdp*. One potential candidate is the initial level of manufacturing output in each sub-period (*man*). This should be highly correlated with the level of gdp and is in general measured with less error.

Thus for our first growth specification, we consider estimating equation 5.8 directly, using the LSDV estimator. Based on the equilibrium unemployment equation (5.6) we use t^l, σ, and π as instruments for u, $(\frac{I}{gdp})_{t-1}$as an instrument for $(\frac{I}{gdp})_t$ and *man* as an instrument for *lgdp*. We need to instrument the investment share as it is potentially endogenous. The reasoning is similar to a capitalization effect. Growth may increase the future returns to capital, and thus cause increased investment. As Barro and Sala-i-Martin (1995) show, $(\frac{I}{gdp})_{t-1}$ is a good instrument for $(\frac{I}{gdp})_t$ as there correlation is very high, around 0.80. The results for both growth specifications are reported in Table 5.2. All regressions include time dummies. The main result is that unemployment has a negative and not significant effect. Human capital has a positive but insignificant effect, whereas *tot* has a positive and significant effect, as expected. *lgdp* has a negative and significant effect. the value of convergence implied, is around 10%. This is much higher than the estimates reported by Barro and Sala-i-Martin (1995), which are around 2%. This is not surprising given the evidence documented by Islam (1995). As he notes, the sample used by Barro and Sala-i-Martin, is very large. When one focuses on OECD, countries convergence estimates tend to be much higher. Also, the Barro and Sala-i-Martin estimates do not take account of fixed effects in the panel of countries considered. As Islam shows, this downwardly biases the convergence estimates and once we take fixed effects into account, the estimates rise considerably[12]. The effect of $(\frac{I}{gdp})$ is not significant.

An alternative to the LSDV estimator, is to first difference and estimate the following equation:

$$\Delta g_{it} = c_1 \Delta u_{it} + c_2 \Delta hu_{it} + c_3 \Delta lgdp_{it} + c_4 \Delta tot_{it} + c_5 \Delta (\frac{I}{gdp})_{it} + \Delta \omega_{it}$$

Here, we use Δt^l_{it}, $\Delta \sigma_{it}$ and $\Delta^3 ml_{it}$ to instrument Δu; $\Delta(\frac{I}{gdp})_{it-1}$ and $(\frac{I}{gdp})_{it-2}$ to instrument $\Delta(\frac{I}{gdp})_{it}$; and finally Δman_{it} and man_{it-1} as instruments for $\Delta lgdp_{it}$. The results are very similar as for the LSDV estimator, with the exception of the magnitude and significance of the human capital effect. The effect of unemployment is slightly higher in magnitude, but slightly lower in significance.. Human capital has a substantially higher effect and is now significant. *Tot* remains positive and significant and the convergence term is around 11% and highly significant. The investment share term remains insignificant. The serial correlation and Sargan tests, suggest that the equation is well specified.

5.4.3 Fixed Effects

There is another avenue open to us to test the importance of R&D effects. We can look at the fixed effects from the growth relationship, equation 5.8. We argued before that the fixed effect could capture the *direct* effects of slowly evolving labour market institutions on the monopoly rents of innovators and thus on growth, under a schumpeterian approach. So could estimate the following equation, across the OECD, to see if the labour market institutions,

[12]Since the initial level of GDP and the equilibrium level are positively correlated, if we do not perfectly control for equilibrium GDP, by omitting the fixed effects, we will tend to bias upward the coefficient on GDP. But since the convergence term is usually negative, this means we would underestimate the rate of convergence. Though as Barro(1996) argues, quasi differencing by using the LSDV estimator, or using first differences directly, could increase the importance of measurement error over the signal, especially in variables with little time series variation. This, as Barro argues, would lead to an overestimate of the rate of convergence.

which we enter as fixed effects in the unemployment regression, matter in growth:

$$\gamma_i = c + e_1 bd_i + e_2 coord_i + e_3 ep_i + e_4 uc_i + \eta_i \tag{5.10}$$

where γ_i are the fixed effects from equation 5.8 estimated by LSDV, bd_i are benefit durations, $coord_i$ is a measure of union and employer co-ordination, ep_i is a measure of employment protection and uc_i is union coverage[13]. Although there has been some time series variation in the labour market institutional variables, since the 1960s, variation across countries has been much greater, within the OECD. To this extent, estimating the above equation should capture the effects of labour market institutions on growth. We would expect e_1, e_3, and e_4 to be < 0 due to the positive effects on wage pressure of an increase in benefit durations, employment protection or union coverage. e_4 should be positive, as coordination reduces wage pressure by encouraging unions and employers not just to think about there own membership, but what effects there actions will have on the aggregate economy. The results of estimating equation 5.10 with statistics robust to heteroscadasticity are reported below[14]:

$\hat{e}_1$= 0.03 (0.15) $\hat{e}_2$= 0.05 (0.21) $\hat{e}_3$= -0.02 (-0.51) $\hat{e}_4$= -1.40 (-2.70)

It can be clearly seen that none of the institutional variables are near significance with the exception of uc_i which is significant and has the expected sign.

5.4.4 Summary

The multivariate evidence sheds some light on the various linkages, which I summarize below:

[13]For a more detailed description of the variables see the data appendix and Layard and Nickell (1997). We took the value of these variables for the 1980s.

[14]The t-ratios are in brackets

The links between growth and unemployment

The evidence is weak. The only term which is significant in any of the specifications used, is the effect of growth on unemployment and even then only at the 10% level[15]. In this case, the effect is negative, suggesting capitalization dominates creative destruction, which is consistent with the bivariate evidence reported in the previous chapter. For this specification (the second unemployment specification), the long run coefficient of growth is -0.98. This suggests that an increase in growth of 1% reduces unemployment by 1%. This is an important though not very large effect. Given that OECD unemployment rates have diverged by as much as 14% and growth rates have only diverged by a couple of % in the post WWII period, it seems obvious that growth is not the main determinant of equilibrium unemployment, even if this specification was the true one. If it is not the true one, then it is difficult to find any affect of growth on unemployment at all. Institutional factors are probably far more important.

Unemployment is not significant in either of the growth specifications. Maybe this is not surprising. Even though we can identify effects of unemployment on growth, for example: loss of skills, learning by doing, cleansing effects and savings, should we really expect them to be significant? Consider the following example. Let us start with an unemployment rate of 5% and hence an employment rate of 95%. Next let unemployment increase by 2% so the employment rate falls to 93%. It is probably through the employment rate that unemployment effects growth. It is agents who are working who contribute to the production of output. Now although an increase in the unemployment rate of 2% from a base of 5% is large can we really say a fall in the employment rate from 95% to 93% is? The percentage increase in unemployed numbers is 40% whereas the percentage fall in employed numbers

[15]These results are slightly different to Daveri and Tabellini (1997). They also find growth has a negative and significant effect in the unemployment equation, when a difference equation is estimated, but not when a levels equation is estimated. They also find unemployment negative and significant in the growth regression, though only for certain specifications.

is only around 2%. It would take a huge increase in unemployment to have a significant effect on the number of employed agents. Maybe this explains why we do not see a significant effect of unemployment on growth.

The link between growth and R&D

The multivariate evidence suggests that the link between steady state growth and R&D is not strong. If there is a creative destruction effect it seems to be dominated by a capitalization effect. Further, the evidence from the effect of unemployment on growth, and from the fixed effects, suggests that effects working through the monopoly rents available to innovators are not significant. This is consistent with the OECD evidence, in the previous section, which did not find a link between growth and R&D, except for the US.

One possible explanation for the lack of importance of $\frac{r\&d}{gdp}$ is that in the post WWII period, many of the European countries and Japan were recovering from WWII. Certainly for a prolonged period, there was lots of creation and very little destruction, as reflected in the post WWII boom. The US may not just have helped with the Marshall plan, but also with providing technological now-how that allowed easy imitation and implementation of its own innovations. Although the data for the OECD panel starts from the 1970s, when the World Economy became less robust in face of the two oil price shocks and the global productivity slowdown, the US was still the frontier economy. Certainly, many argue that Japan's success was based on *imitation* and *process innovation,* rather than *vertical product innovation.* Thus it maybe the case that direct vertical product innovations have not been very important in post WWII growth for most OECD countries with the possible exception of the US. In most other countries, imitation of existing technologies, through technological transfers may have been more important. Although it still requires R&D to imitate existing technologies, for example by backward engineering a product, it probably does not require as much R&D as innovation itself. This suggests that R&D is only one of the main driving forces of growth for countries on the technological frontier. We try to investigate this hypothesis further by looking at the relationship between growth and job flows, in the next section.

The link between growth and physical capital accumulation

The growth regressions suggest that the investment share is not a significant determinant of steady state growth. This is consistent with Jones critique of AK models of growth, as documented in the previous chapter. It is not consistent though with a large body of cross-sectional studies on growth, which usually find a highly significant and positive effect of the investment share on growth. Below I try and explain the source of this difference. Levine and Renelt (1992) did some sensitivity analysis across a large range of cross sectional growth regressions. They found most of the results to be fragile, with the exception of a positive correlation between growth and the investment share. Yet the results here and from Barro and Sala-i-Martin (1995), both across a panel of countries, suggest that the effect of changes in the investment share on growth are insignificant. There could be two reasons for this difference. In cross sectional regressions, country specific effects are not controlled for. Yet as we have discussed at length earlier, these are undoubtedly important in multi-country analysis. It could that investment shares are correlated with these country specific effects, and thus the results would suffer from *fixed effects bias*, in a purely cross country study. Or it could be the case that growth causes investment rather than vice versa and thus the coefficient on the investment share has *endogeneity bias*, in a purely cross-sectional study. Both these effects can be controlled for by using panel data, as one can allow for fixed effects and use instruments to control the endogeneity bias. We suspect that the fixed effects bias is more important than the endogeneity bias. This is based on Jones' evidence, which shows that investment shares are highly trended upwards in the OECD yet growth has been stationary, or if anything shown a slight negative trend, in the post WWII period. Given these facts, it seems unlikely that growth and investment shares have any strong link in *either* direction. This maybe what is being reflected in the lack of significance of the investment share in this study. The positive correlation in cross country studies, could be due to the fact that countries with high growth also happen to have been countries with high investment shares, without any *causality* implied. Once we allow for some time variation, within countries, it seems pretty clear that the link between investment shares and growth is not strong.

5.5 The Link between Growth and Job Flows

It has often been argued that economic growth in a market economy involves reallocation. Schumpeterian 'creative destruction' is exactly this process. If this is the case, then we should see a strong correlation between growth and job flows. Aghion and Howitt (1998) argue that if growth is caused by vertical product innovations, we should see a positive correlation between growth and job destruction. Vertical product innovation leads to business stealing from, and the eventual exit of, firms with outdated technologies. This will cause job destruction.

Vintage capital models use a subtly different conceptualization of Schumpeterian mechanisms but reach the same conclusions. Caballero and Hammour (1994) and Campbell (1997) emphasize the role of entry and exit. If new technology can only be adopted by new establishments, growth occurs only via entry and exit, which requires factor reallocation and job turnover. The importance of this will depend on the size of the *renovation costs,* as modelled by Mortensen and Pissarides (1998) and discussed in Chapter 4. Cooper, Haltiwanger and Power (1997) emphasize that existing plants can adopt new technology by retooling. The retooling process may generate within-plant and between-plant job reallocation.

Davis and Haltiwanger (1998) survey recent plant-level and firm-level studies which have looked at the role of factor reallocation in productivity growth. These studies find that the reallocation of output and inputs from less productive to more productive plants plays a major role in industry-level multifactor productivity growth. Though a closely related literature investigating the connection between employment reallocation and labour productivity growth yields a more mixed set of results and a typically smaller role for reallocation.

Here, we try to determine the importance of reallocation via creative destruction by looking at more aggregate job creation and destruction data, for the US. This has been compiled by Davis, Haltiwanger and Schuh (1994) for the period 1973-1988 in the manufacturing sector. For manufacturing output we use data from Mitchell (1993) and construct growth rates, which we then pass through a low pass filter, to filter out movements of frequency eight years or less[16]. Figure 5.3 plots a scatter of annual job destruction rates against filtered manufacturing growth. It is difficult to discern a clear relationship, but when we plot scatter of job reallocation against filtered manufacturing growth(see figure 5.4), there seems to be clearly positive and significant relationship[17].

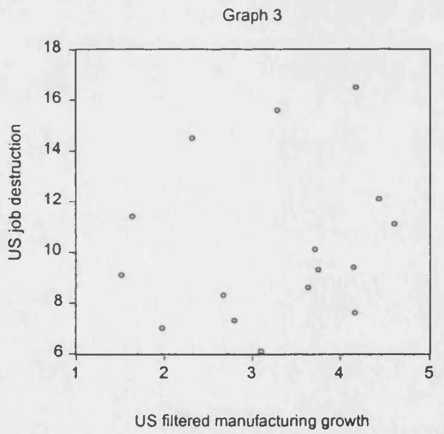

Figure 5.3: scatter of US job destruction vs. growth

[16]Data from Mitchell (1993) was used as the series available was very long. This makes the spectral estimator more reliable. For more details of these issues, see chapter 2.

[17]job reallocation is simply the sum of job creation and job destruction.

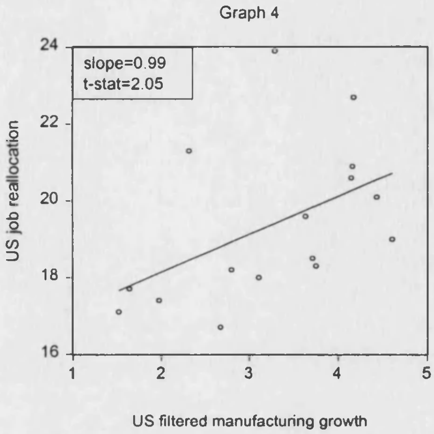

Figure 5.4: scatter of US job reallocation vs. growth

This difference could be due to two things: job reallocation is much less cyclical and volatile than job destruction as can be seen in figure 5.5, and thus the relationship between job reallocation and steady state growth could be less distorted by cyclical factors. Secondly, maybe job reallocation also captures the relationship between growth and job creation. As we noted from the bivariate evidence in chapter 3 and the systems estimates earlier in this chapter, if there is an effect of growth on unemployment, it is negative, suggesting capitalization dominates creative destruction. Maybe this is also being picked up in the relationship between job reallocation and filtered growth.

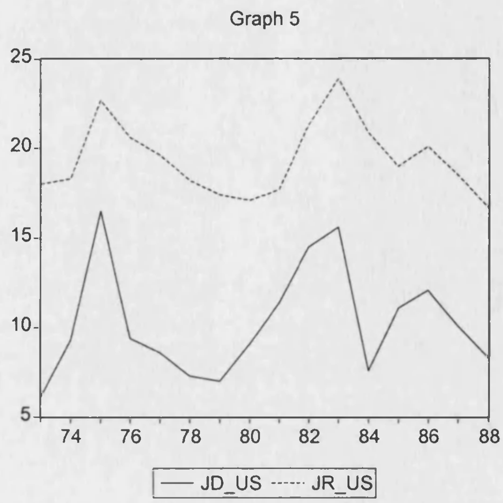

Figure 5.5: graph of US job realloaction and job destruction

To try to filter out cyclical effects more comprehensively, we look at the relationship between filtered manufacturing growth and the minimum of job creation and job destruction. The idea behind this is that at the steady state level of unemployment, we should have similar levels of job creation and job destruction[18]. Looking at the minimum of these two flows may be getting nearer to the steady state flows, with anything above the minimum being due to cyclical forces. Figure 5.6 below plots a scatter of the relationship. It seems that there is a positive relationship, though it is slightly under significance at the 10% level and there are a couple of outliers.

[18]This is, of course, abstracting from other flows into and out of the unemployment pool, such as: quits, new entrants to the labour force and agents leaving the labour force.

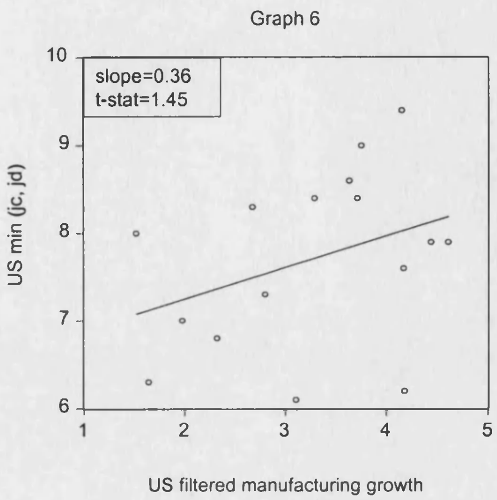

Figure 5.6: scatter of US steady state flows vs. growth

Evidence on job flows does exist for other countries, but we have refrained from trying to pool this data because, as Davis and Halitwanger (1998) note, cross country comparisons with job flow data are very dangerous due to differences in: sector coverage; data quality and business unit definitions. We concentrated on the US because: the data was good quality; the time horizon was relatively long and the US is still the frontier economy.

5.6 Conclusions

The interactions between growth and unemployment are both complex and multi-faceted. We have discovered in this chapter, that once we control for the impact of institutions, that the interactions between growth and unemployment are weak. At best we only discover a weakly significant negative effect of growth on unemployment, in one of the unemployment specifications. If this is the true specification, it suggests capitalization dominates creative destruction, which is consistent with the bivariate evidence. Even if this effect is significant, the magnitude is not very high. A 1% increase in growth will only reduce unemployment by 1%. Given that OECD unemployment has differed by as much as around 15% in the post WWII period, whereas growth has only differed by a couple of %, it suggests that growth has not been the main cause of the structural movements in unemployment. If it is not the true one, then it is difficult to find any affect of growth on unemployment at all. Institutional factors are probably far more important.

Further analysis of R&D and job flows evidence, suggests that R&D models of growth and creative destruction mechanisms may be important in countries on the technological frontier, such as the US, but not so prevalent in other OECD countries. Also, results from estimating a growth and unemployment evidence, suggest that changes in the investment share do not have significant effects on growth. This is consistent with Jone's criticism of AK models of growth and suggests that accumulation of physical capital does not have major effects on steady state growth.

Overall, the evidence from the last three chapters suggest that the interactions between growth and unemployment are small, with some marginal evidence of a capitalization effect. Unemployment can have effects on growth through mechanisms like: learning by doing, loss of skills, cleansing effects and savings; but they do not seem to be very significant in practice.

5.7 Data Appendix

u = standardized unemployment rate. Source: CEP-OECD data set.

g = growth rate of GDP per capita. Source: Maddison (1994)

t^l = the tax wedge, defined as the sum of the payroll tax rate, the income tax rate and the consumption tax rate. The latter are average rates derived from national income and aggregate tax data. Source: CEP-OECD data set.

σ = the gross replacement rate. Source: OECD Database on Unemployment Benefit Entitlements and Replacement Rates.

π = the change in inflation. This is the average of the annual change in inflation, over five years. Source: CEP-OECD data set.

$\Delta^2 m1$ = the change in the growth of m1. This is the average of the annual change in the growth of m1, over 5 years. Source: CEP-OECD data set.

hu = the Barro-Lee measure of the stock of human capital. It represents the average schooling years in the total population, over age 25 and is measured at the beginning of any sub-period. For example, for the sub-period 1980-84, the measure is for 1980. Source: Barro-Lee data set.

gdp = the log of GDP. Measured at the beginning of every sub-period, like hu. Source: Maddison (1994).

tot = terms of trade shock: the growth rate of export prices minus the growth rate of import prices. Sources: Barro-Lee data set and for the last sub-period, various editions of the IMF publication International Financial Statistics.

$(\frac{I}{gdp})$ = ratio of real gross domestic investment (private plus public) to real GDP. Source: Barro-Lee data set, though the primary source is the Summers and Heston data set.

man = the level of manufacturing output. Measured at the beginning of every sub-period, like hu. Sources: CEP-OECD data set for the unemployment/growth regressions and Mitchell (1993) for the correlations between job flows and growth.

$\frac{r\&d}{gdp}$ = R&D expenditure normalized by GDP. Sources: NSF (1996) and OECD (1995).

jd, jr = annual job destruction and job reallocation rates for the US manufacturing sector. Source: Davis, Haltiwanger and Schuh (1996).

bd = benefit duration measured in years. 4 years is considered indefinite. Source: LNJ (1991), see Annex 1.3 of this for more precise details.

$coord$ = is the sum of employer and union coordination indices produced by LNJ (1991). Both are measured on a scale of 1-3 with: 1 = low; 2 = medium and 3 = high. Source: LNJ (1991), see Annex 1.4 of this for further details.

ep = employment protection and is measured on a scale of 1-20 in with the degree of protection in ascending order. Source: OECD Jobs Study (1994).

uc = a union coverage index. on a scale of 1-3. 1 = under 25% covered; 2 = 25-70% and 3 = over 70%. Source: LNJ (1991), see Annex 1.4 of this for further details.

spec.	1	2	3
dep variable	Δu	Δu	Δu
Δg	-0.35 (-1.46)	-0.40 (-1.76)	-0.66 (-1.11)
Δt^l	0.07 (0.70)	0.03 (0.29)	0.35 (0.60)
$\Delta \sigma$	0.028 (1.07)	0.027 (0.59)	-0.21 (-0.56)
$\Delta \pi$	-0.40 (-2.28)	-1.27 (-1.65)	-2.21 (-1.71)
Δu_{t-1}	0.99 (2.20)	0.59 (0.74)	0.04 (0.04)
no obs	70	70	70
serial corr. stat.	-2.13	-0.44	0.47
sargan stat.	2.30 (df=3)	0.55 (df=3)	0.24 (df=3)

Table 5.1: **Unemployment Regressions**

Notes

- We estimate using a one step IV estimator which has test statistics robust to heteroscadasticity across 5 time periods (1965-69, 1970-74, 1975-79, 1980-84, 1985-89). T ratios are shown in brackets.

- The serial correlation test is for second order correlation and asymptotically converges to $N(0,1)$. The estimator is consistent up to first order correlation. The Sargan statistic is based on the two step estimator as performed by DPD. The reason we use this statistic is that the one step Sargan statistic, when heteroscadasticity is present, does not asymptotically converge to a χ^2. See Arellano and Bond (1991) for further details of these test statistics.

- In column 1, we use as instruments: u_{t-2}, Δhu, Δtot, $\Delta(\frac{I}{gdp})$, Δman, man_{t-1} and the time dummies. In column 2 we also use $\Delta^3 m1$. In column 3, we augment the instrument set with t^l_{t-2} and σ_{t-2}.

spec. dep variable	1 g	2 Δg
u	-0.31 (-1.47)	-0.47 (-1.40)
hu	0.0012 (0.40)	0.0055 (2.26)
tot	0.082 (2.33)	0.078 (1.73)
$lgdp$	-0.099 (-2.43)	-0.11 (-2.66)
$\frac{I}{GDP}$	0.10 (0.84)	-0.07 (-0.40)
no obs	88	70
serial corr. stat.	-0.47	-0.281
sargan stat.	na	2.77 (df=3)

Table 5.2: **Growth Regressions**

Notes

- The type of estimator, is the same as for the unemployment equation.
- In column 2 the independent variables are entered in first differences.
- The serial correlation test is for first order correlation in the levels equation and second order correlation in the differences equation.
- In column 1, we use as instruments: t^l, σ, π, man, $(\frac{I}{gdp})_{t-1}$ the fixed effects and the time dummies. In column 2 we use Δt^l, $\Delta\sigma$, $\Delta^3 m1$, Δman, man_{t-1}, $(\frac{I}{gdp})_{t-2}$, $\Delta(\frac{I}{gdp})_{t-1}$and the time dummies as instruments.

Bibliography

[1] Acemoglu, D., (1996) "A Microfoundation for Social Increasing Returns in Human Capital Accumulation", *Quarterly Journal of Economics*, 111-3, August, 779-804.

[2] Acemoglu, D., (1997) "Changes in Unemployment and Wage Inequality: an Alternative Theory and some Evidence", *Mimeo Department of Economics, MIT.*

[3] Acemoglu, D., (1998) "Why do New Technologies Complement Skills? Directed Technical Change and Wage Inequality", forthcoming *Quarterly Journal of Economics.*

[4] Aghion, P. and Howitt, P. (1992), 'A Model of Growth through Creative Destruction', *Econometrica,* 60, pp.323-350.

[5] Aghion, P. and Howitt, P. (1994), "Growth and Unemployment", *Review of Economic Studies,* July, 61(3), pp. 477-494.

[6] Aghion, P., and Howitt, P. (1998), '*Endogenous Growth theory',* MIT press.

[7] Aghion, P. and Saint-Paul, G. (1991) 'On the Virtue of Bad Times: An Analysis of the Interaction between Economic Fluctuations and Productivity Growth', *CEPR Discussion Paper # 578.*

[8] Alogoskoufis, G., C. Bean, G. Bertola, D. Cohen, J. Dolado and G. Saint-Paul (1995), "Unemployment: What Choice for Europe?", *Monitoring European Integration,* 5, C.E.P.R. London.

[9] Alogoskoufis, G.S., and Manning, A. (1988) 'On the Persistence of Unemployment', *Economic Policy no. 7,* October pp. 428-69.

[10] Anderson T.W. and Hsiao C. (1981), 'Estimation of Dynamic Models with Error Components', *Journal of the American Statistical Association,* 76, pp. 598-606.

[11] Arellano. M. and S. Bond (1991), 'Some Tests of Specification for Panel Data: Monte Carlo Evidence and an Application to Employment Equations', *Review of Economic Studies,* 58, pp 277-297.

[12] Arellano. M. and S. Bond (1998), 'Dynamic Panel Data estimation using DPD98 for Gauss', *Institute of Fiscal Studies*, mimeo.

[13] Baltagi, B. (1995) '*Econometric analysis of panel data'*, Wiley Publishers.

[14] Barro, R. J. (1996), 'Determinants of Economic Growth: A Cross-Country Empirical Study', *NBER wp* 5698.

[15] Barro, R.J. and J-W Lee (1993), 'International Comparisons of Educational Attainment', *Journal of Monetary Economics*, 32, pp 363-394.

[16] Barro, R.J. and Salai-Martin, X. (1995), *Economic Growth,* McGrawHill.

[17] Baxter, M. and King, R.G. (1995) 'Measuring Business Cycles Approximate Band Pass Filters for Economic Time Series', *National Bureau of Economic Research,* WP no. 5022.

[18] Bean, C., (1994), " European Unemployment: a Survey", *Journal of Economic Literature, Vol. 32,* June, pp. 573-619.

[19] Bean, C. and Pissarides, C.A., (1993) 'Unemployment, Consumption and Growth', *European Economic Review vol. 37,* pp 837-859.

[20] Bentolila, S. and Bertola, G., (1990), "Firing Costs and Labour Demand: How Bad is Eurosclerosis?", *Review of Economic Studies*, 57, 381-402.

[21] Bernanke, B., (1986), "Alternative Explanations of the Money-Income Correlation", *Carnegie-Rochester Conference Series on Public Policy 25,* 49-100.

[22] Bertola, G. and Rogerson R. (1997), "Institutions and Labor Reallocation", *European Economic Review,* 41-6 June, 1147-1172.

[23] Blanchard, O.J. and Summers, L., (1986) "Hysteresis and the European unemployment problem", *NBER Macroeconomics Annual 1,* 15-78, Stanley Fischer (editor), MIT press.

[24] Blanchard, O.J. and Diamond P. (1989), "The Beveridge Curve", *Brookings Papers on Economic Activity 1990, 2*, 85-155.

[25] Blanchard, O.J. and Diamond P. (1990), "The Cyclical Behaviour of Gross Flows of Workers in the United States", *Brookings Papers on Economic Activity*, 1, 1-76.

[26] Blanchard, O.J. and Diamond P. (1992), "The Flow Approach to Labor Markets", *American Economic Review*, 82, May, 354-359.

[27] Blanchard, O.J. and Jimeno, J.F., (1995) 'Structural Unemployment: Spain versus Portugal', *AEA Papers and Proceedings,* May, pp. 212-218.

[28] Blanchard, O.J. and Katz L. (1996), "What we Know and We do not Know about the Natural Rate of Unemployment?", *NBER Working Paper Series*no. 5822, November.

[29] Blanchard, O.J. and Quah D. (1989), "The Dynamic Effects of Aggregate Demand and Supply Disturbances", *American Economic Review,* 79, 655-673.

[30] Blanchard, O.J. and Summers, L., (1986) "Hysteresis and the European unemployment problem", *NBER Macroeconomics Annual 1,* pp. 15-78, Stanley Fischer (editor), MIT press.

[31] Blundell, R. (1988) 'Consumer Behaviour: Theory and Empirical Evidence - A Survey', *Economic Journal,* 98, March, pp16-65.

[32] Burns, A. and Mitchell, W., (1947) *'Measuring Business Cycles',* National Bureau of Economic Research.

[33] Burda, M. and Wyplosz C. (1994), "Gross Worker and Job Flows in Europe", *European Economic Review,* 38(6), June, 1287-1315.

[34] Caballero, R. and M. Hammour, (1994), "The Cleansing Effect of Recessions", *American Economic Review* Vol. 84 NO.5, December, 1350-1368.

[35] Caballero, R. and M. Hammour, (1996), "On the Timing and Efficiency of Creative Destruction", *Quarterly Journal of Economics,* 805-851.

[36] Campbell, J. R. (1997), 'Entry, Exit, Embodied Technology, and Business Cycles', *NBER wp* 5955.

[37] Canova, F., (1998), 'Detrending and Business Cycle Facts', *Journal of Monetary Economics 41,* pp. 475-512.

[38] Carpenter, R.E. and Levy, D. (1998) 'Seasonal Cycles, Business Cycles, and the Comovement of Inventory Investment and Output', *Journal of Money, Credit, and Banking,* Vol. 30, No.3, pp. 331-346.

[39] Chari V., Christiano L.J. and Kehoe P.J. (1991) 'Analysis of a Business Cycle Model with Distorting Taxes', Northwestern University Mimeo.

[40] Clark, K. and Summers, L. (1979), "Labor Market Dynamics and Unemployment: a Reconsideration", *Brookings Papers on Economic Activity 1990, 1*, 13-60.

[41] Cole, H.L. and Rogerson, R. (1996) 'Can the Mortensen-Pissarides matching model match the business cycle facts?', *Federeal Reserve Bank of Minneapolis,* Research Department, Staff Report 224.

[42] Cooley, T.F. and Ohanian, L.E. (1991), 'The Cyclical Behaviour of Prices', *Journal of Monetary Economics* 28, pp. 25-60.

[43] Cooper, R., Haltiwanger, J. and Power, L. (1997), 'Machine Replacement and the Business Cycle: Lumps and Bumps' *mimeo.*

[44] Daveri, F. and Tabellini, G. (1997), 'Unemployment, Growth and Taxation in Industrial Countries', *Bocconi University*, mimeo.

[45] Davis, S. and J. Haltiwanger, (1990), "Gross Job Creation and Destruction: Microeconomic Evidence and Macroeconomics Implications", *NBER Macroeconomics Annual* , 5, 99-113.

[46] Davis, S. and J. Haltiwanger, (1992), "Gross Job Creation, Gross Job Destruction and Employment Reallocation", *Quarterly Journal of Economics* 107, 819-63.

[47] Davis, S. and J. Haltiwanger, (1994), "Driving Forces and Employment Fluctuations: New Evidence and Alternative Interpretations", *Mimeo, University of Maryland.*

[48] Davis, S. and J. Haltiwanger, (1998), 'Gross Job Flows', *Handbook of Labour Economics* (forthcoming)

[49] Davis, S., Haltiwanger, J. and Schuh, S. (1996) '*Job Creation and Destruction'*, MIT Press.

[50] De Long, B.J. and Summers L.H. (1991) 'Equipment Investment and Economic Growth' *Quarterly Journal of Economics,* CVI, pp. 445-502.

[51] Diamond, P.A. (1982a) 'Aggregate Demand Management in Search Equilibrium', *Journal of Political Economy,* 90, pp. 881-894.

[52] Diamond, P.A. (1982b) 'Wage Determination and Efficiency in Search Equilibrium'. *Review of Economic Studies,* 49, pp. 217-227.

[53] Diebold, F. and Rudebusch, G. (1991) 'Long Memory and Persistence in Aggregate Output', *Journal of Monetary Economics,* 24, pp. 189-209

[54] Dolado,J.J. and Jimeno J. F. (1997), "The Causes of Spanish Unemployment: A Structural VAR Approach", *European Economic Review,* 41-7, July, 1281-1308.

[55] Englund P., Persson T. and Svensson L., (1992) 'Swedish Business Cycles: 1861-1988', *Journal of Monetary Economics 30,* pp 343-371.

[56] Eriksson, C. (1995) 'Is there a Trade-Off between Employment and Growth', *Oxford Economic Papers,* 49, pp 77-88.

[57] Falkinger, J. and Zweimuller J. (1997), 'Learning for employment, innovating for growth', *University of Regensburg Discussion Paper* No 298.

[58] Gali, J. and M. Hammour, (1991), "Long Run Effects of Business Cycles", *Mimeo,* (Columbia University, New York).

[59] Garibaldi, P. (1998) 'Job Flow Dynamics and firing restrictions', *European Economic Review,* 42, pp. 245-275

[60] Garibaldi P., Konings, J. and Pissarides C. (1996), "Gross Job Reallocation and Labour Market Policy" in *Unemployment Policy: Government Options for the Labour Market,* edited by Snower, D. and De la Dehesa G., C.E.P.R., London.

[61] Gordon, R.J. (1984), 'Unemployment and Potential Output in the 1980s', *Brookings Papers on Economic Activity,* 2, pp. 536-68.

[62] Gordon, R.J. (1995) 'Is there a Trade-Off between Unemployment and Productivity Growth?' *CEPR Discussion Paper* #1159.

[63] Granger, C.W.J. (1966), "The Typical Spectral Shape of an Economic Variable", *Econometrica* 34, no.1, pp. 150-161.

[64] Granger, C.W.J. and Hatanka, M, (1964) *Spectral Analysis of Economic Time Series,* Princeton University Press.

[65] Hendry, D.F. (1995) *Dynamic Econometrics,* Oxford University Press.

[66] Haan, W.J. (1996), 'The Comovements between Real Activity and Prices at different Business Cycle Frequencies', *National Bureau of Economic Research,* WP no.5553

[67] Hosios, A. (1994), "Unemployment and Vacancies with Sectoral Shifts", *American Economic Review,* 84-1, March, 124-144.

[68] Islam, N. (1995), 'Growth Empirics: A Panel Data Approach', *Quarterly Journal of Economics,* pp 1127-1171.

[69] Jackman, R., Layard,R. and Pissarides, C. (1989), "On Vacancies", *Oxford Bulletin of Economics and Statistics,* 51, November, 377-95.

[70] Jones, C. (1994) 'Economic Growth and the Relative Price of Capital', *Journal of Monetary Economics,* XXXIV, 359-82.

[71] Jones, C. (1995a) 'Time Series Tests of Endogenous Growth Models', *Quarterly Journal of Economics,* 495-526.

[72] Jones, C.I. (1995b), 'R&D Based Models of Economic Growth', *Journal of Political Economy,* 103, pp759-784.

[73] Jovanovic, B. (1979), "Job Matching and the Theory of Turnover", *Journal of Political Economy,* 87, 972-990.

[74] Jovanovic, B. (1984), "Matching, Turnover and Unemployment", *Journal of Political Economy,* 92, 108-122.

[75] Juhn C., Murphy K. and Pierce B. (1993), "Wage Inequality and the Rise in the Returns to Skill", *Journal of Political Economy,* 101-3, 410-442.

[76] Katz L. and Murphy K. (1992), "Changes in Relative Wages, 1963-1987: Supply and Demand Factors", *Quarterly Journal of Economics,* February, 35-78.

[77] King R.G., and Watson, M.W. (1996) 'Money, Prices, Interest Rates and the Business Cycle', *The Review of Economics and Statistics.*

[78] Koopmans, L.H., (1974) *The Spectral Analysis of Time Series*, Academic Press.

[79] Layard R. and S. Nickell (1997) 'Labour Market Institutions and Economic Performance', *Handbook of Labour Economics* (forthcoming)

[80] Layard R., Nickell S. and Jackman R. (1991), *Unemployment: Macroeconomic Performance and the Labour Market,* Oxford University Press.

[81] Liebfritz, W., Thornton, J. and Bibbee, A. (1997), 'Taxation and Economic Performance', *OECD Economics Department Working Paper #* 176.

[82] Liesner, T. (1989) '*One Hundred Years of Economic Statistics'*, Economist Publications.

[83] Lilien, D. (1982), "Sectoral Shifts and Cyclical Unemployment", *Journal of Political Economy,* 90, 777-793.

[84] Lindbeck,A., and Snower D.J. (1988), *The Insider-Outsider Theory of Employment and Unemployment*, Cambridge: MIT Press.

[85] Levine, R. and Renelt, D. (1992) 'A Sensitivity Analysis of Cross-Country Growth Regressions.', *American Economic Review,* 82, pp 942-963.

[86] Lucas, R.J.E.Jr. (1988), 'On the Mechanics of Economic Development', *Journal of Monetary Economics,* 2-40.

[87] Lynch, L. (1994), *Training and the Private Sector: International Comparisons,* National Bureau of Economic Research Comparative Labor Market Series, University of Chicago Press.

[88] Maddison, A., (1994) '*Monitoring the World Economy, 1820-1992'.*

[89] Marimon, R. and Zilibotti, F. (1996), "Actual versus Virtual employment in Europe: is Spain different?", *European Economic Review*, 42-1, January, 123-53.

[90] Michelacci, C. and Zaffaroni, P. (1998), "(Fractional) Beta Convergence", *Journal of Monetary Economics.*

[91] Millard, S. and Mortensen, D.T. (1997) 'The unemployment and welfare effects of labour market policy: A comparison of the US and UK', in D.Snower and G. de la Dehesa (eds.), *Unemployment Policy: Government Options for the Labour Market,* Cambridge: Cambridge University Press.

[92] Millard S., Mortensen D.T. and Rosenblat T.S. (1996) 'A Computational Approach to labour market Flows and Policy', Northwestern University working paper.

[93] Mitchell, B.R. (1993) '*International Historical Statistics: The Americas 1750-1988*', Macmillan Publishers.

[94] Mortensen, D.T., (1982a), 'The Matching Process as a noncooperative/bargaining game', In J.J. McCall (ed.), *The Economics of Information and Uncertainty,* pp. 233-254. Chicago: University of Chicago Press.

[95] Mortensen, D.T., (1982b), 'Property Rights and Efficiency in Mating, Racing and related Games', *American Economic Review* 72, pp. 968-979.

[96] Mortensen, D.T., (1994), "The Cyclical Behaviour of Job and Worker Flows", *Journal of Economic Dynamics and Control,* 18, July, 1121-1142.

[97] Mortensen, D.T. and C. Pissarides,. (1994), "Job Creation and Job Destruction in the Theory of Unemployment" *Review of Economic Studies,* 61, July, 397-415.

[98] Mortensen, D.T. and C. Pissarides,(1998), "Technological Progress, Job Creation and Job Destruction", *Review of Economic Dynamics,* 1-4, October, 733-753.

[99] Mortensen, D.T. and C. Pissarides,(1999a), 'Job Reallocation, Employment Fluctuations and Unemployment.' *Centre for Economic Performance dp.* 421.

[100] Mortensen, D.T. and C. Pissarides,(1999b), 'Unemployment Responses to Skill-Biased Technology Shocks: The Role of Labour Market Policy', *Economic Journal, 109 (*April*), pp. 242-265.*

[101] Nickell, S. (1981), 'Biases in Dynamic Models with Fixed Effects', *Econometrica,* 49, pp 1417-1426.

[102] Nickell, S. (1997), 'Unemployment and Labour Marker Rigidities', *The Journal of Economic Perspectives,* August.

[103] NSF (1996), *National Patterns of R&D Resources: 1996,* NSF special report.

[104] OECD (1994a), *Employment Outlook 1994,* OECD, Paris.

[105] OECD (1994b), *The OECD Job Studies,* OECD, Paris

[106] OECD (1995), *Main Science and Technology Indicators 1995-1,* OECD, Paris.

[107] Okun, A.M., (1962) 'Potential GNP: its Measurement and Significance', *Proceedings of the Business and Economic Statistics Section 1962,* American Statistical Association.

[108] Patterson, K.D. and Pesaran B. (1992) 'The Intertemporal Elasticity of Substitution in Consumption in the United States and the United Kingdom', *The Review of Economics and Statistics,* LXXIV, pp573-584.

[109] Phelps, E.S. and Zoega, G. (1998) 'Natural-Rate Theory and OECD Unemployment' The Economic Journal, 108, pp.782-801.

[110] Pissarides, C. A., (1984a), 'Search Intensity, Job Advertising and Efficiency', *Journal of Labour Economics,* 2, pp.128-143.

[111] Pissarides, C. A., (1984b), 'Efficient Job Rejection', *Economic Journal Conference Papers,* 94, pp.97-108.

[112] Pissarides, C. A., (1986), "Unemployment and Vacancies in Britain", *Economic Policy,* 3, 499-559.

[113] Pissarides, C.A. (1990), *Equilibrium Unemployment Theory,* Oxford: Basil Blackwell.

[114] Pissarides, C.A. (1992) 'Loss of Skill during Unemployment and the Persistence of Employment Shocks', *Quarterly Journal of Economics,* pp 1371-1391.

[115] Pissarides, C. A., (1994), "Search Unemployment with On-the-job Search", *Review of Economic Studies*, 61, July, 457-475.

[116] Priestley, M.B. (1981), *Spectral Analysis and Time Series*, Academic Press.

[117] Romer, P.R. (1986), 'Increasing Returns and Long-Run Growth', *Journal of Political Economy,* 94, 1002-1037.

[118] Romer, P.R. (1990), 'Endogenous Technical Change', *Journal of Political Economy,* 98, S71-S102.

[119] Saint-Paul, G. (1991), 'Unemployment and Productivity Growth in OECD Countries', *DELTA mimeo.*

[120] Sargent, T.J. (1979), *Macroeconomic Theory,* Academic Press.

[121] Schumpeter, J.A. (1942) '*Capitalism, Socialism and Democracy*', New York: Harper and Brothers.

[122] Thoma, M.A. (1994), 'The Effects of Money Growth on Inflation and Interest Rates across Spectral Frequency Bands', *Journal of Money, Credit and Banking, vol. 26*, no. 2, pp. 218-231.