The Dynamics of Growth: Econometric Modelling and Implications for Employment

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Abstract

This thesis presents the author's work in two parts. Part I contains two studies of the modelling of growth and convergence, Part II examines empirical issues regarding the determinants of labour market outcomes.

In Chapter 1 we tackle and solve a methodological issue in the application of the distribution dynamics method for studying the evolution in time of an entire cross section distribution. The problem of discretisation of a continuous state space Markov process is solved by employing a new method proposed in the statistical literature. The method is applied to the distribution of per capita income across countries and the (non-) convergence phenomenon is reassessed.

In Chapter 2 we model the evolution of per capita incomes across countries as a semi-markov process, with variable sojourn times between states. We uncover asymmetries in the distribution of transition times and find very low persistence of income dynamics, especially in the high portion of the income distribution.

In Chapter 3 we investigate the existence of a long run equilibrium relationship between unemployment and a set of labour market institutional variables by means of newly developed panel unit root and cointegration models. We find that these variables are integrated of order one and cointegrated. We estimate the long run effects of institutions on unemployment.

In Chapter 4 we estimate a model of equilibrium employment with endogenous technological progress. Innovation arises as a consequence of investment in research and development and impacts on job creation and job destruction. We find that technological progress increases unemployment on impact, but has a positive long run effect on job creation.

A Pino e alla memoria di Lucia

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Declaration

I declare that the work presented in this thesis is my own.

Sandra Bulli

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Introduction

Differences in patterns of economic growth across countries have important implications in terms of welfare of the individuals. This explains the interest of researchers in the determinants of economic growth. Research in this area involves a large number of theoretical studies as well as a great variety of empirical investigations. Earlier economic models generated long-run growth through the inclusion of a parameter to capture the effects of technological change: this source of growth, however, was determined by factors that were outside the model. Later, models developed to allow the rate of growth of income to be affected by characteristics of the economy such as improvements in human capital embodied in the labour force, externalities induced by private capital accumulation, deliberate action by economic agents engaging in research and development activities. A detailed survey of the literature on growth that is generated endogenously by the models is contained in chapter four.

The second important research area to which growth economists have devoted their attention is income convergence. Besides addressing the question of what determines growth, researchers also aim at assessing whether economies tend to approach common growth rates and income levels, whether poor countries are catching up with rich ones and whether there is a tendency in the disparities in the income distribution to diminish over time. Many different empirical approaches have been suggested for the study of cross country convergence, in particular: time-series analysis, cross section and panel data regressions and distribution dynamics models.

Many empirical studies estimate "growth regressions", that is regressions in which growth rates are the dependent variable and the right hand side contains initial levels of income. A negative parameter on the initial condition is said to imply *absolute $\beta-$convergence:* poor countries tend to grow at a faster rate than rich ones.

Augmented cross section regressions have also been largely employed: they include on the right hand side a set of economic and socio-demographic control variables – levels of educational attainment, extent of government intervention, measures of democracy and political stability, inequality indices, trade and trade policy measures. A negative parameter on the initial condition is interpreted as indication of *conditional $\beta-$convergence:* the further away a country is from its steady state level of income, the faster its rate of growth. A number of econometric problems have been associated with this type of analysis: for example, it is not clear whether the regressions can be interpreted within some economic model. Moreover, some of the factors under analysis induce nonlinearities in the growth relation and findings of statistical significance may be fragile due to dependence on additional controls whose presence is not strongly motivated by economic theory (Levine and Renelt, 1992). Durlauf and Quah (1999) provide a comprehensive discussion of these issues.

To permit unobservable country-specific heterogeneity in growth regression, several authors (e.g. Islam, 1995, Caselli, Esquivel and Lefort, 1996) have used panel data methods in order to decompose the constant in the model into economic-specific and time-specific effects. Leaving free those individual heterogeneities, instead of modelling them explicitly as functions of observable right-hand side explanatory variables, does not allow, however, to determine whether poor economies are catching up with rich ones. In order to shed light on this last problem, the analysis has also focused on *$\sigma-$convergence*, which is said to occur when the cross section standard deviation of per capita incomes diminishes over time (Barro and Sala-i-Martin, 1995). Again, several problems with this approach have been emphasized: for example, the fact that varied behaviour of the cross section distribution is consistent with *absolute* $\beta-$*convergence* (see Quah, 1993b, and his discussion of Galton's fallacy). As a result, regressions to identify $\beta-$*convergence* cannot give information on the patterns of $\sigma-$*convergence* nor reveal whether the poor will catch up with the rich. The existence of this problem has suggested directly analysing the dynamics of the cross section distribution instead. This is the approach followed by Bianchi (1997), Jones (1997) and Quah (1992, 1993a, 1996a,b, 1997). While the first two authors consider the cross section distribution at each time period, Quah goes further and addresses the issue of transition dynamics by estimating the law of motion of such distribution over time. He finds evidence of polarization and non convergence across countries. He also shows that these "twin peak" dynamics can be explained by spatial spillovers and patterns of cross-country trade.

The analysis presented in chapter one is a contribution to this strand of research: it addresses and solves a methodological issue in the application of the distribution dynamics method to cross-country income and, more in general, to economic analysis. An implication of the study in chapter one is that the evolution of per capita incomes across countries is well approximated by a stochastic process that allows variable transition times between states of the process. These results motivate the analysis carried out in chapter two, where this type of stochastic process is modelled and estimated.

A third important question in the theory of economic growth, and relevant to the present work, is the following: what are the effects of growth on unemployment? Early studies did not focus on this issue, since unemployment did not constitute a serious problem until the 1970s: in the 1950s the economy was reaching full employment and attention focused rather on the possibility of labour shortages. This explains why the Solow (1957) growth model does not include the unemployment rate:

wages adjust such that all available labour force is employed as input in the production process. The economic crisis of the 1970s and the persistence of unemployment brought new attention to the relationship between technological progress and jobs: technological progress became an endogenous process subject to uncertainties and with possible consequences on the creation of new jobs. This possibility, however, is controversial. The standard view among labour economists is that the equilibrium rate of unemployment is not affected by technological progress in the long run: this belief stems from the stylized fact that while productivity is a trended variable, the unemployment rate is essentially untrended (see e.g. Layard et al., 1991).

The focus of traditional research into the causes of unemployment mainly rests on the importance of different institutional settings across countries: unemployment is caused by the presence of rigidities in the labour market and these rigidities are caused by labour market institutions. Under the heading of "labour market institutions" researchers list features of the labour market such as laws and regulations covering employee's rights, the social security system and the treatment of the unemployed, trade unions and the structure of wage bargaining but also those aspects of the tax system that affect the operation of the labour market. In general, these variables increase unemployment, either directly by discouraging the creation of new jobs, or indirectly by raising the bargained wage. Chapter three contains a contribution to the literature on the effects of labour market institutions on unemployment: theoretical models of equilibrium unemployment predict that rigidities in the labour markets caused by the presence of institutions have long run negative effects on the unemployment rate. We use cointegration analysis to investigating the existence of a long run equilibrium relationship: by exploiting recent results in the literature on panel cointegration, we study long run effects of institutions on unemployment. We find evidence that more generous labour market institutions are associated with higher unemployment rates in the long run.

We do not believe, however, that adverse labour market institutions can explain most of the unemployment experience, and in particular the persistence of the unemployment rate at high levels since the 1970s. Motivated by the recent theoretical literature on the effects of the pace of economics growth on the equilibrium level of unemployment pioneered by Aghion and Howitt (1994) and Mortensen and Pissarides (1998) we carry out an empirical investigation on a panel of European countries, which is presented in chapter four. We estimate a model of equilibrium employment where technological progress affects job creation and job destruction and is endogenously determined by research activities. Our results confirm the importance of investment in research and development for generating innovation. Moreover, we find that technological progress destroys jobs in the short run but the effect on employment is positive in the long run. Thus we believe that the theory based solely on labour market institutions (or on the interaction between institutions and macroeconomic shock) cannot account fully for the patterns of employment across countries and that a large part of these variations can be explained by the effects of technological innovations.

Part I

Modelling the Dynamics of Growth

Chapter 1

Distribution dynamics: a new approach

1.1 Introduction

The debate on convergence of per capita income across countries has been extremely lively in the past decade: the aim of this chapter is to contribute to this debate. More precisely, this work aims at addressing and possibly solving a methodological issue that has arisen in the application of distribution dynamics methods to convergence analysis.

Distribution dynamics represents an answer to the dissatisfaction with traditional econometric techniques and their failure to identify some important features in the evolution of the cross-country income distribution. It is an innovative econometric method introduced by D. Quah (1993a, 1997) to describe the dynamics of income across countries, taking into account the entire cross sectional distribution of per capita incomes. The purpose of the analysis is to find the law of motion of this distribution, rather than simply computing few, less informative, moments of it. Given the distribution at a point in time, the *transition* or *stochastic kernel* is the econometric tool that allows the description of its evolution, highlighting both the changes in the shape and the intra-distribution mobility. Quah (1997) outlines a method for estimating the stochastic kernel and applies it to the relative per capita income data across world economies. He finds clear evidence of non-convergence of per capita incomes across countries: the stochastic kernel reveals instead a tendency of the world income distribution to bimodality ("twin peaks") with middle income classes disappearing and world economies clustering into low and high income groups.

Although conceived as a tool to analyse cross-country convergence, this method has found application in many areas of economic research, as different as finance (Stanca and Gallegati, 1999), international trade (Redding, 2002), industrial organisation (Koopmans and Lamo, 1995 and Mancusi, 2001).

As the literature on distribution dynamics developed, however, a methodological issue emerged: the problem of discretisation of the state space. Most economic variables are defined on a continuum of values, thus a continuous state space process seems appropriate to describe their behaviour. Although continuous distributions and kernels are very informative, sometimes the researcher can be tempted to lump some portions of the state space together and work with finite state space processes: this allows the analysis to be carried out by means of discrete probability distributions and transition matrices, which are much easier to interpret and present. Various descriptive indices and the invariant distribution are much easier to compute in a discrete setting and the theory underlying discrete processes is accessible and well developed (see, for example, Kemeni and Snell, 1976). More precisely, while the researcher observes realizations of a process which is continuous in nature, he will assign those realizations to a discrete space, whose states are constituted by portions of the continuous space.

Although convenient in practice, lumping portions of the state space has the effect of removing the Markov property (Kemeni and Snell, 1976, Billingsley, 1961, Guihenneuc-Jouyaux and Robert, 1998), thus the derived finite process is not Markovian. Despite the vast theoretical agreement on this issue, most of the applications of distribution dynamics have used discretisation freely, claiming that, in practice, the loss of the Markov property was unlikely to change the results much. In this chapter we show instead that the loss of the Markov property is a very important problem with serious practical consequences. Theoretically, the estimated transitions should not be called "transition probabilities" and, as demonstrated in this chapter, ergodic distributions computed from them can lead to very misleading inference.

In section 1.3, a rigorous method to derive a proper finite state space Markov chain from a continuous state space process is outlined. This method, first introduced in the Markov Chain Monte Carlo literature, allows the construction of a sequence of occurrences that, although generated by a continuous state space process, constitute a proper Markov chain on a discrete state space, and therefore allow the correct estimation of transition probability matrices and limiting distributions.

In section 1.4, we apply the regenerative discretisation method to the world income distribution. Using data from the Penn Tables mark 5.6 from 1960 to 1989, we estimate a stochastic kernel describing the evolution of the distribution of per capita income across countries relative to the world average. The results we obtain are compatible with previous work (Quah, 1997). A discrete Markov process is then derived from the kernel using the new methodology and a proper transition matrix is estimated. An interesting exercise is then to compare this matrix with the one estimated from an arbitrarily discretised chain. The two matrices present similar features in terms of diagonal persistence, and the "twin peaks" property is inherited from the continuous chain. The rigorously discretised chain, however, shows much more intra-distribution mobility; that is, the transition probability in the off-diagonal cells is much higher. Thus discretisation does matter, as this example on world income dynamics shows, because it affects the properties of the estimated transition matrix.

Even more striking results are obtained if one compares the implied stationary distributions: the limiting distribution of the properly discretised chain offers a much more accurate approximation to the continuous process than the naively discretised chain. One interesting feature of the new discretisation method is that moves from one state to another have variable time length, instead of occurring in one single period steps. The newly derived discrete chain can thus be thought of as part of a *Markov renewal process* embedded in the continuous chain. A Markov renewal process transits from one state to another in a finite set of states, with transition times that are random (and may depend on the two states of departure and arrival). This is a very desirable property for the evolution of the income distribution across economies: allowing a variable transition time could, for example, help in explaining some of the persistence in the evolution of the world income distribution.

The analysis in this chapter tackles a difficult and important problem in the literature of distribution dynamics. Many authors have employed arbitrary discretisation of the state space claiming that the results were not significantly affected, but no formal investigation was ever performed into the extent of possible bias induced by discretisation. This chapter deals with this issue for the first time and the regenerative discretisation method is for the fist time applied in a distribution dynamics setting. The method was developed in Markov Chain Monte Carlo theory mainly to assist new convergence control methods based on a discretisation of continuous state space.[1] In the present context, the method is applied to investigate the bias generated by the arbitrary discretisation of a continuous state space process. The contribution of the present chapter to the existing literature on distribution dynamics is therefore to show to what extent transition matrices computed by arbitrarily

[1]In Markov Chain Monte Carlo, a distribution π is sampled obtaining sample paths from a Markov Chain constructed to have equilibrium distribution π. Thus convergence control algorithms are needed to ensure that the chain converges to the desired distribution.

discretising the state space offer a biased estimate of the transition probability of the underlying continuous process. For the first time transition matrices are computed from a rigorous discretisation and it is clearly shown that discretisation matters, and that arbitrary discretisation can lead to misleading inference on the discretised process.

A second contribution of the analysis in this chapter is to highlight that the embedded Markov chain with variable transition times has a stationary distribution which well approximates the limiting distribution of the continuous process. A natural extension is therefore suggested by this work, that is to adopt a Markov renewal model for the evolution of incomes across countries (as, for example, in Quah, 1992). These ideas are developed more extensively in the next chapter.

The rest of this chapter is organised as follows:[2] in Section 1.2 the method of distribution dynamics is briefly described, Section 1.3 outlines the issues involved in the arbitrary discretisation of the state space and the approach to deal with those, Section 1.4 contains an application of the new methodology to the per capita world income distribution, Section 1.5 summarises and concludes.

1.2 Distribution Dynamics

The purpose of distribution dynamics is to study the evolution of a cross sectional distribution over time. In general, this analytical tool can be employed to study the evolution of the distribution of any variable of interest. Thus Stanca and Gallegati (1999) study firms' financial characteristics, Mancusi (2001) investigates the dynamics of the distribution of a technological index, Redding (2002) analyses patterns of international specialisation.

Although in the present chapter we study the distribution of per capita incomes across the world economies, the focus of the analysis in on a methodological issue,

[2] This chapter is based on Bulli (2001).

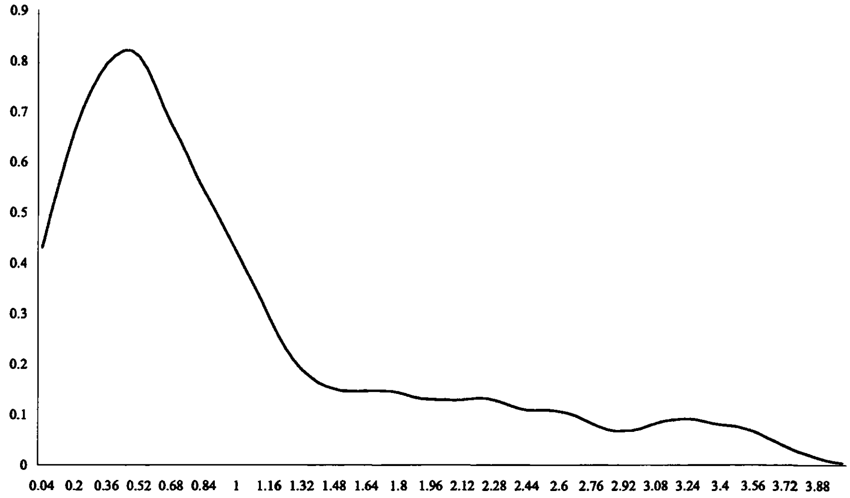

Figure 1.1: Per capita income relative to the world average: distribution in 1960

and therefore the findings of this line of research should be considered valid for any application of this econometric tool.

Consider the distribution of income per capita across the world economies: Figure 1.1 shows the empirical density function of the per-capita income relative to the world average in 1960, estimated from the Penn Tables Mark 5.6 (Summers and Heston, 1991).[3]

This is a non-parametric density plot of the variable "real GDP per worker" in 1960 normalized by the world average. The estimation is carried out along the lines of Bianchi (1997) and using the techniques described in Silverman (1986).[4] The values on the horizontal axis represent the position of a country relative to the world average: the possible values are all the real numbers between 0 and 4, with 1 indicating the world's average level of per capita income. As expected, the

[3] A detailed description of the data set used in this and the next chapter is contained in Appendix B.

[4] All the computations were performed using GAUSS. The author is indebted to Geoffrey Shuetrim for making available his code on univariate and bivariate density estimation. She has also benefited from the normal random generator routine provided by Gary King. The responsibility of any errors is solely the author's.

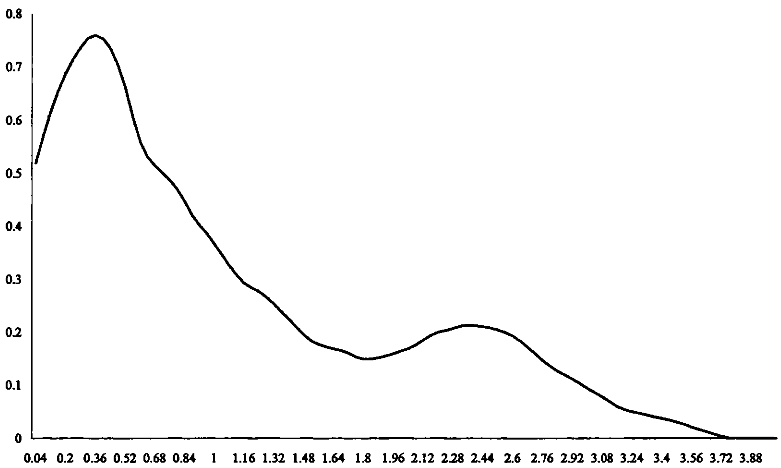

Figure 1.2: Per capita income relative to the world average: distribution in 1989

distribution is highly skewed, with a unique mode situated at a level of income per capita equal to approximately half of the world average .

Figure 1.2 shows the same distribution in 1989: the external shape has changed quite dramatically since the 1960s, the distribution is now bimodal, and the first mode is situated at a lower level of per capita income relative to the world average.

Besides changes in the external shape, the world income distribution evolves over time in different ways. Intra-distribution movements are also present: a given part of the distribution at time t transits to another part of the distribution by the time $t + s$. The mechanism governing this evolution can be summarised by a transition density similar to the one depicted in Figure 1.3.

The possible values the variable of interest can assume – per capita income relative to the world average – are reported on both axes. A section of the graph from a point x on the t axis parallel to the $t + 1$ axis represents the probability density function of each state in the next period, conditional on the process being currently in state x. The transition function, therefore, maps each portion of the distribution in period t to one in period $t + 1$ and thus describes the law of motion

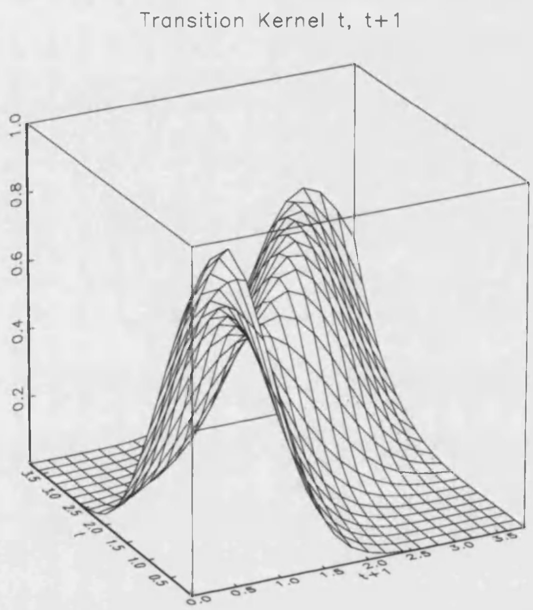

Figure 1.3: Transition density, annual transitions

of the entire distribution.[5] The next paragraph focuses on this law of motion and draws an important distinction for the subsequent discussion.

1.2.1 Discrete and continuous processes

Call X_t (with t an integer) the variable of interest for the researcher at time t, and assume it can take values in a certain set E. In the present framework, the variable of interest is the per capita income of the world economies. Let ϕ_t be the distribution of that variable at time t and describe its law of motion by a first order autoregressive process (Quah, 1997):

[5]The stochastic kernel in Figure 1.3 is a conditional density function. Estimation of the kernel is carried out by first estimating non-parametrically the joint density function of the process at times t and $t+1$ and then normalizing it by the marginal in t (see, for example Quah, 1996a). The estimated transition probability density is independent of the time period t (it is a *stationary* transition density): this is a common assumption in Markov chain theory. In the present context this is perfectly plausible as it refers to relative income per capita.

$$\phi_{t+1} = T^* (\phi_t)$$

where the operator T^* maps the distribution from period t to period $t+1$.

If X_t is discrete, it can assume only a finite or countable number of values.[6] For simplicity, assume there exists a finite number J of possible states. The operator T^* can be interpreted as the *transition probability matrix* M of a Markov process:

$$\phi_{t+1} = M' \phi_t$$

Thus ϕ_t is a $1 \times J$ vector of probabilities and M a $J \times J$ matrix whose elements $p_{x,y}$ are the probabilities of transition from state x to state y in one step.

In many cases, however, and for most economic variables, X_t can assume infinite values, for example any number on the real line.[7] In this case, the operator T^* must be interpreted as a *transition function* or *stochastic kernel* $P(x, \cdot)$. Let A be any subset of the sample space E. The stochastic transition function, or stochastic kernel, $P(x, A)$, describes the probability that the next step will take us in a certain set A, given that we are currently in state x:

$$P(x, A) = \Pr (X_{t+1} \in A \mid X_t = x)$$

for all values x in E and all the subsets A of E. The distribution at time $t+1$ is thus defined by:

$$\phi_{t+1} = \int P(x, A) \phi_t(dy)$$

Thus the transition function $P(x, A)$ describes the evolution of the distribution ϕ_t in time.

[6] I.e. the set E is either finite or countably infinite.

[7] I.e. the state space E is an uncountably infinte set, $E \subseteq \mathbb{R}$.

Now let $p(x, y)$ be a measurable function which is non-negative: $p(x, y) \geq 0$ and integrates to one: $\int_E p(x, y)dy = 1$ (where x, y are points in E). Suppose that the kernel $P(x, A)$ can be defined as the integral of this function over the set A:

$$P(x, A) \equiv \int_A p(x, y)dy$$

then $p(x, y)$ is the *transition density function* associated with $P(x, A)$. This is precisely the function depicted in Figure 1.3.

Although it assumes a Markovian structure for the underlying process, the approach of distribution dynamics is different from the traditional Markov process theory. In the latter, the emphasis is on a scalar process, from which an unobservable sequence of probability distributions is usually inferred. Distribution dynamics shows its originality in the fact that a sequence of entire (empirical) cross section distributions is actually observed, while the (*dual*) scalar process is implied but never observed (Quah, 1996a). It is possible, however, to construct such an artificial scalar process on the basis of some initial distribution and its law of motion described by the stochastic kernel: elements that completely characterise a Markov process (Doob, 1962). This is precisely the approach followed in the present work: the advantage is that the theory of general state space Markov processes can be fully exploited. These processes have received attention for a relatively long period of time (the classical reference is Doob, 1962), but the most recent developments are particularly relevant for the present analysis, especially the work of Nummelin (1984) and Meyn and Tweedie (1993).

In what follows, the stochastic kernel $P(x, A)$ will summarize the (time-invariant) evolution of a process $\{X_t, t > 0\}$ which can assume any real value in some subset E of $\mathbb{R}$ at t discrete points in time.[8]

[8] Although the interpretation of the kernel as a function that relates two distributions at different points in time is appropriate in this context, Quah (1997) points out that the definition of stochastic kernel does not require that the two measures be sequential in time: instead, the kernel can be used

1.3 The discretisation process

The stochastic kernel is a useful tool to analyse the dynamics of the entire distribution of the process. There are some reasons why, however, the researcher may find it useful to "discretise" the state space; that is to partition the continuous state space in a finite number of intervals. These sets would then constitute the states of a newly defined *finite* state Markov process.[9] The reasons why this approach is appealing are many: first of all, the theory of finite state space Markov processes is accessible and well developed (see for example Kemeni and Snell, 1976). The estimation of the transition matrix is computationally simpler and results are easier to interpret and present; many indices and statistics are also easier to compute.

The method of distribution dynamics was initially employed in a discrete framework (Quah, 1993a): relative per capita incomes were grouped into classes and transition probabilities between classes were estimated. The partition was either in equi-sized cells or in cells with variable upper endpoint, with approximately the same number of occurrences in each group (Quah, 1993a, 1996b). To avoid the possible bias induced by the discretisation, Quah (1997) refined the analysis employing a continuous state space framework, but the discrete version remained very popular in the literature.

In an attempt to "reduce the degree of arbitrariness in the discretisation", Magrini (1999), in an article that describes the evolution of regional disparities in per capita income within the European Union, suggests a procedure that eliminates subjectivity in the choice of the income class size, by concentrating on histograms as approximations to continuous distributions of income across regions. The method consists of choosing the bin width for the histogram optimally, such that the same

to relate any two different distributions.

[9] The process of interest in the present work is in any case a discrete *time* process, X_t, with t an integer and the problem analysed is the discretization of the *state space* of the process. The issue of time discretization is a different one and has often been addressed in the statistical literature.

grid allows the discretisation of the empirical distribution at two different points in time, and such that some measure of the error of approximation (mean-squared error or integrated absolute error) is minimised. The choice between possible grids of income classes is thus made in terms of the ability of the discrete distributions to approximate the observed (continuous) distributions. This method does not, however, represent the correct approach to the discretisation problem because it focuses only on the distribution of the process at some point in time, and this can be very misleading: what actually characterises this kind of processes are both their initial distribution and the associated transition law. The main problem induced by the discretisation is not solved, as the next paragraph illustrates.

1.3.1 The discretisation problem

All the discretisation methods described above share a common problem: arbitrary discretisation of the state space is almost certain to remove the Markov property of the process.[10]

Consider, for example, an equi-sized discretisation of the empirical distribution of per capita incomes of Figure 1.1. Assume that the state space is partitioned in five intervals of the same size. That is, the first interval includes all the observations of per capita income between 0 and 0.8, the second interval contains all values between 0.8 and 1.6 and so on. Thus a new (discrete) process can be defined as follows: when the underlying continuous process X_t assumes values included in the first interval, this occurrence is recorded as a visit to *state one*; when it assumes values in the second interval, as a visit to *state two* and so on. The new process is then defined on 5 states and claimed to be a discrete Markov chain.

Why is such a procedure not correct? Any arbitrary discretisation corresponds to creating a partition of the space into a finite number of subsets $A_1, ..., A_J$ and

[10] The theoretical literature on Markov processes agrees on this: see, for example, Billingsley (1961), Kemeni and Snell (1976) and Guihenneuc-Jouyaux and Robert (1998).

then associating each subset with a distinct state in a discrete state space. In the present example, the lowest relative income cell would be subset A_1 and it would correspond to *state* 1 of the discrete process. Thus, in terms of the underlying scalar process, this is equivalent to creating a sequence:

$$\eta^{(t)} = \sum_{j=1}^{J} j\mathbb{I}_{A_j}(X_t) \tag{1.1}$$

where $\mathbb{I}_{A_j}$ is the indicator function:

$$\mathbb{I}_{A_j} = \begin{cases} 1 & \text{if } X_t \in A_j \\ 0 & \text{otherwise} \end{cases}$$

The sequence $\eta^{(t)}$ in (1.1) is not normally a Markov chain because of the dependence on the previous values of $\eta^{(k)}$.

To clarify this issue, assume a time path of the process under analysis, that is, a time series of per capita incomes for a given country, has been observed. An example of such a process is shown in Figure 1.4. The horizontal axis represents time (200 years), while the vertical axis indicates the possible values for income per capita (relative to the world average).[11]

The naive discretisation is simply done as follows: all realizations that fall in the band with values on the y axes between 0 and 0.8 would be included in state 1, and so forth, all the realizations falling in the same income group would end up in the same (discrete) state. A transition probability matrix would then be estimated from this sequence.[12] Looking at the sample path in Figure 1.4, however, it appears clearly that the probability of crossing the border between two states is not the same for a point close to the border and for a point far from it. That probability depends

[11] A description of the way such a sample path is obtained is presented in Section 1.4 below.

[12] Transition probabilities are usually estimated as the sample proportion of the transitions from a given cell to another, relative to the total transitions from that cell. This is the Maximum Likelihood Estimator (see, for example, Anderson and Goodman, 1957).

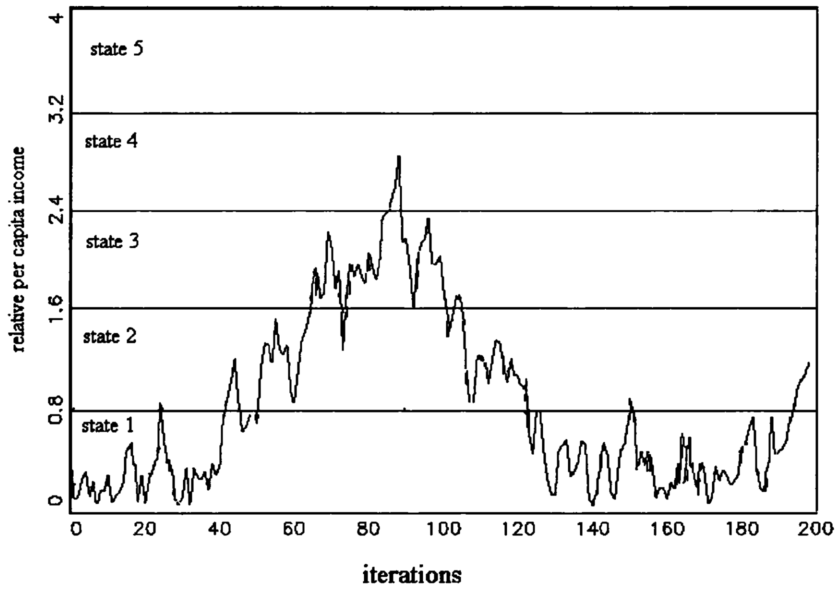

Figure 1.4: A sample path of the simulated process

also on past values: the new process has certainly lost the Markov property.

This naive discretisation is a common procedure, although recently it has been mainly used in conjunction with the continuous analysis (see, for example, Stanca and Gallegati, 1999 and Redding, 2002). The researcher is faced with the realization of a process which is continuous; he partitions the sample space and redefines it as a discrete process, but in doing this obtains a process which is not Markovian. What are the consequences? From a theoretical point of view, the matrix obtained from this procedure cannot be defined a "transition probability matrix", as the properties of the underlying process are not clear. Nor calculating the limiting distribution from the estimated transition matrix is correct.[13] In practice, discretisation has been used extensively in the applied distribution dynamics literature, with the claim that the

[13]The limiting – or invariant – distribution π of a discrete Markov chain with transition matrix M satisfies: $\pi = M'\pi$. Thus π describes the long run, stable behaviour of the process.

loss of the Markov property is not likely to have a large impact on the final results and conclusions. This work will show, with an example, that this claim is not always correct, and that the loss of the Markov property can have severe consequences for the analysis.

1.3.2 The methodology

A rigorous method to obtain a discrete state space Markov chain from a continuous state space Markov process has been recently proposed in the statistical literature on Markov Chain Monte Carlo techniques (see, in particular, Gilks et al., 1996, 1998 and Mykland et al., 1995). The method is based on the concept of *proper atom*, due to Nummelin (1984). A Markov chain is said to have a *proper atom* A if, once the chain enters the set A, the future realizations of the chain are conditionally independent of the past. The chain is then said to *regenerate.* In a discrete chain, every state is a proper atom, since the Markov property guarantees that the transition to the next state only depends on the current and not on the past states. In a continuous state space Markov process, where the states are the (uncountably) infinite points of a continuum, the probability of entering each state is zero, thus a meaningful small set can only be some appropriately defined interval. In general, intervals having the characteristics of a proper atom need not exist. The idea of proper atom has, however, been generalized into the concept of *small set* by Guihenneuc-Jouyaux and Robert (1998). When the chain enters a small set, it regenerates only with a certain positive probability. Consider a Markov chain with transition kernel $P(x, \cdot)$; the definition of a *small set* A is as follows: there exists a real number $\varepsilon > 0$ and a probability measure ν such that the kernel satisfies the minorization condition:

$$P(x, B) \geq \varepsilon \nu (B) \qquad (1.2)$$

for every point $x \in A$ and for every measurable set B in E. Thus, when the chain enters state x in A, the probability of moving to any set B is bigger than the measure ν of B appropriately rescaled by a real number ε. As will become clear later, this real number ε is the *probability of regeneration* in the small set A.

Following Mykland et al. (1995), one can write the transition kernel in terms of its density with respect to some measure μ (the Lebesgue measure):

$$P(x, dy) = p(x, y)\mu(dy)$$

thus the minorization condition becomes:

$$p(x, y)\mu(dy) \geq \varepsilon\nu\,(dy)\,.$$

Now assume $\nu(\{x\}) = 0$ for all $x \in E$: this implies that ν has a density with respect to μ, denoted by $\nu\,(y)$. Then the minorization condition can be written in terms of the transition density:

$$p(x, y) \geq \varepsilon\nu(y). \tag{1.3}$$

Therefore, the minorisation condition is satisfied if there exists a univariate density $\nu(y)$ that, multiplied by a positive (and smaller than 1) number ε, is entirely contained underneath the curve $p(x, y)$.

Assume now that a triplet (A, ε, ν) has been identified. Write the transition kernel $P\,(x, dy)$ as:

$$P(x, dy) = \varepsilon\nu(dy) + (1 - \varepsilon)\,\frac{P(x, dy) - \varepsilon\nu(dy)}{1 - \varepsilon}.$$

Thus P can be represented as a mixture of two distributions, ν and, say, Λ, where

$$\Lambda(x,dy)=\frac{P(x,dy)-\varepsilon\nu(dy)}{1-\varepsilon}.$$

The transition from X_t to X_{t+1} can then be modified into:

$$X_{t+1}=\begin{cases} X_1\sim\nu\left(X_1\right) & \text{with probability } \varepsilon \\ X_2\sim\Lambda(X_t,dy) & \text{with probability } (1-\varepsilon) \end{cases}. \tag{1.4}$$

Thus, once entered state X_t, with probability ε the chain evolves according to $\nu(dy)$ and with probability $(1-\varepsilon)$ it evolves according to $\Lambda(x,dy)$.[14] The important point to notice is that there are epochs when X_{t+1} is generated from X_t according to $\nu\left(\cdot\right)$ and thus *independent* of the previous value X_t. These occurrences are called *renewal events*: with probability ε the future path of the chain is conditionally independent of the past and the chain is said to *regenerate.*

How can this notion of regeneration be used for discretisation purposes? Consider a chain with J disjoint small sets A_j, $j=1,...,J$[15] and consider the corresponding parameters (ε_j,ν_j). *Renewal times* τ_n $(n>1)$ are defined as follow:

$$\tau_n=\inf\left\{t>\tau_{n-1};\ \exists\quad j\in 1,...,J\ ,\quad X_t\in A_j \text{ and } X_{t+1}\sim\nu_j\right\}$$

that is, the renewal times are the epochs at which the chain, after entering a small set, has regenerated (a renewal event has occurred).

Although the finite valued sequence $\eta^{(t)}$ deduced from X_t according to (1.1) is not a Markov chain, Guihenneuc-Jouyaux and Robert (1998) show[16] that the subchain $\xi^{(n)}$ obtained from $\eta^{(t)}$ taking only the values of the chain at renewal times τ_n

[14] With this procedure, the transition is not modified marginally in X_{t+1}.

[15] Which, however, do not necessarily constitute a partition of the sample space.

[16] See their theorem 1.

$$\left(\xi^{(n)}\right) = \left(\eta^{(\tau_n)}\right)$$

is a proper Markov chain on the discrete state space $1, ..., J$.

In practice, the small sets can be found by inspection of the kernel, but they need to be exhibited. However, relatively weak conditions for their existence can be stated (Nummelin, 1984).

Consider the stochastic kernel in Figure 1.3 again: take a point x on the t axis and consider the section of the kernel from point x parallel to the $t+1$ axis. This is a conditional density function (thus integrating to one) that describes the probability of reaching each portion of the state space in the next period, given that we are in state x in the current period. For the minorization condition (1.3) to hold at point x, therefore, one must find a density function $\nu(y)$ which (appropriately rescaled by ε) can be entirely contained underneath this section.

The important point here is that the minorization condition (1.3) must hold at every point contained in the set A on the t axis, for A to be defined a *small* set. This is where the number ε plays an important role: once a density ν is chosen, this has to be used for all points in the set A. The number ε then allows rescaling of the function to "squeeze" it below each section of the kernel corresponding to each point in the interval A. The bigger the interval considered, the smaller ε will have to be to ensure that (1.3) holds at every point in the interval.

Thus there appears to be a trade-off in the choice of the triplet (A, ε, ν). On the one hand, the researcher would like to have a partition of the space in few intervals, thus creating a discrete process with few states – easier to deal with. On the other hand, having large intervals means low values for ε, and thus a low probability of regeneration in the small set.

As a special example, consider (as in Mykland and Al., 1995) a transition density which is a fixed function f regardless of the current state of the chain, that is,

$p(x, y) = f(y)$. In this case, we can choose ε to be 1 and $\nu(y) = f(y)$. Thus regeneration occurs with probability 1 at each point. This is intuitive since the transition function is independent of the current state.

The next section describes an application of the preceding methodology to the discretisation of the kernel in Figure 1.3.

1.4 Application: the cross-country income distribution

How can the procedure outlined above be made operative to solve the discretisation problem described at the beginning of Section 1.3? Clearly, to construct a proper Markov chain from the continuous process at hand, one should select the observations only at renewal times. Imagine, in other words, that it would be possible to observe the exact times at which the regenerations occur. Figure 1.4 is shown again in Figure 1.5 with the addition of the black dots: these represent the regenerations, that is, the occurrences at renewal times, when the process evolves independently from the past. If a new process were constructed using only these observations, a proper discrete Markov chain would be obtained. But, although the existence of the renewal events can be guaranteed by some properties of the kernel, these events are not in general observable, since they occur only with a certain probability ε. The approach followed in Guihenneuc-Jouyaux and Robert (1998) and in the present work is therefore a simulation approach.

The procedure is as follows: first, paths like the one in Figure 1.4 need to be constructed. The data generating process is assumed to be a continuous state space Markov process described by an initial distribution and a certain transition density $p(x, y)$. A sample path of length T for the process is then constructed by a random draw from the initial distribution and repeated iterations of the transition density, as described, for example, in Gamerman (1997).

More precisely, first an observation X_0 from the initial distribution is generated.

Then, given the transition density $p(x, y)$ and given X_0, the value of X_1 is distributed with density $p(X_0, \cdot)$ that is, with density equal to the section of the transition density from point X_0, and can be generated from it. For X_2 this procedure is repeated by drawing from a distribution with density $p(X_1, \cdot)$. Iterating this scheme leads to a sequence of values that represent a sample realization of the process.

How are the renewal events obtained? They can be generated – once the small sets have been identified – by modifying this procedure slightly. More precisely (for a more detailed discussion see Guihenneuc-Jouyaux and Robert, 1998) assume that, given the properties of the transition density, J small sets A_j, $j = 1, ...J$, with corresponding triplets $(A_j, \varepsilon_j, \nu_j)$ were found. Each time the process enters the small set A_j, the process is known to regenerate with probability ε_j, thus the next state is generated according to $\nu_j(y)$ with probability ε_j and according to Λ_j with probability $(1 - \varepsilon_j)$. When the first case occurs, renewal events are produced. A path similar to the one in Figure 1.5 will thus be created: the regenerations are represented by the black dots.

Once such a sample realization is obtained, the two different methods to compute the transition matrix can be implemented and compared. The first method, the naive discretisation commonly used in applied work, considers all the realizations of the process and partitions them in discrete cells. The second method, the regeneration method of Guihenneuc-Jouyaux and Robert, only considers those observations that occur at regeneration times - and thus constructs a proper Markov sequence (as was described in Section 1.3 above).

In the present work, this methodology is applied to the distribution of per capita incomes across countries (relative to the world average) in the following way. The data generating process is assumed to be a continuous state space Markov process with the transition density depicted in Figure 1.3 and initial distribution corresponding to the density plot in Figure 1.1 that is, the world income distribution in

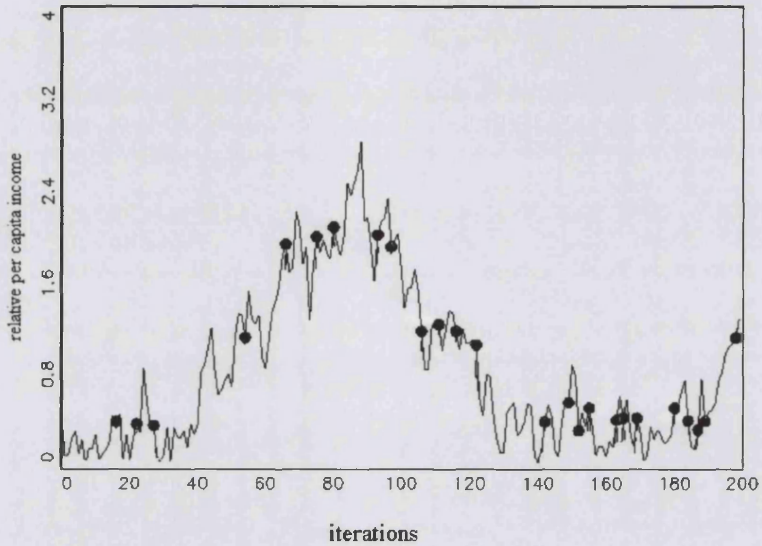

Figure 1.5: Sample path and regenerative discretisation

1960.

The next step necessary to implement the procedure is to identify the small sets, whose existence ensures the occurrence of the renewal times: these are normally identified by inspection of the transition density. More precisely, the sets A_j must satisfy the minorization condition (1.3), thus there must exist a univariate density $\nu(y)$ that, multiplied by a positive (and smaller than 1) number ε, is entirely contained underneath the curve $p(x, y)$. The small sets are thus specific to the kernel: they need not exist and they might not even constitute a partition of the sample space. Moreover, as discussed at the end of Section 1.3, there is a trade-off between choosing a limited number of relatively large interval and being able to pick the ε big enough to ensure enough regenerations.

In this work we chose the simple partition in five equi-sized cells described in Section 1.3. The reasons for this choice are twofold: first, it is interesting to consider a partition of the space[17] and second, a comparison with a naive discretisation is straightforward. The existence of the elements $\nu_j(y)$ and ε_j for this partition is, however, by no means guaranteed. Can the partition $A_1, ..., A_5$ (with $A_1 = [0, 0.8)$, $A_2 = [0.8, 1.6)$, $A_3 = [1.6, 2.4)$, $A_4 = [2.4, 3.2)$, $A_5 = [3.2, 4]$) deliver five small sets necessary to the discretisation? First, one has to find five univariate density functions that approximate the sections of the transition kernel from below. By inspection of the kernel, it is clear that the sections along the $t+1$ axis are approximately normal, as demonstrated by the fact that a rescaled normal distribution well approximates the univariate section of the density. Thus, five normal distributions have been chosen as densities $\nu_j(y)$. Next, the numbers ε_j must been selected such as to "squeeze" the densities $\nu_j(y)$ entirely underneath the kernel for all x in the set A_j. Since these numbers represent the probability of regeneration within each small set, they should be as large as possible: they were thus chosen as the maximum numbers satisfying the minorization condition $p(x, y) \geq \varepsilon\nu(y)$ in each small set.[18]

Once the triplet $(A_j,\ \varepsilon_j, \nu_j)$ for each small set j has been identified , the simulation proceeds as described. Several thousand sample realizations have been generated with this procedure, to mimic the actual data generating process for country income data.[19]

1.4.1 The transition matrices

The sample thus generated was used in two different ways. First, transition matrices were estimated according to the two different approaches to discretisation: the naive and the regenerative approach. The matrix obtained from the "naive discretisation"

[17] Guihenneuc-Jouyaux and Robert (1998) present an example with three disjoint small sets which do not constitute a partition of the sample space, but their article focuses on issues that differ from those of the present work.

[18] More precisely: ε_1=0.10012, ε_2=0.07711, ε_3=0.06388, ε_4=0.081913, ε_5=0.06780. As explained earlier, these represent the regeneration probability in each small set A_j, $j = 1, ..., 5$.

[19] Since the transition probabilities are computed as sample proportion of transitions from a given state to the others in the sample space, to obtain comparable results in terms of limiting properties, approximately the same number of transitions starting from each cell were included.

is shown in Table 1.1, which represents a one-period transition matrix of a discrete process over five states. It was estimated using the entire sample path, simply associating occurrences in one of the five portions of the continuous state space with the corresponding discrete state. The results obtained are compatible with previous studies (Quah, 1993a): the diagonal values are far more important than the off-diagonal ones, with extreme transitions (e.g. from state 1 to state 4 or 5) having negligible probability. The "twin peaks" are also present: the intermediate classes tend to disappear, as shown by a slightly lower value in the second and third diagonal cells.

As mentioned in Section 1.3, however, this discretised process has almost certainly lost the Markov property, thus it is not clear what kind of process is under analysis.

			Upper	Endpoint	
	0.80	1.60	2.40	3.20	4
	0.90	0.10	0.00	0.00	0.00
	0.16	0.77	0.07	0.00	0.00
	0.00	0.09	0.77	0.14	0.00
	0.00	0.00	0.13	0.79	0.08
	0.00	0.00	0.00	0.22	0.78
Ergodic	0.365	0.229	0.166	0.179	0.062

Table 1.1: Transition matrix computed from a naive discretisation of the continuous state space Markov chain

The generated sample has also been used to construct a proper discrete Markov chain as described in Section 1.3, that is, only considering the values at regeneration times. Thus, estimating a transition probability matrix from this process is legitimate, and the results are presented in Table 1.2.[20]

First, it is interesting to notice how the regenerated chain retains most of the features of the continuous chain. First, highest transition probabilities are contained in main diagonal: this indicates high persistence in the distribution, since it more

[20]The rows do not always sum to one due to roundings.

			Upper	Endpoint	
	0.80	1.60	2.40	3.20	4
	0.87	0.13	0.01	0.00	0.00
	0.42	0.52	0.05	0.01	0.00
	0.09	0.21	0.48	0.21	0.02
	0.02	0.05	0.21	0.65	0.09
	0.00	0.01	0.09	0.44	0.45
Ergodic	0.683	0.206	0.050	0.050	0.009

Table 1.2: Transition matrix computed from a regenerative discretisation of the continuous state space Markov chain

likely to remain in the current state after a one-step jump. Second, transitions from very low to very high income and vice versa are still very unlikely, as shown by the zero values in the extreme off-diagonal cells. Again, the twin peaks can be observed: persistence in the low-income class is high (87%) compared to intermediate states 2 and 3 (52% and 48% respectively). Persistence is also high in high-income state 4: the probability of remaining in 4 is 65%, higher the probability of remaining in the intermediate states 2 and 3. Thus intermediate states are more volatile and tend to disappear.

One feature, however, is very different in the transition matrix derived from the regenerative discretisation: the intra-distribution mobility is now much higher than in the first matrix, as shown by higher values in the cells close to the diagonal. Persistence is still present in Table 1.2 but to a lesser degree than in Table 1.1. Transitions from state 2 to state 1 now occur with much higher probability (42%) than before (16%); the same pattern is evident for all states. In general, it seems much more likely for a country to loose its position in the world income distribution and fall back to a lower income class. This is particularly evident for the highest income state: it is almost as likely to remain in state 5 (45%) than to fall back to state 4 (44%).

This points to another feature of the transition matrices: there appears to be an asymmetry in the direction of transitions, as it is more likely to transit to a lower income class than to a higher income one. This is true for states 2 and 4 in particular, and for both transition matrices.[21]

The asymmetry, however, is much more pronounced in the regenerative discretisation than in the naive discretisation: this is due to the higher mobility exhibited by the former compared to the latter. One reason for this difference could be the fact that, while in a naive discretisation all one-step transitions are taken into account, regenerative discretisation only takes into account one-step transitions that result in regeneration, and therefore features variable transition times. As a consequence, more transitions will result in a move to higher or lower states. This pattern is not likely to be a feature of this dataset, but can be expected to occur whenever comparing results of naive and regenerative discretisation.

The "regenerative discretisation", therefore, leads to an estimated matrix that conveys quite a different message than the naively discretised chain. Not only the first matrix in not theoretically correct, but it appears that the implications of the arbitrary discretisation are much more important than believed, when the process is compared with an appropriately discretised one.

Thus discretisation matters, in practice as well as in theory. The consequences of a naive discretisation can lead to very misleading results. This conclusion is even stronger if one considers the limiting distributions of the two processes.

1.4.2 The limiting distributions

Figure 1.6 depicts the invariant – or stationary – distribution relative to the continuous state space markov process, computed (numerically) from the transition kernel.[22] This distribution represents the limiting or long run behaviour of the process un-

[21] The pattern is not observed, however, for moves from state 3: here the probability of moving up or down the income distribution is approximately equal.

[22] The invariant distribution $\pi(\cdot)$ of a continuous state space Markov chain with transition density $p(x,y)$ solves: $\pi(y) = \int \pi(x)p(x,y)dx$.

der analysis: the figure thus depicts what the per capita income distribution across countries might look like in the long run. The polarization is still present, although somewhat less pronounced compared to the levels of 1989 and depicted in Figure 1.2.

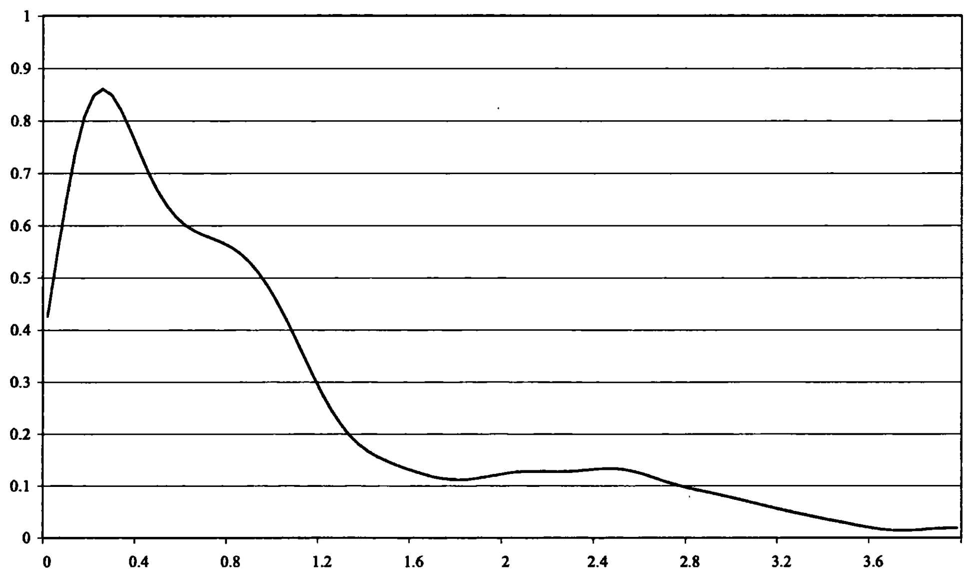

Figure 1.6: The limiting distribution for the continuous state space process

Figures 1.7 and 1.8 compare the invariant distribution for the continuous process with the invariant distributions obtained from the "naively" discretised chain and the "rigorously" discretised chain, respectively. Two features are evident: first, the two limiting distributions convey very different messages.

The second (accurate) discretisation of Figure 1.8 shows a very pronounced probability mass corresponding to the low income countries, while the probability of becoming a middle income or rich country is much smaller, with the latter case slightly more likely. The comparison with Figure 1.7 is striking: an incorrect discretisation can lead to a much more optimistic conclusion about the relative income distribution in the long run. In Figure 1.7, the probability is more uniformely distributed among

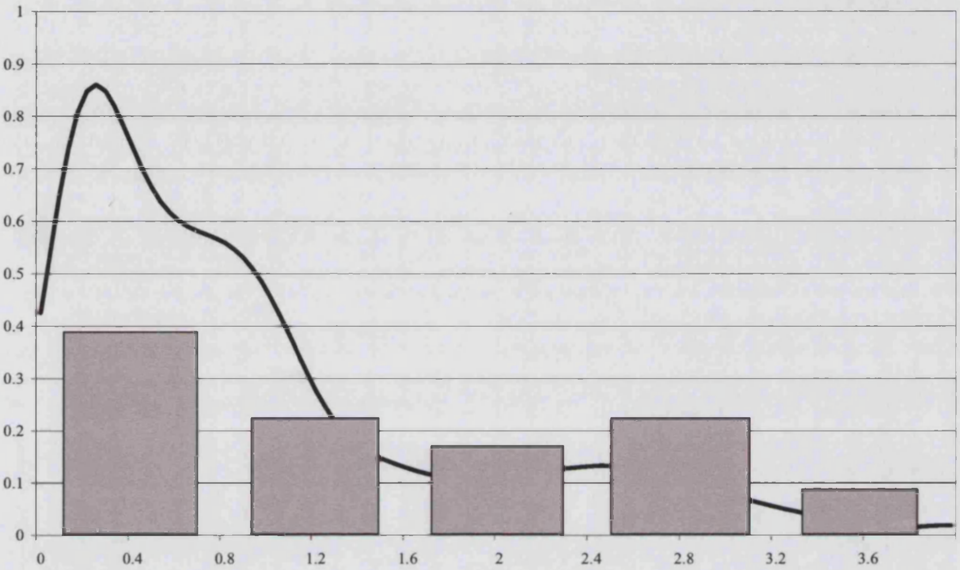

Figure 1.7: The continuous limiting distribution and the discrete limiting distribution obtained from a naive discretisation

the low and high income classes, with the former only slightly more pronounced.

The second feature emerging very clearly from these graphs is that the limiting distribution of the continuous chain is well approximated by the limiting distribution of the properly discretised chain, while the arbitrary discretised chain provides a very poor approximation.

This results can be intuitively explained as follows: in every continuous state space Markov chain there is a series of embedded renewal processes (Nummelin, 1984), the renewals happening precisely at the renewal times identified above. Thus one can think of a more complex stochastic process embedded in the continuous Markov chain: precisely, a *Markov renewal process* (Pyke, 1961). This is a process that transits from one state to another in a discrete Markov chain, the time of transition between two states being itself a random variable. The transition matrix in Table 1.2 could then be associated with estimated distributions of transition times from state to state, possibly different for each pair of states. This would allow

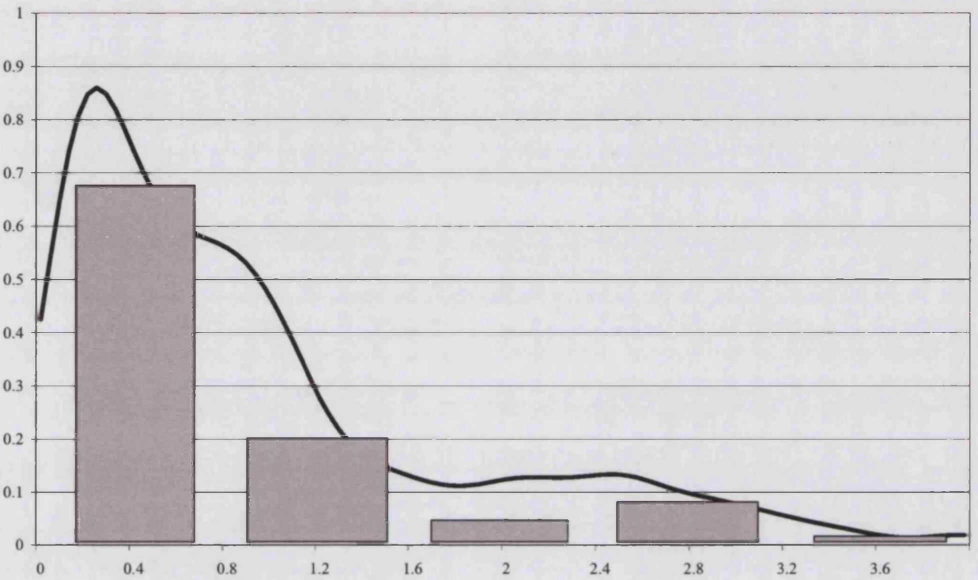

Figure 1.8: The continuous limiting distribution and the discrete limiting distribution obtained from a regenerative discretisation

modelling of, not only the mobility pattern of per capita incomes across countries, but also the persistence of some income states (for an example, see Quah, 1992).

1.5 Concluding remarks.

The aim of the present work is to encourage those researchers who use distribution dynamic methods to think about discretisation and its consequences. What is the answer to the question posed in the introduction, whether discretisation matters? At least in the context of the dynamics of the world income distribution, the answer is *yes:* different discretisation methods give very different results in practice.

Section 1.3 of this chapter has presented a theoretically sound method to discretise a continuous state space Markov chain. This method has been employed in a simulation exercise to compare the effects of two different discretisation approaches. It has been shown clearly that the arbitrary discretisation of a continuous state space

Markov process can lead to very misleading conclusions. This is true both in terms of the transition probabilities and in terms of the limiting distributions.

The analysis in the present chapter suggests that it is possible to derive a rigorous discretisation of the state space and thus compute an unbiased transition matrix for the process. This approach, however, is not immune from limitations. The discretisation procedure is borrowed from Markov Chain Monte Carlo theory and is somewhat involved. Given regeneration is based on the concept of small sets, and certain properties of the stochastic kernel need to be satisfied for the small sets to exist, the regenerative discretisation is data-dependent and not always viable. Even if possible, the procedure requires a complex simulation algorithm. Nevertheless, the analysis of this chapter constitutes an important robustness test in the study of cross-country income distribution and for the methodology of distribution dynamics in general.

Another interesting result of this work is the accuracy in the approximation of the continuous limiting density by the rigorously discretised chain. This property clearly derives from those of the embedded Markov renewal process, and it indicates that this kind of process deserves further attention in the analysis of income distribution across countries. This topic is explored in the next chapter.

Chapter 2

Persistence and evolution in the cross country income distribution

2.1 Introduction

In the previous chapter we discovered that the evolution of per capita incomes across countries is well approximated by a stochastic process with variable transition times between states. In this chapter we explore this issue further.

As before, we focus on the distribution of per capita incomes across world economies. Every portion of the world income distribution can be interpreted as one of the possible states visited by the stochastic process that governs the evolution of such distribution. The aim of Chapter 1 was to estimate the probability of transition from one state to another in this distribution, conditional on the present state; the interest thus focused on transitions in a spatial sense. The main aim in this chapter is to investigate temporal rather than spatial patterns. We now abstract from the spatial aspect of transition and focus on the time it takes to a representative economy to move across the various states of the world income distribution.

We model these time patterns as a semi-Markov process: this is a stochastic process which moves from one to another of a series of states and stays in a given state a random length of time, the distribution function of which may depend on this state as well as on the one to be visited next.

For convenience, we arbitrarily partition the state space of relative per capita incomes across countries into equi-spaced cells. As discussed in Chapter 1, if the true data generation process was markovian, arbitrary partition of the state space will result in the loss of the Markov property. In Chapter 1, however, it was shown that a continuous state space Markov process is well approximated by a stochastic process with variable transition times. A transition matrix for such process can be constructed by regenerative discretisation as illustrated in that chapter. Estimation of the transition probability is not therefore discussed here. Rather, we focus on transition times. We examine the length of time a country spends in a given state of the distribution before transiting to another state and then estimate the distribution of these transition times. We allow such distribution to vary across states in two ways. First, different states have different exit times, i.e. the distribution of time spent in each state is a function of the current state. Second, we allow the distribution to be different for each different arrival state. These distributions are estimated non-parametrically.

As before, we begin by examining the position of a representative economy in the world income distribution. Consider a representative economy that remains in a given state for a random period of time, before moving to a different state i.e. before a *move exposure* occurs. Define the random length of time until the first move *waiting time*: the aim of this Chapter is to analyse the behaviour of the random variable defined by these waiting times in terms of its distribution.

In Quah (1992) move exposures are assumed to arrive following a stationary

Poisson process with parameter $\lambda > 0$; λ is thus the arrival rate for move exposures. It follows that waiting times are exponentially distributed with parameter λ. Since the mean of the distribution is $1/\lambda$, the larger is λ, the faster the move exposures arrive.

Quah (1992) then estimates the distribution of sojourn times parametrically, under different assumptions on the parameter λ: by replacing the hypothesis of constant λ, he incorporates different notions of heterogeneity and state and duration dependence in the model. More precisely, a constant λ is replaced by a non-degenerate distribution G of λ and different parametric forms of G are then modelled. First, G is chosen to be a gamma distribution with unknown parameters alpha and beta, which imply different λ parameters for different cross-sectional individuals (economies).

A second form of heterogeneity is modelled allowing different growth dynamics to be related to different states rather than different economies. Thus a different parameter λ applies to each state of the cross-sectional income distribution and the move exposure arrival rate varies with the current state. The analysis in the present Chapter directly relates to this state-dependent parameterisation.[1]

There are three main differences between the work described in the present Chapter and that of Quah (1992). First, while in Quah the distribution of sojourn times is estimated parametrically, the approach of the present Chapter is entirely non-parametic and no distributional assumption is made. Thus the present approach has the advantage of being more general and flexible than the existing parametric approach.

The second important difference is that in Quah (1992) the arrival rates are allowed to depend on the current state but not on the next state: thus he only estimates exit rates from each state. In the present Chapter, arrival rates are a

[1] A third way to relax the assumption of constant arrival rate λ is by allowing the parameter to vary over time; this approach is not investigated in the present Chapter: see Quah (1992) for more details.

function of both states: the state of departure and that of arrival. The value added of this generalisation is that it allows for asymmetries in the time pattern of transitions along the cross-country income distribution. More precisely, asymmetries might arise when transitions to higher states in the income distribution exhibit very different patterns from transitions to lower states. The analysis in the present Chapter is able to capture precisely this phenomenon, which had remained practically uncovered in previous studies.

A third difference with Quah's work is that there is no attempt, in the present chapter, to estimate transition probabilities for the stochastic process under analysis; and this constitutes a limitation of the present work.

This chapter is once again based on the Penn Tables Mark 5.6 (see Appendix B for details). This Chapter focuses on the time pattern of transitions across different states of the cross-country relative income distribution: once again the variable of interest is relative income per capita as measured by real GDP per worker divided by the world average.[2]

2.2 Empirical specification

Consider the process $Y = (Y_t)_{t>0}$ on the time interval $[0, \infty)$, with values in some arbitrary state space E, which stays in state x for a length of time s and then jumps to state y according to a transition distribution given by:

$$Q(x, dy, ds). \tag{2.1}$$

Let T_i denote the i-th jump time. Set $T_0 = 0$. Write $X_i = Y_T$ for the state of Y at time T_i and $S_i = T_i - T_{i-1}$ for the sojourn time of Y in state X_{i-1}. Then (X_i, S_i), $i \geq 0$, is a Markov chain with values in $E \times [0, \infty)$ and with transition distribution

[2]This is the fourth difference between the present analysis and that of Quah (1992), where the distribution of relative growth rates rather than incomes is examined.

$Q(x, dy, ds)$. Let $S_0 = 0$ and

$$T_i = \sum_{j=0}^{i} S_j, \qquad i \geq 0, \qquad N_t = \max\{i \geq 0 : T_i \leq t\}, \qquad t \geq 0.$$

Then $Y_t = X_{N_t}$, $t \geq 0$, is called a *semi-Markov process.* The process stays in state X_{i-1} for a *sojourn time* S_i. At jump time T_i it then jumps to state X_i. Semi-Markov processes were introduced by Pyke (1961) and studied, among others, by Moore and Pyke (1968). It is worth emphasizing that the definition given above refers to a very general type of process, defined on a continuous state space and in continuous time. In practice, we never observe economic variables in continuous time, and finite approximations are always used. Even with continuous time recording, estimating functionals of the form (2.1) is extremely demanding on the data.[3] A survey of parametric estimators for semi-Markov processes is contained in Jain (1990); Greenwood and Wefelmeyer (2003) investigate the properties of the fully nonparametric semi-Markov model.

What are the features of interest that can be inferred by modelling the income process in such a fashion? In general, we are interested in quantities such as:

$$P(S_j \leq c \mid X_{j-1} \in A, X_j \in B) \tag{2.2}$$

These quantities summarise the probability that the time a country spent in part A of the distribution before moving to B is not longer than some value c. A natural estimator for the sojourn times is the empirical estimator, computed as sample proportion of sojourn times between two states.[4]

[3] See Silverman (1986) for a discussion on the data requirements for nonparametric density estimation in higher dimensions.

[4] More precisely:

$$P(S_j \leq c | X_{j-1}, X_j) = \frac{P(S_j, X_{j-1}, X_j)}{P(X_{j-1}, X_j)}.$$

2.3 Empirical results

In this chapter, our empirical analysis focuses on those properties of the distribution of per capita income across countries that are associated with mobility in time, rather than across space: we are interested in the length of time each country spends in a given portion of the world income distribution. We hope to discover patterns of persistence in the evolution of the distribution of income across countries.

As mentioned in the previous section, a process with both continuous state space and continuous time parameters can soon become intractable. We therefore rely on a discrete approximation: we make use of observations collected at discrete points in time and construct a partition of the state space in a finite number of income classes. The limitations of such a partitioning in the context of a pure Markov model have been identified in the previous chapter; however, it was also shown that a model with variable transition times provides a far better approximation to the income process compared with the fixed step transition of the pure Markov process.

We carry out estimations of the distribution of sojourn times under two different partitions of the sample space (as in Quah, 1992). As a first example, the space of relative per capita incomes is partitioned into low, middle and high relative income levels.[5] The quantities in (2.2) are then estimated nonparametrically for the time span allowed by our sample (i.e. thirty years): these probabilities are then mapped into a probability distribution function.[6]

In Figure 2.1 we present estimated probability distributions for transition times in the three-state model. Panel (a) depicts the distribution of sojourn times spent in the low income class before moving to the middle class: although the transition can be fast for many countries, there is a positive density in correspondence of longer time

[5] Since the space of relative income per capita is the interval $[0, 4]$, the upper bounds of the income classes are: 1.33, 2.66 and 4.

[6] All computations were performed in GAUSS.

spans of ten and even fourteen years. These represent normal development patterns, whereby countries slowly move up in the income distribution. Panel (b) represents times of transition from the low to the high income portion of the distribution. The spike corresponding to a sojourn time of fifteen years could represent an economic "miracle" – eventually, some poor countries "take off" and reach the upper end of the income distribution in only one step.

Panel (c) represents time patterns of movements from the middle to the low income class. The distribution shows that many countries only survive in the middle income class for one period, before falling in the low income class. This is another aspect of polarization of the world income distribution: there is very little persistence in the middle class. Sojourn times are more uniformely distributed when the economy moves towards the upper end of the distribution, as shown in panel (d). Thus it takes time to reach high income positions but the descent is much faster.

The volatility is very pronounced in panels (e) and (f), representing sojourn times in high income levels before becoming poorer: 90% of the countries only survive one period among the rich, before they return to the bottom of the distribution. These "disasters" appear to be faster than the descent to the middle income class: the same asymmetric behaviour of the previous two panels is present.

This exercise was repeated experimenting with a finer partition of the income space into five equi-spaced classes.[7] The distributions of sojourn times for each pair of these income classes are presented in Figures 2.2-2.5. The transitions from state one (Figure 2.2) to state two have a roughly uniformly distributed pattern; faster growth is possible in moving to states three and four, but the big jump to the upper portion of the distribution is never immediate. The "jump" takes longer also if leaving state two, as panel (d) of Figure 2.3 shows. Another familiar feature is the asymmetry of transition: faster towards a lower part of the distribution (a),

[7] The upper bound limits of the five classes were thus 0.8, 1.6, 2.4, 3.2 and 4.

slower towards the upper part (b and c). Leaving state three for state five is also slower than any other movement (Figure 2.4, panel (d)), whereas going from four to five happens in one period with probability one (Figure 2.5, panel (d)). The upper portion of the income distribution (state five) however, is the most volatile: results are not reported because the sojourns before transition to every other portion of the state space lasted one period with probability one. Thus, leading the world income distribution is not a long lasting privilege.

2.4 Concluding remarks

In this chapter we adopted a more general model for the process governing per capita income dynamics. This process – the semi-Markov process – is characterized by variable sojourn times between visits to two different states. Our aim was to discover patterns of persistence in the evolution of income across countries. With the exception of low-income states, there does not appear to be much persistence in the process under analysis. Sojourn times are often very short, and exit from high-income states happens in only one year with very high probability. This result, however, is based on few observations and should be interpreted with care. In general, the results of this chapter are based on non-parametric estimates based on a limited sample, and this constitutes a limitation of the present work. Moreover, the result differs from that in Quah (1992), who finds that high-growth states are more persistent than low-growth states.

The analysis in this chapter omits any treatment of the joint estimation of transition probabilities and sojourn times, an approach followed by Quah (1992) instead. This omission certainly constitutes a limitation of the present approach.

In general, the results of this chapter are consistent with the transition probabilities computed in Chapter 1 by regenerative discretisation methods. Low-income states are more persistent than high-income states both in terms of probability of transition and of sojourn times. The message, however, is different when the transition probabilities are estimated using a naive discretisation: persistence appears higher in all states. Thus it appears that the conclusions on the persistence in the cross-country income distribution are dependent on the assumptions regarding the data generation process. As the analysis of the previous chapter has demonstrated, however, the dynamics of the distribution of per-capita incomes across countries are well approximated by a stochastic process with variable transition times, and the results of this chapter are consistent with that approach.

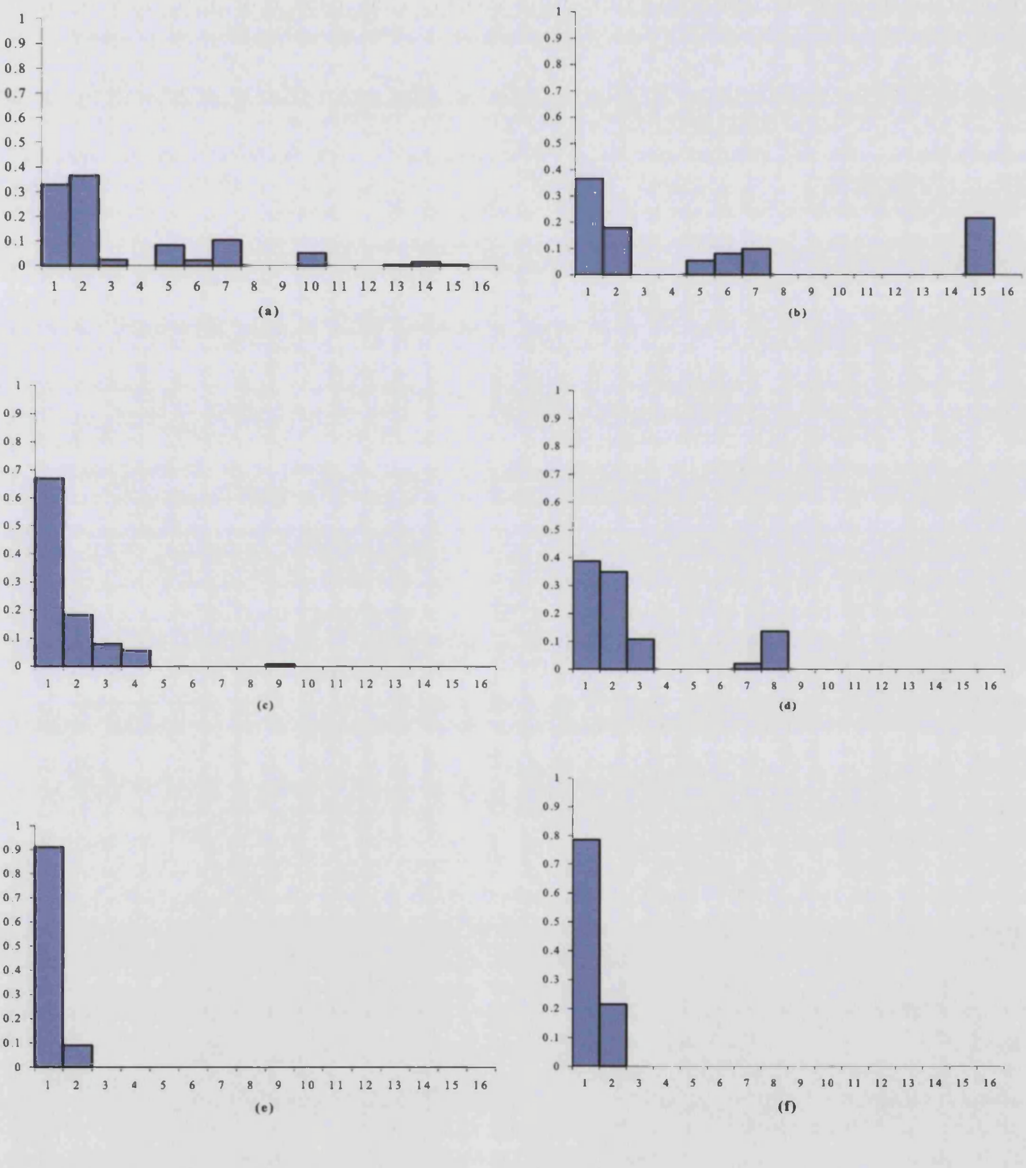

Figure 2.1: Distribution of transition times from low (a, b) middle (c, d) or high (e, f) income levels

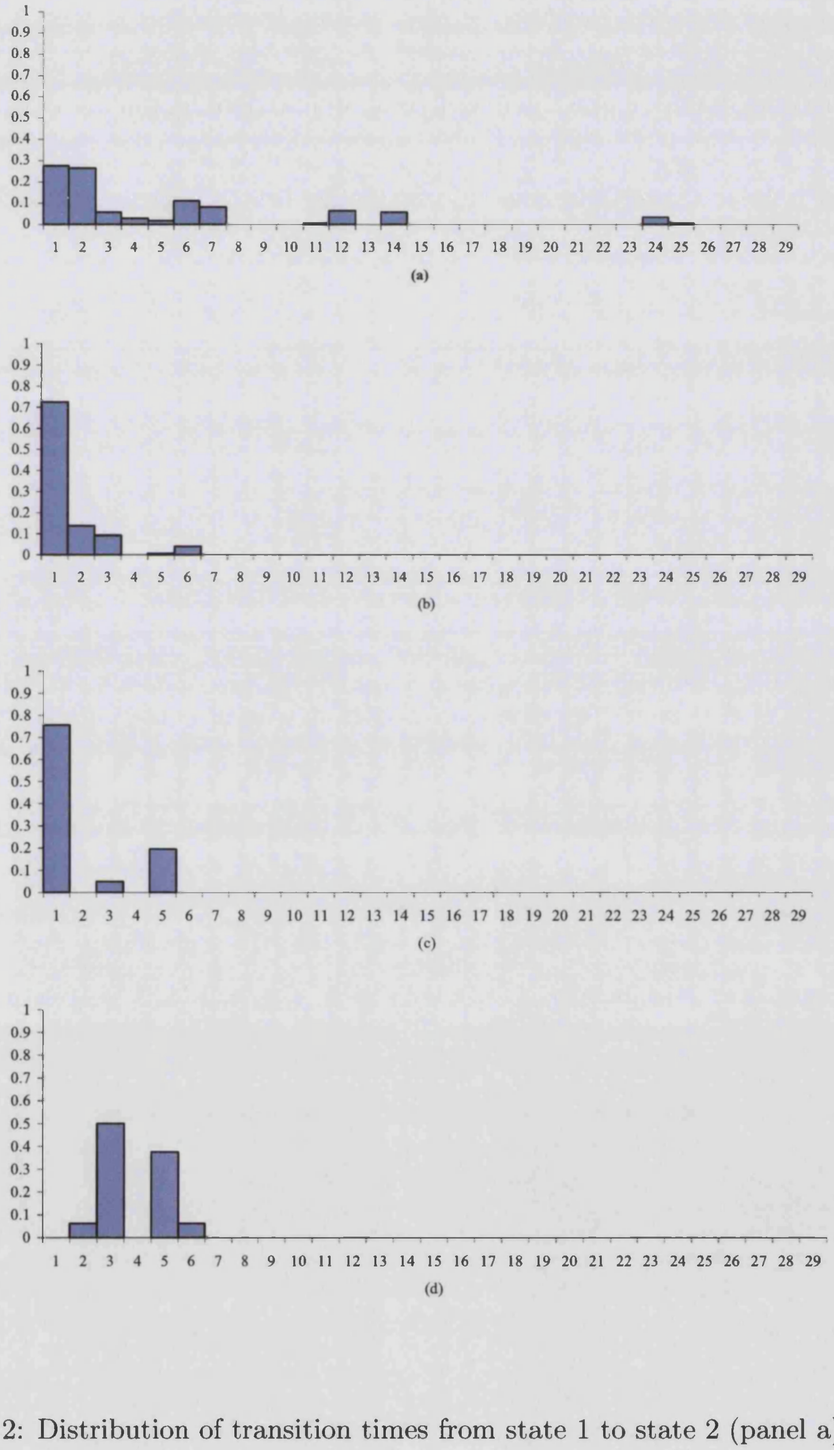

Figure 2.2: Distribution of transition times from state 1 to state 2 (panel a), 3 (b), 4 (c) and 5 (d)

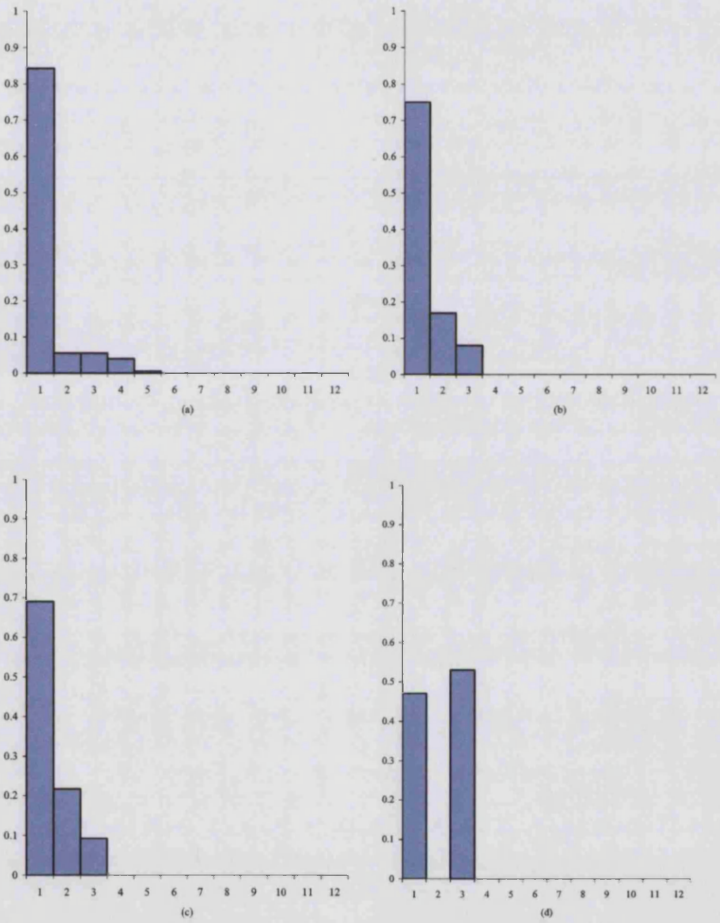

Figure 2.3: Distribution of transition times from state 2 to state 1 (panel a), 3 (b), 4 (c) and 5 (d)

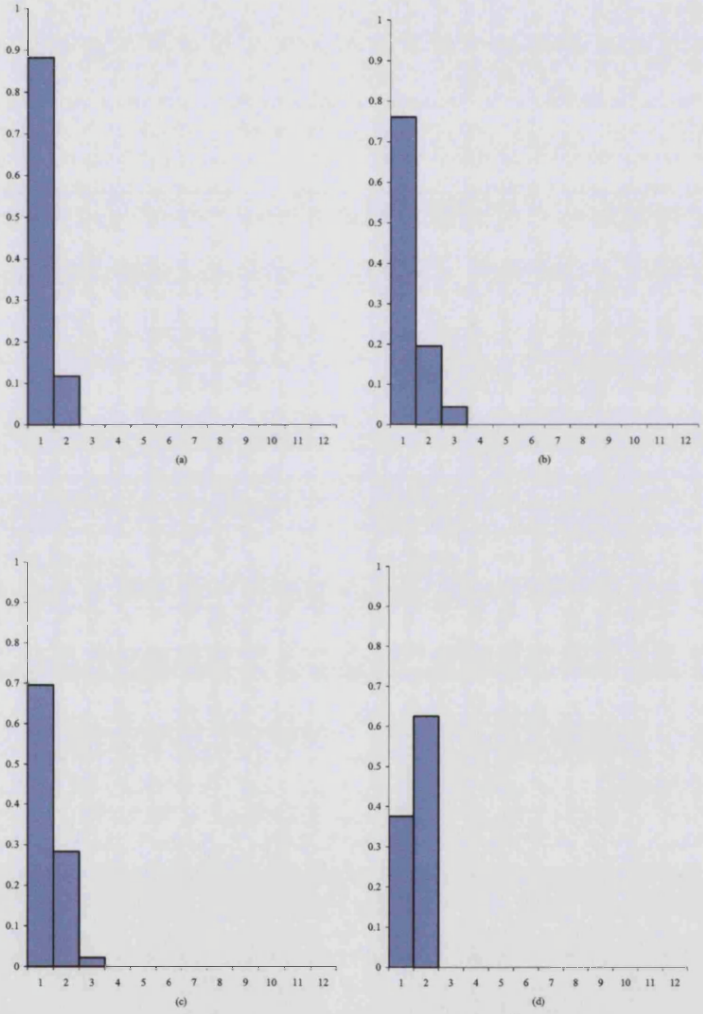

Figure 2.4: Distribution of transition times from state 3 to state 1 (panel a), 2 (b), 4 (c) and 5 (d).

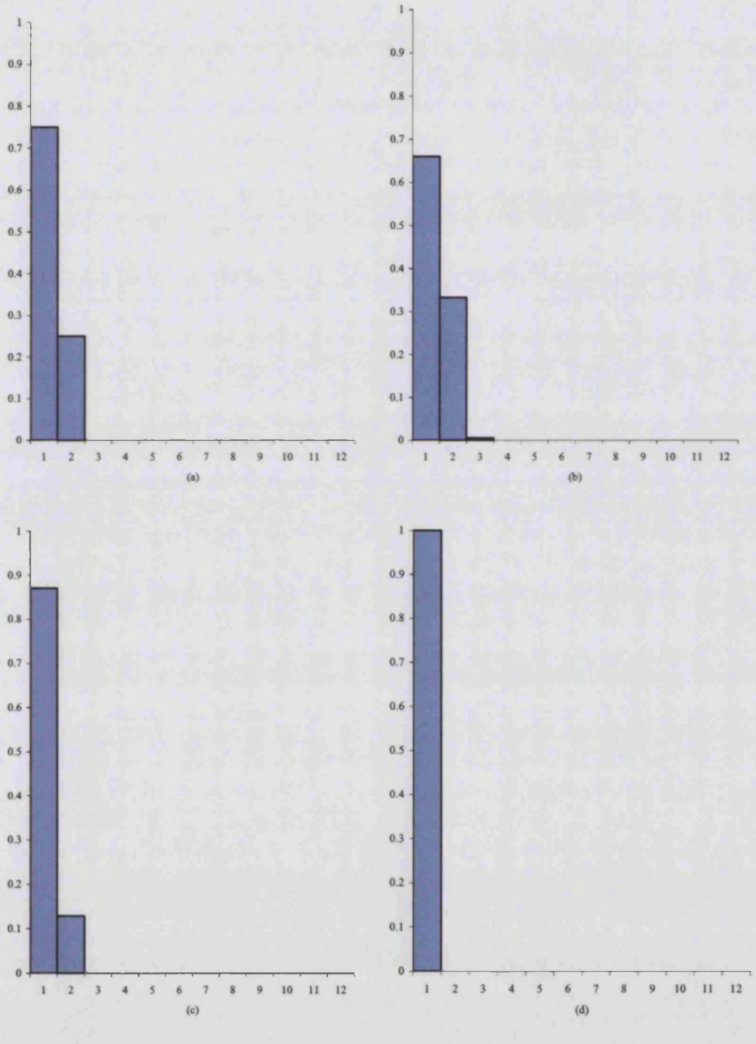

Figure 2.5: Distribution of transition times from state 4 to state 1 (panel a), 2 (b), 3 (c) and 5 (d)

Part II

Technological progress, labour market institutions and employment

Chapter 3

Labour market institutions and unemployment: a panel cointegration approach

3.1 Introduction

Unemployment rates across OECD countries have increased somewhat dramatically in the 1980s and 1990s compared to the levels of the 1960s and 1970s. The unemployment experience, however, has been very different across economies. These two features emerge clearly when observing the time series of the unemployment rate depicted in Figures 3.1 and 3.2 at then end of this chapter.[1]

For more than a decade researchers have been investigating the possibility that high unemployment is the product of rigidities in the labour markets and of adverse effects of labour market institutions such as trade unions, unemployment benefits systems, taxes on labour, laws and regulations on employee rights and active labour market policies (see e.g. Layard et al., 1991). Ever since the OECD Job Study

[1] A detailed description – including sources – of the dataset used in this and in the following chapter is contained in Appendix C.

(1994) argued that, in an environment in which structural change and adaptation of firms is increasingly important, countries with high labour market rigidities will have higher unemployment, the importance of labour market institutions has become an even more active area of research.

Most existing empirical studies tend to investigate the contemporaneous impact of institutional factors on equilibrium unemployment: this effect, however, is more likely to manifest itself in the long run and the existence of a long run relationship between measures of labour market institutions and unemployment should be the focus of empirical research. One exception among these studies is the article by Nickell et al. (2003): in their work, the authors estimate a fixed effect dynamic model of equilibrium unemployment as determined by labour market institutions and mean reverting macroeconomic shocks. They then perform a panel cointegration test to confirm that their equations explain unemployment in the long run. Some aspects of their approach, however, appear problematic, and the time series properties of the variables under study are not fully investigated. In the present chapter we systematically analyse the time series properties of labour market institutions and we investigate their long run effect on equilibrium unemployment. For this purpose, we explicitly allow for nonstationarities of the variables under analysis. The importance of correct specification of the time series properties of the model has been extensively discussed in the literature, mainly with reference to the problem of spurious regressions. When the dependent variable is integrated of order one, regression results will be spurious unless the error term is stationary. A related issue is that of equation balance: caution should be used when combining stationary and integrated variables in a regression. Since *I(1)* variables will dominate *I(0)* variables in any linear combination, the equation might be "unbalanced" and it might not be feasible to relate certain variables in a regression. Allowing for nonstationary panels has the main advantage of avoiding the problem of spurious regressions and of unbalanced equations. Another advantage of explicitly modelling nonstationarity is that improved estimation methods are available. Traditional panel estimators, such as the within estimator, suffer large biases compared with the more sophisticated estimation methods described in Section 3.3.

The present work differs from previous studies in some important ways. First, the main aim of this chapter is to investigate the existence of a long run equilibrium relationship between the unemployment rate and a set of institutional labour market variables using a cointegration approach. For this purpose, we run cointegrating regressions among variables that have the same order of integration.[2] Based on recent developments in the theory of nonstationary panels, we perform panel unit root tests to confirm the order of integration of the variables under study and cointegration tests to establish the existence of a long run equilibrium relationship: we find that these variables are *I(1)* processes and are cointegrated. In other words, although all the variables are individually nonstationary, there exists a linear combination of these variables such that the regression containing these variables has a stationary error term. This implies the existence of a long run equilibrium relationship among unemployment and labour market institutions. Furthermore, a panel cointegration equation is estimated using recently developed techniques for nonstationary panel data sets: inference on the parameter estimates supports the view that more favourable labour market institutions are associated with lower unemployment rates.

In recent studies on unemployment and labour market institutions, another problem has emerged, that is the possibility that the evolution of the institutional setting in a particular country might be a result of the pattern of the unemployment rate in that country. Some labour market institutions might have been shaped by policies directed at alleviating the social problems caused by persistently high rates of

[2] Nickell et al. (2003) aim at explaining the actual behaviour of the observed unemployment rate and therefore include in their regression both non-stationary variables and mean reverting shocks. Inclusion of stationary variables in a cointegrating regression, however, can be problematic.

unemployment and thus might have been determined simultaneously to the unemployment rate. In this chapter, we explicitly take this possibility into account by employing estimation methods that allow for the endogeneity of the right hand side variables in the regression and thus correct for possible endogeneity biases on the coefficients.

The contribution of this work to the existing literature is therefore twofold: first, it contains a rigorous approach to the estimation of the long run relationship between labour market institutions and unemployment; second, it allows for endogenously determined labour market institutions.

This chapter is organised as follows: Section 3.2 describes the theoretical background and related literature, Section 3.3 briefly reviews the recent development in the econometrics of nonstationary panels. The empirical specification is contained in Section 3.4 while Section 3.5 reports the empirical results and Section 3.6 summarises the conclusions.

3.2 Motivation and related literature

3.2.1 Unemployment, institutions and shocks

Researchers believe that some labour market institutions – namely, the unemployment benefit system, trade unions and organised bargaining and labour taxes – may have the effect of increasing unemployment and they have incorporated these ideas in various theoretical models of equilibrium unemployment (see Layard et al., 1991, Mortensen and Pissarides, 1998). The two key features of unemployment benefit systems are the amount of benefit (benefit replacement ratio) and the length of time for which the benefit is available (benefit duration). Unemployment benefits can increase unemployment through two separate channels: by reducing the job search intensity of the unemployed and by raising the bargained wage. Figures 3.5 and 3.6

at the end of this chapter depict the behaviour of these two variables in our OECD sample.

In countries where wages are set as a result of collective agreements, the action of trade unions will tend to increase the wage pressure, and higher unemployment rates will be observed. The variable "union density" represents the proportion of workers who are members of a trade union: Figure 3.7 at the end of this chapter presents union density across the OECD countries. When unions and firms can coordinate their wage bargaining activity, however, they can achieve wage moderation and thereby reduce the negative impact of wage bargaining on unemployment.

Taxation on labour operates via the wedge between the real cost of a worker to an employer and the real consumption wage received by the worker: the tax wedge is thus the sum of payroll, income and consumption tax rates. An increase in the tax wedge will tend to raise the bargained wage and thus unemployment. The importance of the tax wedge in our sample is depicted in Figure 3.8.

Another important source of rigidity in the labour market is low labour mobility: Oswald (1997) suggested that one of the most significant barriers to labour mobility is home ownership and found that this is highly correlated with unemployment across countries.

Other labour market institutions can change the nature of unemployment, but have ambiguous effects on the equilibrium unemployment rate: this is the case of employment protection regulations governing hiring and firing. Employment protection will tend to reduce the rate at which workers are separated from their existing jobs (separation rate) and also the rate at which workers exit unemployment to start new jobs, since firms will be more cautious when hiring. Although this might lead to a reduction in short term unemployment and an increase in long term unemployment, the overall impact will be ambiguous.

It has become clear, however, that explanations based solely on institutions run into a major empirical problem: many institutions were already present in the 1960s when unemployment was low; moreover, since the 1970s, they have become more employment-friendly: thus while differences in labour market institutions can potentially explain cross country differences today, they do not seem to be able to explain the general evolution of unemployment over time. More realistically, it is believed (Nickell, 1997, Blanchard and Wolfers, 2000) that institutions shaped the way in which economies responded to the major macroeconomic shocks of the 1970s' and affected the persistence of unemployment in the following two decades, in response to those shocks.

Empirical investigations have attempted to quantify the effects of both macroeconomic shocks and labour market institutions on unemployment, often allowing for the possibility of interactions between these two effects. Empirical studies can thus be interpreted in the framework of a more general specification, as outlined, for example, in Blanchard (2000). In his comment to Fitoussi et al. (2000), Blanchard presents the following model of equilibrium unemployment:

$$u_{it} = \alpha(X_{it}) + \beta(X_{it})u_{it-1} + (S_{it}\gamma)\delta(X_{it}) + \varepsilon_{it}$$

where u_{it} is the unemployment rate in country i at time t, X_{it} indicates a set of labour market institutions, S_{it} indicates a set of macroeconomic shocks, α is a constant term. Both the degree of unemployment persistence – measured by the parameter β – and the the extent to which the unemployment rate responds to the contemporaneous shocks – measured by δ – can potentially be affected by labour market institutions in the general setting. This specification is used, for example, in Fitoussi et al. (2000), who attempt to capture the effect of institutions on the persistence of unemployment and the interaction of institutions with macroeconomic shocks. The authors estimate their equation in two steps: first they estimate a dynamic unemployment equation where the regressors consist of a series of measures of macroeconomic shocks, allowing for country specific fixed effects, country specific persistence parameters β on the lagged dependent variable and country specific sensitivity parameters δ. They then investigate the possibility that institutional structures across countries explain the differences in these parameters and find that labour market institutions explain around 50 percent of the variation. They conclude, therefore, that it might be the combination of labour demand shocks and institutions that cause the unemployment problem.

A similar approach was followed earlier by Phelps (1994): in the first stage, he estimated a pooled time series cross-section version of the above equation across 17 OECD countries for the period 1957-1989. The model did not include institutional variables in the first stage, but allowed country-specific variation in two sets of coefficients: the country constant terms and the coefficients that measure the sensitivity of unemployment to labour market conditions. At a second stage, the country-specific sensitivity coefficients were regressed on a set of time-invariant labour market institutions: unemployment benefit replacement ratio and benefit duration, an index of centralization of wage-bargaining and per-capita public expenditure on labour market programmes. Results show that shocks have least effect on unemployment in those countries where benefit duration and replacement ratio are lowest, where corporatism is low and where expenditure on labour market programmes is high.

Some other authors have studied the effects of institutions only: Nickell et al. (2003) study a specification with $\alpha(X_{it}) = \alpha$, $\beta(X_{it}) = \beta$, $S_{it}\gamma = I$ (where I is the identity matrix). These authors present fixed effect estimates of a dynamic unemployment equation and find that evolving labour market institutions explain around 55 percent of unemployment variation across the sample.

Finally, some authors allowed for interactions of shocks and institutions: in Blanchard and Wolfers (2000) the effect of a given shock on unemployment is allowed to depend on the set of labour market institutions in the country. In their model

$\beta(X_{it}) = 0$, that is, they estimate a static specification using five-year averages, rather that a dynamic specification with annual data. Three macroeconomic shocks are considered in their study: starting in the early 1970s, the large decrease in the rate of total factor productivity growth, the higher interest rates of the 1980s, and the adverse labour demand shifts that account for high unemployment in the 1990s. In their first specification, shocks are treated as unobservable, but are common across countries and the common time effects on unemployment are allowed to depend on the specific set of labour market institutions in the country. The model delivers plausible coefficients and does a good job in explaining the different evolution of unemployment rates across countries. Their results, however, deteriorate when time-varying measures of institutions instead of time-invariant measures are used. Next they build time series for the macroeconomic shocks and show that these cannot account for much of the heterogeneity of the unemployment evolution. They then allow both for shocks and for their interaction with institutions and find that the new specification provides a good explanation of the differences in unemployment evolutions across countries.

Bertola, Blau and Kahn (2001) use the same framework as Blanchard and Wolfers (2000) to explain trends in unemployment rates by the interaction of macroeconomic shocks and labour market institutions. One notable difference in their analysis is the inclusion of demographic variables, such as the proportion of young workers in the labour force. Their results, however, are sensitive to the specification used.

Elmeskov, Martin and Scarpetta (1998) aim at assessing the effectiveness of the recommendations from the OECD Jobs Study (1994). They use a panel dataset of OECD countries to estimate a (random effect) static model of structural unemployment. They use several measures of labour market institutions and allow for interactions between policy variables and institutional settings. They find evidence that different collective bargaining arrangements affect labour market outcomes and that unemployment benefits and strict employment-protection legislation lead to higher structural unemployment. The tax wedge is also significantly positive in the regressions. They find, however, that an important fraction of the estimated change in structural unemployment cannot be accounted for by changes in the explanatory variables included in their analysis.

Belot and van Ours (2000) are specifically interested in the existence of complementarities among labour market institutions, thus they investigate both the direct effects of institutions and the effects of interactions among them. Two institutions are defined complementary when, in a particular institutional framework, the effect of one of them is reinforced by the other. The authors present a theoretical model that illustrates the mechanisms through which institutions interact and influence unemployment. They then present an empirical investigation on the existence of complementarities based on annual data for eighteen OECD countries from 1960 to 1995. They present panel fixed-effect estimates of different models: first with institutions treated independently, then allowing for complementarity among sets of variables. They find that the model including complementarities among variables performs better that the one that excludes them.

3.2.2 Endogenous institutions

Empirical studies typically include a set of labour market institutional variables on the right hand side of a regression under the assumption that these variables are exogenous with respect to the unemployment rate. Several authors, however, acknowledged the possibility of endogeneity of the institutional setting, and claim that institutional differences could have arisen through policies directed at alleviating social problems caused by high levels of unemployment.

Blanchard and Katz (1997) express the view that hysteresis may come from the political response to unemployment: higher prolonged unemployment creates pressure for government policies to offer more generous programmes to help the unemployed. These programmes aim at decreasing the negative social effects of unemployment, but they are also likely to increase the natural rate in the process. Blanchard and Wolfers (2000) find that going from time invariant to time varying measures of institutions decreases the fit of their regressions and interpret this result as a possible sign of reverse causality. Elmeskov, Martin and Scarpetta (1998) carry out Granger causality tests from unemployment rates to benefit generosity and the tax wedge and find evidence of reverse causality. Bertola, Blau and Kahn (2001) acknowledge that some institutional differences (such as the high incidence of government employment or the generosity of the unemployment benefits) may be in part a response to high unemployment in some countries. Fitoussi (2003) admits there is a strong presumption that institutions are endogenous since "rising unemployment in Europe in a period during which stabilisation policies were aimed at disinflation and at maintaining monetary parities has led to structural activism to alleviate the pain of the unemployed". Nickell et al. (2003) acknowledge the problem but admit their inability to solve it in absence of suitable instruments.

Di Tella and MacCulloch (2002) provide an attempt at evaluating how much of the variation across countries in the generosity of their unemployment benefit programmes can be explained by economic and political factors. Their article probably constitutes the first published empirical work on the determinants of an unemployed worker's benefit allowance. They present a simple theoretical model in which workers desire insurance against unemployment but higher benefits require higher taxes and bring about higher unemployment. Using OECD data for 1971-1989 they then investigate to what extent economic and political variables affect the parameters of the unemployment benefit system. They first run Granger causality tests and find that it is as likely that causality runs from unemployment to benefits as it is that causality runs the opposite way. They then estimate a two-way fixed effect model where the level of unemployment benefits is a function of: the unemployment rate, inflow into unemployment, a political variable that measures how far the political preferences of the government lean toward the right and the long run interest rate to proxi for workers' discount rate. To control for endogeneity of the unemployment rate, they instrument it with the level of openness in the economy. Their conclusions, however, are ambiguous: on one hand, they find that economics matters much in the determination of unemployment benefits, even more than politics. On the other hand, the regression evidence shows that higher unemployment reduces the level of benefits with a lag. This casts doubt on the possibility of hysteresis through endogenous unemployment benefits.

Despite this result, it appears overall that the problem of endogenous institutions could potentially seriously affect the validity of existing empirical studies. In the present work, we allow for the possibility of endogenously determined institutions in our long run regression estimates: we achieve this goal by employing estimation methods (fully-modified and dynamic OLS estimators) that explicitly provide a correction for the bias introduced by the endogeneity of the regressors.

3.2.3 Time series properties

One important issue when trying to establish long run relationships among a set of economic variables relates to the order of integration of the series being investigated: the researcher seeks evidence of a long-run or cointegrating relationship among variables that are integrated of the same order. Thus the first step in any cointegrating analysis is the assessment of the order of integration of the series under study. The time series properties of the unemployment rate and the possibility that this series contains a unit root – and therefore is integrated of order one – have been investigated extensively in the literature. Various empirical studies exploit the time series properties in a cointegration framework: examples include Jacobson, Vredin and Warne (1997, 1998), Arestis and Biefang-Frisancho Mariscal (1998, 2000). Although a detailed survey is outside the scope of this chapter, it is important to mention some of the most recent studies: these tend to find evidence of the unemployment rate being characterized by a process that is stationary around a changing mean. Thus Papell, Murray and Ghiblawi (2000) test the hypothesis of a unit root in the postwar (1955-1997) unemployment series for 16 OECD countries . Allowing for multiple structural breaks, they are able to reject the null hypothesis of nonstationarity for ten of the sixteen countries. They conclude that the evidence is in favour of the structuralist theory of unemployment (Phelps, 1994), according to which most shocks cause temporary movements of unemployment around the natural rate, but occasional shocks cause permanent changes in the natural rate itself. Unemployment is thus found to be stationary around a process that is subject to structural breaks. Murray and Papell (2002) develop a panel unit root test in the presence of structural breaks and apply it to a data set of annual unemployment rates for 17 OECD countries from 1955 to 1990. The panel test with a one-time structural change indicates very strong evidence of regime-wise stationarity. Bianchi and Zoega (1998) use a Markov switching-regression model to identify the dating of the shifts in the mean rate of unemployment; they use quarterly observations for fifteen OECD countries during the period 1970-1996. They find that, once the changing means have been taken into account, the remaining persistence (measured by the sum of significant coefficients in an autoregressive process) is significantly smaller and always significantly less than one. They conclude that a considerable part of the unemployment persistence in many of the OECD countries can be attributed to infrequent shifts in mean unemployment.

The evidence discussed above suggests that the assumption of nonstationarity of the unemployment rate across OECD countries might not be entirely plausible. As a result, estimating a cointegrating regression with the unemployment rate as the dependent variable might not be the most appropriate option.[3] In this chapter, a different approach is taken: the dependent variable included in the cointegrating regression is (the logarithm of) total employment, for which the assumption of a unit root is more plausible. Figure 3.3 depicts our employment variable, that is the logarithm of the number of people who are in employment in each OECD country.

3.3 The methodology of nonstationary panels and its new developments

Over the past decade a number of important panel datasets covering different industries, regions and countries over relatively long time spans have become available: one example is the OECD dataset used in the analysis of the present and the next chapter. This consists of annual observations dated from the 1960s for 19 OECD countries (see Appendix C for details).[4]

With the growing use of cross-country data over time, the focus of panel data econometrics has shifted towards studying the asymptotics of macro panels with large N (number of countries) and large T (length of time series) rather than the usual asymptotics of micro panels with large N and small T.

Large N, large T panels have different characteristics and implications for theoretical and empirical analysis from the large N, small T panel data sets which have been the traditional object of study in panel data analysis. When T is large, there is an obvious need to consider serial correlation patterns in the panel more carefully, including any persistent components. In some panel data sets, the time series components have strong evident nonstationarity, a feature which received virtually no attention in traditional panel regression analysis.

With over 30 years of observations for each cross section series, a substantial

[3] This is the approach followed, for example, by Nickell et al. (2003).

[4] Another example is the Summers and Heston (1991) data set introduced in Part I.

time dimension is introduced. The potential presence of unit roots and cointegrating relationships in the data requires attention.

There are several reasons why a researcher might prefer a panel data approach to country-by-country time series analysis. One reason is the increased power of various tests: panel unit root and cointegration models combine methods of dealing with the nonstationary data from the time series and the increased data and power from the cross-section. The justification is that addition of the cross section dimension, under certain assumptions, can act as repeated draws from the same distribution. Thus as the time and cross section dimensions increase, panel test statistics and estimators can be derived which converge in distribution to normally distributed random variables.

Another reason for preferring a panel approach is that some economic theories suggest various economic relationships that might be valid across countries. In general, while there can exist time series cointegrating relations among the individual units of the panel, these relations will be heterogeneous, i.e. the individual cointegrating vectors will be different. For this reason, Pesaran and Smith (1995), in their study of panel cointegrating regressions, use an average of the cointegration coefficients from individual country regressions. A different approach was adopted by Phillips and Moon (1999). They defined the existence of a long-run *average* regression coefficient irrespective of the existence of individual cointegrating relations: this average relationship relies only on the long run average variance matrix of the panel. Precisely this common cointegrating relation may be suggested by an underlying economic theory. This is the approach followed also in the present chapter.

Several surveys on the recent developments in the theory of nonstationary panels are available, among them: Baltagi and Kao (2000), Banerjee (1999) and Phillips and Moon (2000). These recent studies mainly investigate the limiting properties of nonstationary panels, new unit root and cointegration tests and new methods for estimating cointegrating equations. The remainder of this section briefly discusses these topics: a more detailed description is contained in Appendix A.

One feature of panel datasets is that they are indexed both by their cross sectional units (individuals or firms, countries or regions) and by time. Let the cross sectional units be indexed by i (with $i = 1, ..., N$) and time by t ($t = 1, ..., T$). There are three possible approaches to limit theory: *(i)* sequential limits, where one index, say N, is fixed and the other is allowed to increase to infinity giving an intermediate limit: N is allowed to go to infinity subsequently; *(ii)* diagonal path limits: the two indexes, N and T are allowed to pass to infinity along a specific diagonal path in the two dimensional array; *(iii)* joint limit theory: allowing both N and T to pass to infinity simultaneously without placing specific path restrictions on the divergence. The last case is extensively investigated in Phillips and Moon (1999).

The new limit theory led to the development of new unit root tests for panel data. Initial theoretical work focused on testing for unit roots in univariate panels. Early examples include Quah (1994), who studied the unit root null in panels with homogeneous dynamics, and Levin and Lin (1992, 1993) who studied unit root tests in panels with heterogeneous dynamics, fixed effects and individual-specific deterministic trends. These tests take the autoregressive root to be common under both the unit root and the stationary alternative hypothesis. More recently, Im, Pesaran and Shin (2003) and Maddala and Wu (1999) suggested several panel unit root tests which also permit heterogeneity of the autoregressive root under the alternative hypothesis.

Many empirical questions involve multivariate relationships and the researcher might be interested in knowing whether a particular set of variables is cointegrated. Pedroni (1995) studied the properties of spurious regression and tests for the null of no cointegration in both homogenous and heterogeneous panels. For the case of heterogeneous panels, asymptotic distributions for the test statistics are appropriate for various cases with heterogeneous dynamics, endogenous regressors, fixed effects, and individual-specific deterministic trends. Tests are also appropriate both for the case with common autoregressive roots under the alternative hypothesis as well as tests that permit heterogeneity of the autoregressive root under the alternative hypothesis in the spirit of Im, Pesaran and Shin (2003).

As for traditional time series analysis, the theory of nonstationary panels also focused on the appropriate estimation technique for cointegrating regression models. In a classical linear regression among nonstationary time series variables (but with stationary errors) it is possible to define a long run regression coefficient between two variables Y and X in terms of the long run covariance matrix Ω of the stationary errors. In nonstationary panel regressions Phillips and Moon (1999) extend the concept to that of a long run *average* relation valid for the entire cross section. They allow for some heterogeneity across individuals i in the population, characterized by heterogeneous long-run variance matrices Ω_i. The Ω_i are assumed to be randomly drawn from a population whose mean is $\Omega = E\Omega_i$. Thus the panel regression coefficient corresponds to the average long run covariance matrix Ω.

Several methods have been suggested for the estimation of the coefficients of the cointegrating regression with panel data. The traditional "within" estimator is available: in the literature on nonstationary panels, this estimator is called "pooled OLS" estimator and this convention will be followed here.

It can be shown (Kao and Chiang, 2000, Phillips and Moon, 1999) that the pooled OLS estimator suffers from a bias due to the endogeneity of the regressors and the serial correlation in the time series component of the error term (a well known problem in traditional cointegration analysis). In the panel data setting, this bias is serious enough also to alter the rate of convergence of the estimator. To address the problem, more specialised estimation procedures have been suggested.

Apart from a bias-corrected OLS estimator based on a consistent estimate of the bias, a fully-modified OLS estimator (FMOLS) was also suggested (Phillips and Moon, 1999) as an extension of the time series estimator originally suggested by Phillips and Hansen (1990). In the FMOLS estimator the endogeneity correction is achieved by transforming the variable y_{it}, and a serial correlation correction is applied to the pooled OLS estimator. Phillips and Moon show, under certain assumptions, that this estimator is $\sqrt{N}T$ consistent and has a normal distribution.

Kao and Chiang (2000) also suggested a panel cointegration estimator: this is a panel version of the dynamic OLS estimator (DOLS) proposed for traditional time series models by Saikkonen (1991) and Stock and Watson (1993). In the DOLS estimator, the correction for endogeneity is achieved by adding leads and lags of the differenced regressors to the cointegrating equation. More precisely, the cointegrating equation is estimated including among the original regressors, together with a series of differenced leads and lags of the same regressors. Kao and Chiang (2000) showed that the DOLS estimator has the same limiting distribution of the FMOLS estimator and can outperform both the OLS and FMOLS estimator in finite samples.

Several applications of the new methodology can be found in the recent empirical literature. McCoskey and Kao (1999) investigate the importance of urbanization as a factor of production in a cointegrating framework. Kao, Chiang and Chen (1999) re-estimate Coe and Helpman's (1995) regressions investigating spillover effects from foreign R&D to domestic Total Factor Productivity (TFP) and find that this effect is not significant when the regressions are estimated by DOLS. Mark and Sul (2002) estimate the coefficients of the long run money demand function for a panel of 19 countries, while Pedroni (2001) investigates the validity of the strong version of the purchasing power parity hypothesis.

3.4 Empirical specification

Although there exist numerous research studies that focus on the effects of labour market institutions on unemployment, we are not aware of any study that systematically investigates the long run relationship between unemployment and institutions: this is the main focus of this chapter.

A study that closely relates to the present chapter is the article by Nickell et al. (2003), who estimate a dynamic reduced form model of unemployment by fixed-effect and then perform a residual-based test for cointegration to assess the existence of a long run equilibrium relationship. There are, however, some difficulties in their approach. First, results on unit root tests are not reported and both stationary and integrated variables are included in the regression. In the present chapter, the time series properties under analysis are rigorously investigated using recently developed econometric methods for non stationary panel data sets. Another difficulty with the analysis of Nickell et al. is that fixed-effect (pooled OLS) estimation suffers from significant biases: these are so severe in a panel data setting that they can modify the rate of convergence of the estimator. The results of two alternative estimation methods are presented in this chapter: these are the fully-modified OLS method by Phillips and Moon (1999) and the dynamic OLS method suggested by Kao and Chiang (2000). As mentioned in the previous section, it is particularly important to correct for possible finite sample biases of the pooled OLS (fixed-effect) estimator, biases that are due to autocorrelated residuals and endogeneity of the regressors. The last problem seems to be especially important in the present context, as made clear in the discussion on the possible endogeneity of the labour market institutions in Section 3.2.2.

In this chapter, we estimate a long run equilibrium equation for employment as a reduced form cointegrating regression. More specifically, the following cointegrating equation is estimated:[5]

$$\ln E_{it} = \beta_0 + \beta_1 \ln L_{it} + \Gamma' X_{it} + \varepsilon_{it} \tag{3.1}$$

where E_{it} is total employment, L_{it} is the labour force and X_{it} contains the labour market institutional variables: the benefit replacement ratio (*brr*), benefit duration (*bd*), union density (*union*), bargaining coordination (*coord*) and the tax wedge (*tax*). Interactions between labour market institutions are also allowed, more precisely between coordination and unionisation ($coord * union$) and coordination and the tax wedge ($coord * tax$).[6] Finally, the proportion of owned occupied household (*owner occupied*) is also included. In summary, $X =$ (*brr*, *bd*, *union*, *coord*, *tax*, $coord * union$, $coord * tax$, *owner occupied*).[7]

In the long run, employment is proportional to the labour force, thus the coefficient of the labour force variable should be one:

$$H_0 : \beta_1 = 1 \tag{3.2}$$

Imposing this restriction to (3.1) gives the long run equilibrium equation:

$$l - e \simeq u = \gamma_0 - \Gamma' X \tag{3.3}$$

where $l \equiv \ln L$, $e \equiv \ln E$ so that the left hand side variable is the (level of the) unemployment rate.[8] Equation (3.3) thus describes a long run equilibrium relation between the unemployment rate and labour market institutional variables.

A similar equation is derived from a theory of equilibrium unemployment, for

[5] Equation (3.1) is a reduced form equation in the sense that it expresses the endogenous variable in terms of exogenous variables only, thus all the endogenous variables have been substituted out.

[6] The variables in the interaction terms are expressed as deviations from the sample means.

[7] We experimented with the inclusion of measures of employment protection, but these were not found significant in any of the regressions, and were thus omitted.

[8] If L is the labour force and E is employment, the unemployment rate is defined as $u = \frac{L-E}{L} = 1 - \frac{E}{L}$. Now write $\frac{E}{L} = 1 - u$. Taking logs: $\ln E - \ln L = \ln(1-u) \simeq -u$.

example, in Layard et al. (1991). They present a macroeconomic model of the labour market with price-setting firms and non-competitive wage determination. In their model, there are many identical firms, each possessing some degree of market power, which, in order to maximise profit, set prices as mark-up over expected wage costs. Wages are influenced by firm-specific or "insider" factors, such as productivity and the interests of the existing workforce, and by "outsider" factors, such as wages paid elsewhere and the state of the labour market. Outside factors include, in particular, the generosity an coverage of unemployment benefits, the degree of union power and the wedge between product wages and consumption wages. Long run equilibrium is defined as a situation where exogenous factors are kept fixed and expectations are fulfilled. Solving for the equilibrium level of unemployment and real wages gives a reduced form equation of the type of (3.3), where the equilibrium level of unemployment depends only on exogenous wage pressure variables.

The main difference between equation (3.3) and that estimated by Nickell et al. (2003) is that, together with labour market institutional variables, they include mean reverting shocks in their regression in an attempt to explain current variations in the unemployment rate.

Before proceeding further, it is worth mentioning that if the labour market institutions were indeed endogenous, as discussed in Section 3.2.2, equation (3.3) would not represent a reduced form anymore. Separate equations for each endogenous institution, of the sort of those estimated by Di Tella and MacCulloch (2002), should be included in the model. Estimation of the model would be possible if each equation was identified, that is, if each equation in the model contained at least one variable not included in the other equations. The methods used in this chapter to allow for endogeneity in the labour market institutions provides a correction in case the researcher is unaware of the problem, and does not represent an attempt to estimating a full model.

To test the hypothesis that (3.1) represents a long run equilibrium relationship, we first examine the time series properties of the variables to establish whether they are all accurately represented by *I(1)* processes. We then test for cointegration among the variables included in equation (3.1) and finally estimate this cointegrating equation and proceed to test hypothesis (3.2).[9]

3.5 Empirical results

In our empirical investigation we use annual data for 19 OECD countries for the period 1960 to 1995. The countries are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, the United Kingdom and the United States. A detailed description of the data is contained in Appendix C.

Im, Pesaran and Shin's (IPS, 2003) tests for unit root were performed to investigate the time series properties of the variables in the model, namely (log) employment and (log) labour force. The results are presented in Table 3.3 at the end of this chapter. Since Im, Pesaran and Shin (2003) do not suggest a procedure for the choice of lags to include in the regressions, we experimented with different lag structures: we report the results of the test with 1 to 4 lags. Moreover, there does not appear to be a clear procedure to choose whether or not to include country specific time trends in the tests. Therefore we performed the tests with and without individual time trends: both cases are reported in Table 3.3. The results do not appear to be particularly sensitive to the specification chosen: the null hypothesis of a unit root in the panel cannot be rejected at conventional significance levels: this result is consistent across specifications for both the series. We thus conclude that the series (log) employment and (log) labour force are integrated of order one. And since the

[9] All computations were performed in GAUSS using Chiang and Kao's (2002) NPT 1.3 routines. All errors are solely the author's responsibility.

log-differences are stationary, the growth rates of these series are stationary.[10]

The labour market institutional variables were also tested for unit roots: tests on the benefit replacement ratio, benefit duration, union density, bargaining coordination, tax wedge and the proportion of owned occupied household are also reported in Table 3.3. There is evidence in favour of the null hypothesis of a unit root in all cases, except for the benefit replacement ratio: in this case, when a country-specific time trend was included, the null hypothesis could be rejected in three of the four lag specifications. When the time trend was not included, however, evidence on the presence of a unit root was strong.[11] Finally, the interaction terms were tested and results are again reported in Table 3.3. Also in this case there was strong evidence that the null hypothesis of a unit root could not be rejected.

The presence of a unit root creates a conceptual difficulty when dealing with the labour market institutional variables, for these series are bounded by construction. However, since it is not possible to determine the exact structure of the underlying data-generating mechanism with a finite sample, the evidence for a unit root should be considered as an approximation.[12]

Of the institutions presented in Figures 3.5-3.8, only benefit duration clearly appears to be subject to shifts, whereas the other graphs appear smoother and there seem to be enough countries in which the behaviour appears genuinely nonstationary, to drive the IPS tests. However, as mentioned above, these quantities are bounded and thus this should be considered an approximation.[13]

To rule out the possibility that the variables follow an *I(2)* process, we performed

[10] As an alternative to labour force, one could use working age population. An IPS test showed this series is also integrated of order one.

[11] In comparative studies, the power of the IPS test was shown to deteriorate rapidly when individual time trends are included (see e.g. Baltagi and Kao, 2000). Results of the tests including time trends should therefore be interpreted with caution.

[12] See, for example, Mocan (1999).

[13] A panel unit root tests to allow for structural breaks was proposed by Murray and Papell (2002) and carried out on a sample of unemployment rates data for OECD countries. A similar test could be carried out in this setting.

panel unit root tests on the series in first differences: the results are reported in Table 3.4 at the end of this chapter. With the exception of the owner occupancy rate, we were able to reject the null hypothesis of nonstationarity for all the variables:[14] it was therefore concluded that the variables under analysis are well characterized by an *I(1)* process.

Given the evidence on the order of integration of the variables under analysis, it is appropriate to proceed with the investigation into the existence of a cointegrating relationship among the variables. For this purpose, we performed various types of cointegration tests for panel data. The tests are based on the residuals of a homogeneous OLS cointegrating regression of (log) employment on (log) labour force and a set of labour market institutional variables, as described by equation (3.1).

Table 3.1: Panel cointegration test results

DF_ρ	DF_t	DF^*_ρ	DF^*_t	ADF	PC_1	PC_2
-4.1714	-2.5460	-11.2933	-3.5851	-5.6076	-25.0228	-24.6728
(0.000)	(0.005)	(0.000)	(0.001)	(0.000)	(0.000)	(0.000)

Note. In all tests, H_0: no cointegration. The critical probabilites are reported in parenthesis. Cointegration test statistics are calculated through the residuals from the OLS estimation. The ADF test includes one lag; the number of lags was chosen according to the SIC and AIC.

Kao's (1999) DF- and ADF- type cointegration test results are reported in the first two columns of Table 3.1. The DF_ρ and DF_t tests, designed for testing for cointegration in presence of exogenous regressors, strongly reject the null hypothesis of no cointegration. As discussed in Section 3.2.2, however, labour market institutions might arise as a result of high levels of unemployment, thus the hypothesis of exogenous regressors might be inappropriate in the present setting. For this reason,

[14] The data on the proportion of owned occupied households are provided by Oswald (1997). Since the information is available for four periods only, the series were heavily interpolated (Nickell et al., 2003). This is likely to create distortions when testing for unit roots on the differenced series: this test is therefore not reported here. The stationarity of the differenced series is, however, a plausible assumption.

two other tests were performed: Kao's (1999) DF_ρ^* and DF_t^* tests are designed to allow for endogeneity of the right hand side variables in the cointegrating relationship. The results of these two tests are also reported in Table 3.1: again, the null hypothesis of no cointegration is strongly rejected. Kao's ADF test is reported in the fifth column of the Table 3.1: again the null hypothesis of no cointegration is strongly rejected. Furthermore, we performed the two tests suggested by Pedroni (1995): these are reported in the two right-most columns of the Table 3.1. Again the null of no cointegration is strongly rejected. Overall, there appears to be strong evidence in favour of the existence of a stationary linear combination among the variables under analysis: the relationship expressed in equation (3.1) can be interpreted as a cointegrating equation, where coefficient reflect a long run equilibrium among the variables. Coefficient estimates of the cointegrating equation (3.1) are reported in Table 3.2.

The three different estimation methods described in section 3.3 were implemented. Since pooled (within) OLS suffers from second order biases that can be potentially very severe in panel data settings, the first column reports the bias-corrected pooled OLS coefficients and standard errors.

The coefficient on the labour force is very close to one, although the null hypothesis (3.2) is rejected at conventional significance levels. Neither the benefit replacement ratio nor the benefit duration are significantly different from zero at conventional levels. The coefficients on union density and tax wedge have the expected negative sign and are significantly different from zero. The presence of coordination in the bargaining process is expected to offset the negative impact of unionisation: this is confirmed in our regression, where the coefficient of the coordination variable is significantly positive.[15] Finally, the coefficient on the proxi for labour mobility (owner occupancy) has a significantly negative impact on employment, as expected.

[15] Note, however, the negative impact of the interaction between union density and coordination.

Table 3.2: Estimated cointegrating equation for employment

dependent variable $\ln E_{it}$	(1)	(2)	(3)
$\ln L_{it}$	0.9451	1.0013	0.9960
	(57.198)	(58.915)	(69.771)
brr_{it}	-1.3987	-6.4395	-12.4856
	(-0.730)	(-3.268)	(-3.944)
bd_{it}	-0.5496	2.268	-0.6107
	(-0.672)	(2.701)	(2.917)
$union_{it}$	-5.5525	1.8019	-3.2984
	(-2.161)	(0.682)	(0.116)
$coord_{it}$	1.0343	1.4168	1.8479
	(2.985)	(3.976)	(3.868)
$(coord * union)_{it}$	-22.119	-21.6578	-22.4116
	(-4.818)	(-4.586)	(0.773)
tax_{it}	-6.4149	-8.8278	-4.2942
	(-3.294)	(-4.408)	(-8.751)
$(coord * tax)_{it}$	2.2219	33.4231	8.5213
	(0.536)	(7.847)	(3.859)
$owner\ occupied_{it}$	-8.0616	-14.058	-6.8615
	(-1.327)	(-2.251)	(-5.652)
N	19	19	19
NT	684	684	684
country effects	✓	✓	✓
country specific trends	✓	✓	✓
R^2	0.9784	0.9741	0.9946

Note. (1) is bias-corrected OLS, (2) is FMOLS, (3) is DOLS. All estimations include unreported country-specific constants and individual time trends. The conventional t-statistics are reported in parentheses.

Column (2) of Table 3.2 reports the results from the estimation of the cointegrating regression using the FMOLS estimator suggested by Phillips and Moon (1999) and described in more detail in Appendix A.

Here the coefficient of the labour force is not significantly different from one,[16] thus the regression coefficients can be also interpreted as marginal effects of labour market institutions on the unemployment rate (with opposite sign).[17] In this regres-

[16]The t-statistics for testing the null hypothesis (3.2) is -0.0765.

[17]In the three regression, the coefficients have been rescaled to represent percentage effects on the unemployment rate.

sion, the benefit replacement ratio appears to have a significantly negative impact on employment (positive on unemployment). The benefit duration, however, has a positive and significant effect on employment, in contrast with expectations. The coefficient on union density has no significant impact, whereas the coefficient of bargaining coordination has the expected sign and is significant. The tax wedge and home ownership variables also have the expected sign and have a significant impact.[18]

Column (3) of Table 3.2 contains the coefficient estimates obtained from the DOLS method of Kao and Chiang (2000). Again, the coefficient on the labour force is not significantly different from one,[19] thus the regression coefficients are the effects of labour market institutions on the unemployment rate (with opposite sign).

As expected, the coefficient of the benefit replacement ratio is significantly negative and has a much larger magnitude than in the previous two regressions. The benefit duration coefficient has the expected negative sign and is significant. Union density does not appear to have any significant effect on its own[20] nor when interacted with the coordination index. One possible explanation for these results is the fact that union density does not represent entirely the importance of trade unions in the bargaining process. In Spain, for example, just above 10% of workers are union members, but over 70% of workers receive a wage that is fixed by union bargaining. Thus a better measure of union coverage might deliver a different message.

The extent to which bargaining is coordinated seems to have a positive effect on employment. The tax wedge has the expected negative (and significant) effect on employment but is modified by the interaction with the coordination index.

Finally, we find again the expected negative effect of owner home occupancy on

[18]Note, however, the positive effect of the interaction between tax and coordination.

[19]The t-statistics for the test of hypothesis (3.2) is 0.280.

[20]Nickell et al. (2003) include the first difference of union density in their regression and find a significant and positive effect on the unemployment rate. The first difference of this variable, however, is integrated of order zero, thus we prefered to include the variable in levels.

employment: reduced labour mobility is associated with higher levels of unemployment.

Thus it appears that the reduced form unemployment rate in equation (3.3) is supported by the empirical evidence: labour market institutions affect the long run equilibrium rate of unemployment. The three estimation methods, however, deliver somewhat different results and caution is needed when interpreting the results. How can we choose between columns 2 and 3 in Table 3.2?

It has been shown that DOLS outperforms FMOLS in small samples so the choice could be made on this basis. More precisely, Montecarlo simulation performed in Kao and Chiang (2000) showed that the DOLS method outperforms both pooled OLS and FMOLS and the authors pointed out that the FM estimator could be inferior to the OLS in some cases. This could explain why in our regressions the coefficients of the FMOLS estimation are quite different in magnitude and sign from the pooled OLS and the DOLS estimations. How do these two methods compare? In Section 3.2.2 we raised the possibility that the pooled OLS might be biased due to endogeneity of the regressors: estimation by DOLS should instead correct for any endogeneity bias. This suggests therefore that a large discrepancy between the results from these two estimation methods might be an indication of endogeneity of the regressors. From the results reported in Table 3.2 it appears that the coefficients have comparable magnitude, with the exception of the benefit replacement ratio, where the OLS estimate is much smaller than the DOLS estimate. The direction of the bias, however, does not have an intuitive interpretation: if the benefit replacement ratio was positively increased by unemployment, we would expect its effect to be overestimated by OLS. Thus the results of this chapter show that endogeneity of labor market institutions is not likely to constitute a serious problem in empirical studies.

3.6 Conclusions

Our aim in this chapter was to establish the existence of a long run equilibrium relationship between the unemployment rate and a set of labour market institutional variables. This type of empirical analysis was motivated by a series of theoretical models that derive equilibrium unemployment in terms of labour market institutions. We followed the traditional cointegration approach to investigating long run equilibrium relationships, but employed newly developed techniques for nonstationary panel data. We performed panel unit root tests on the variables in our empirical models and we found that they are correctly characterised by integrated processes of order one. We then tested for cointegration among the unemployment rate and a set of labour market institutional variables. We found that the variables are cointegrated, thus there appears to be a long run equilibrium where the unemployment rate is determined by labour market institutions.

We estimated the coefficients of the cointegrating relationship with new estimation methods that allow for endogeneity of the regressors and correct for the presence of serial correlation in the error term. We found that the unemployment rate is higher when the benefit system is more generous, when the tax wedge is more pronounced and when labour is less mobile. Unionisation does not appear to have a consistent effect in our regressions, but coordination of wage bargaining seems to reduce the unemployment rate, both on its own and when interacted with the tax system.

Several extensions are possible. The cointegration approach followed in this chapter is a panel version of the Engle and Granger (1987) residual-based two step procedure: one cointegrating vector is estimated by linear regression and panel unit root tests are conducted on the residuals. This procedure implies homogeneous long run coefficients and the adjustment parameters. An alternative approach in which some or all the model parameters are assumed to be heterogeneous could be explored.

The existence of more than one cointegrating relationship could also be explored: we are not aware of any testing procedure designed to establish the number of homogeneous cointegrating vectors in a panel, although some authors have developed tests that combine information on the individual cointegrating rank to test for a common cointegrating rank in the panel: see e.g. Groen and Kleibergen (1999) and Larsson and Lyhagen (2000).

Table 3.3: Panel Unit Root Tests in levels: IPS t-bar test results

(1) Without trend				
lag	$\ln E_{it}$	$\ln L_{it}$	brr_{it}	bd_{it}
1	2.557	3.038	0.259	0.791
	(0.995)	(0.999)	(0.602)	(0.785)
2	2.592	2.543	1.407	1.654
	(0.995)	(0.994)	(0.920)	(0.951)
3	2.576	2.921	-0.979	1.836
	(0.995)	(0.998)	(0.164)	(0.967)
4	2.316	2.130	1.529	1.746
	(0.990)	(0.983)	(0.937)	(0.960)
(2) With trend				
lag	$\ln E_{it}$	$\ln L_{it}$	brr_{it}	bd_{it}
1	2.042	4.414	-1.725	0.178
	(0.979)	(1.000)	(0.042)	(0.042)
2	2.336	3.962	1.592	2.274
	(0.990)	(1.000)	(0.944)	(0.989)
3	2.490	3.617	-3.763	1.200
	(0.994)	(1.000)	(0.000)	(0.885)
4	3.348	3.618	-1.576	2.150
	(1.000)	(1.000)	(0.058)	(0.984)

Table 3.3: (continued)

(1) Without trend			
lag	$union_{it}$	$coord_{it}$	tax_{it}
1	3.187	0.986	-0.080
	(0.999)	(0.838)	(0.468)
2	2.888	1.120	-0.389
	(0.998)	(0.869)	(0.349)
3	2.873	1.478	-0.281
	(0.998)	(0.930)	(0.390)
4	2.410	1.903	-0.356
	(0.992)	(0.971)	(0.361)
(2) With trend			
lag	$union_{it}$	$coord_{it}$	tax_{it}
1	3.860	0.100	1.554
	(1.000)	(0.540)	(0.940)
2	3.067	-0.029	1.316
	(0.999)	(0.488)	(0.906)
3	3.313	0.453	0.779
	(1.000)	(0.675)	(0.782)
4	2.866	0.898	0.373
	(0.998)	(0.815)	(0.645)

Table 3.3: (continued)

lag	$(coord * union)_{it}$	$(coord * tax)_{it}$	$owner\ occupied_{it}$
(1) Without trend			
1	0.667	0.538	-0.985
	(0.748)	(0.705)	(0.162)
2	1.648	0.630	-1.149
	(0.950)	(0.736)	(0.125)
3	0.779	0.859	-1.111
	(0.782)	(0.805)	(0.133)
4	1.142	1.215	-1.236
	(0.873)	(0.888)	(0.108)
(2) With trend			
lag	$(coord * union)_{it}$	$(coord * tax)_{it}$	$owner\ occupied_{it}$
1	1.807	4.800	-0.186
	(0.965)	(1.000)	(0.426)
2	2.717	4.707	-0.714
	(0.997)	(1.000)	(0.238)
3	1.201	4.859	-0.981
	(0.885)	(1.000)	0.163
4	0.869	5.545	-1.580
	(0.808)	(1.000)	(0.057)

Notes. H_0 : unit root. The normalized IPS t-bar statistic has a N(0,1) distribution. The critical probabilities are reported in parentheses.

Table 3.4: Panel Unit Root Tests in differences: IPS t-bar test results

(1) Without trend			
lag	$\Delta \ln E_{it}$	$\Delta \ln L_{it}$	Δbrr_{it}
1	-8.346	-8.168	-12.624
	(0.000)	(0.000)	(0.000)
2	-6.749	-6.513	-6.188
	(0.000)	(0.000)	(0.000)
3	-6.267	-5.273	-7.307
	(0.000)	(0.000)	(0.000)
4	-4.235	-4.269	-7.328
	(0.000)	(0.000)	(0.000)
(2) With trend			
lag	$\Delta \ln E_{it}$	$\Delta \ln L_{it}$	Δbrr_{it}
1	-6.115	-6.668	-10.772
	(0.000)	(0.000)	(0.000)
2	-4.647	-5.198	-4.084
	(0.000)	(0.000)	(0.000)
3	-4.364	-4.113	-4.684
	(0.000)	(0.000)	(0.000)
4	-2.202	-2.822	-4.245
	(0.000)	(0.000)	(0.000)

Table 3.4: (continued)

(1) Without trend			
lag	Δbd_{it}	$\Delta union_{it}$	$\Delta coord_{it}$
1	-12.133	-8.598	-1.969
	(0.000)	(0.000)	(0.024)
2	-8.373	-7.034	-2.634
	(0.000)	(0.000)	(0.004)
3	-8.361	-5.821	-3.201
	(0.000)	(0.000)	(0.001)
4	-6.383	-5.647	-4.424
	(0.000)	(0.000)	(0.000)
(2) With trend			
lag	Δbd_{it}	$\Delta union_{it}$	$\Delta coord_{it}$
1	-10.351	-6.909	0.920
	(0.000)	(0.000)	(0.821)
2	-6.194	-5.528	0.282
	(0.000)	(0.000)	(0.611)
3	-6.470	-4.117	-0.465
	(0.000)	(0.000)	(0.321)
4	-4.487	-4.335	-2.151
	(0.000)	(0.000)	(0.016)

Table 3.4: (continued)

(1) Without trend			
lag	Δtax_{it}	$\Delta(coord * union)_{it}$	$\Delta(coord * tax)_{it}$
1	-10.450	-5.930	-4.727
	(0.000)	(0.000)	(0.000)
2	-7.957	-4.788	-4.124
	(0.000)	(0.000)	(0.000)
3	-6.257	-4.144	-4.828
	(0.000)	(0.000)	(0.000)
4	-5.711	-5.726	-3.413
	(0.000)	(0.000)	(0.000)
(2) With trend			
lag	Δtax_{it}	$\Delta(coord * union)_{it}$	$\Delta(coord * tax)_{it}$
1	-10.957	-3.957	-3.530
	(0.000)	(0.000)	(0.000)
2	-8.187	-2.867	-3.042
	(0.000)	(0.000)	(0.001)
3	-6.017	-2.143	-4.258
	(0.000)	(0.016)	(0.000)
4	-5.226	-3.970	-3.041
	(0.000)	(0.000)	(0.001)

Notes. H_0 : unit root. The normalized IPS t-bar statistic has a N(0,1) distribution. The critical probabilities are reported in parentheses.

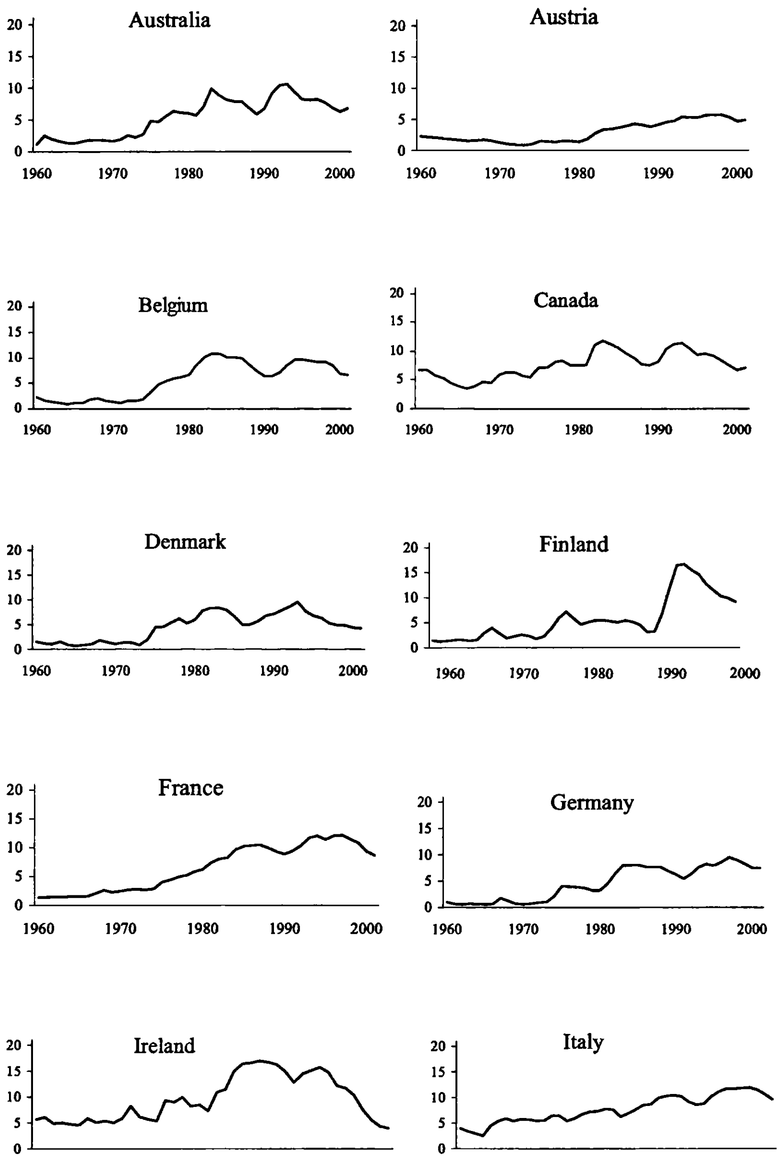

Figure 3.1: Unemployment rates (%) across OECD countries

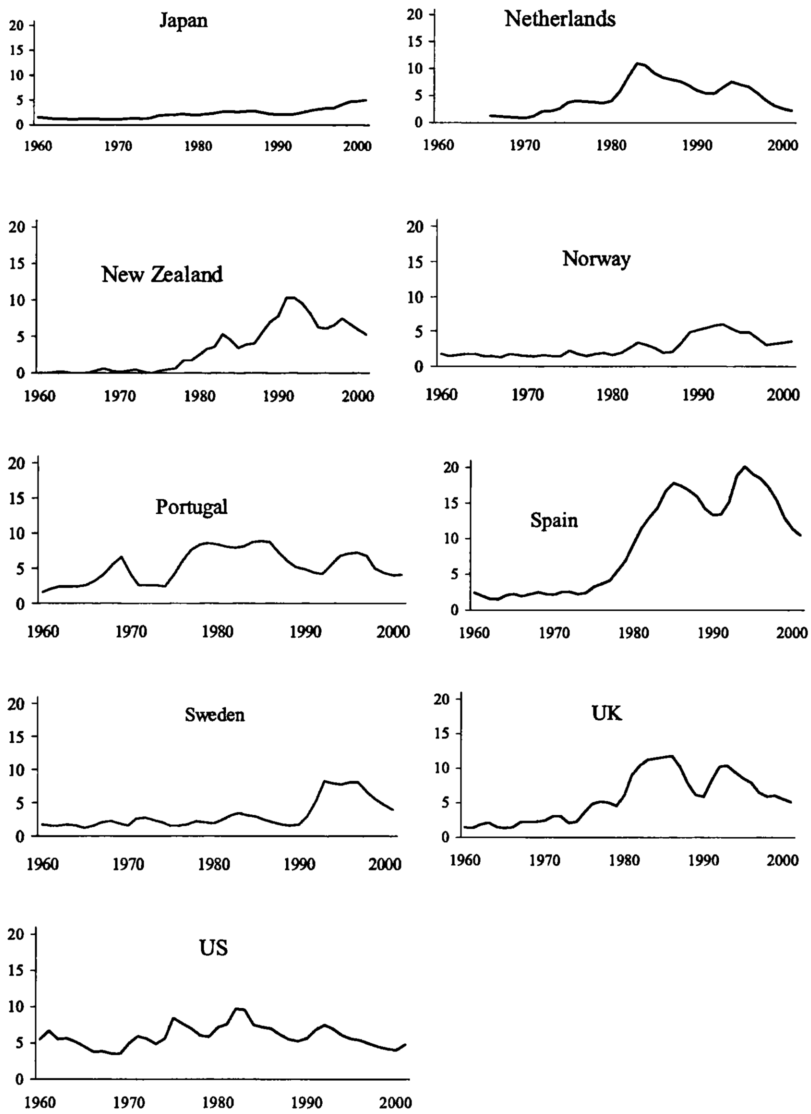

Figure 3.2: Unemployment rates (%) across OECD countries (cont.)

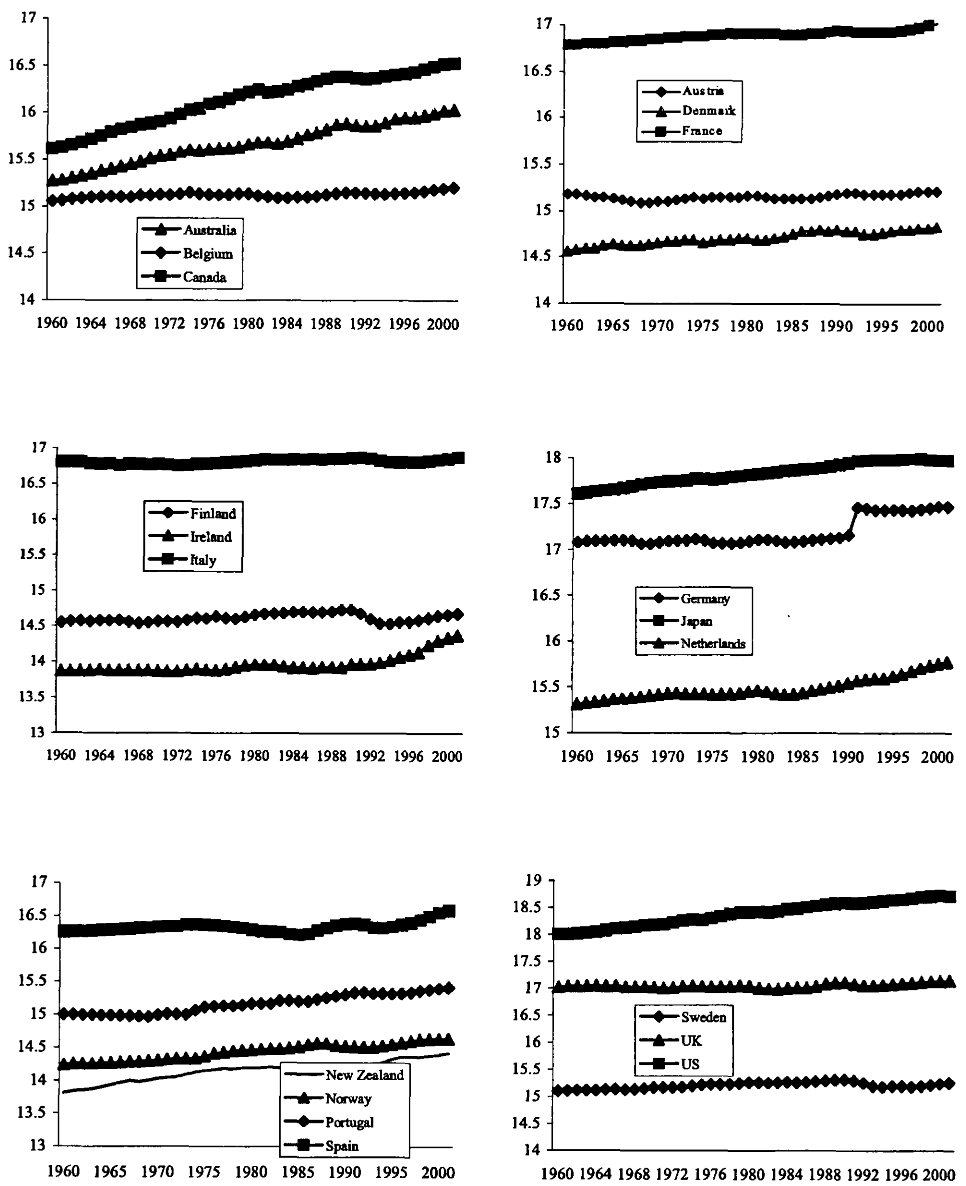

Figure 3.3: Employment across OECD countries (logarithms)

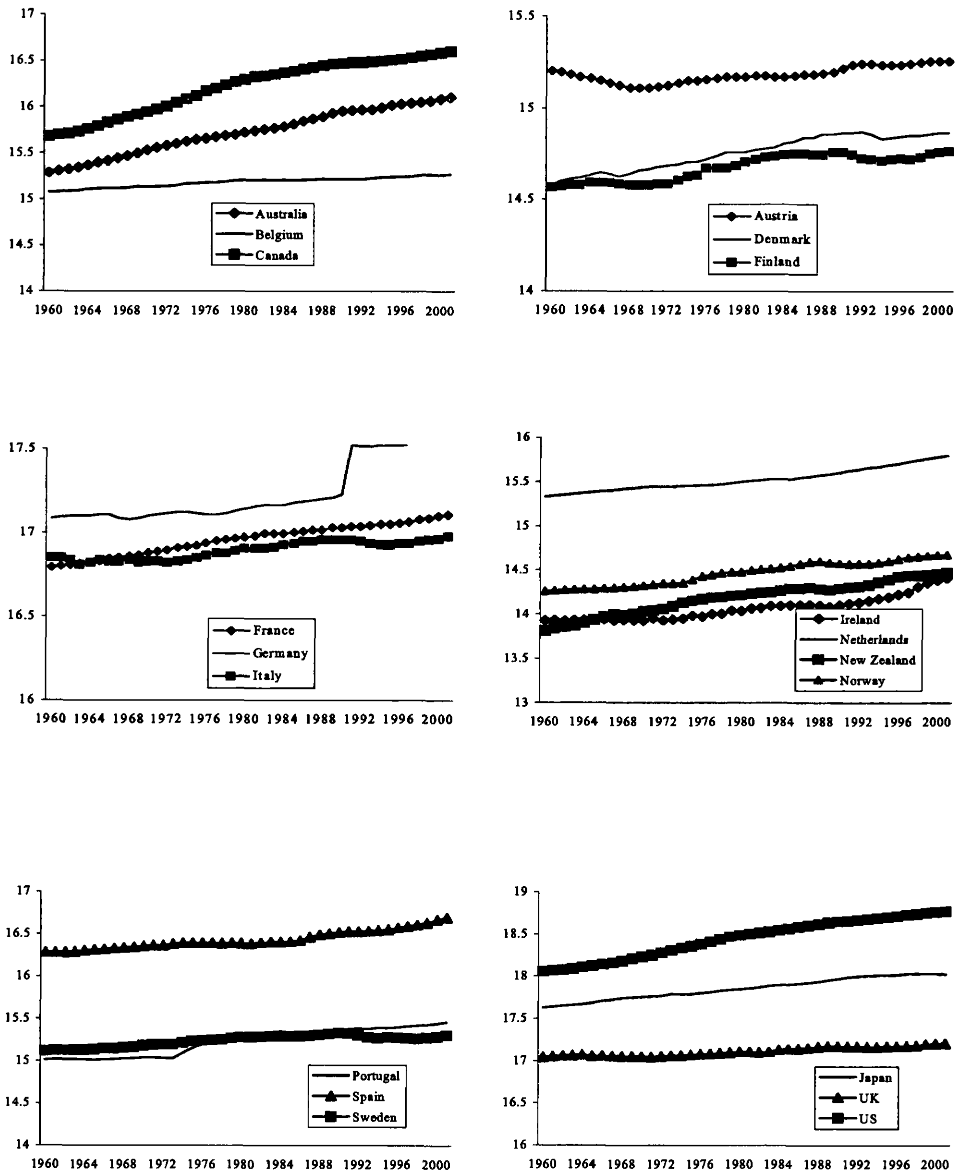

Figure 3.4: Labour force across OECD countries (logarithms)

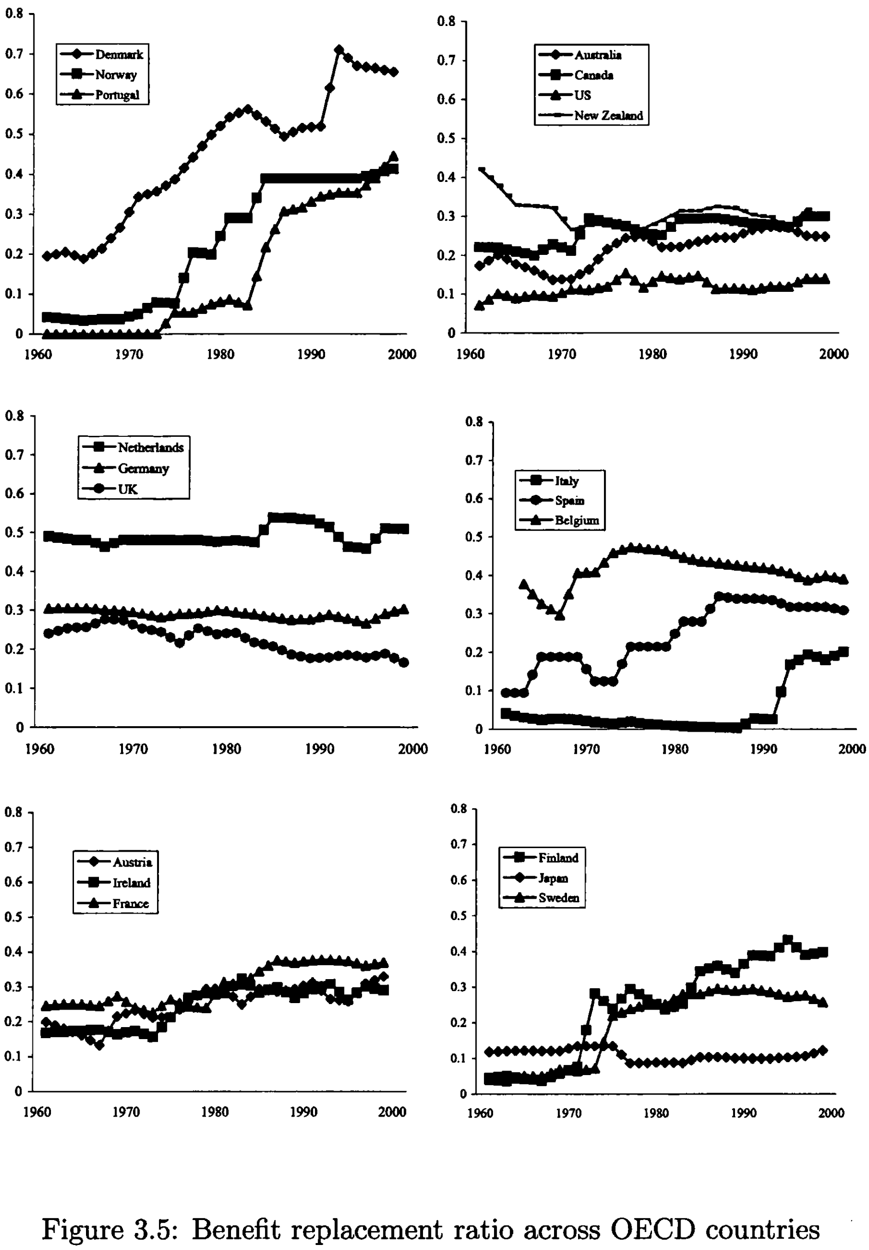

Figure 3.5: Benefit replacement ratio across OECD countries

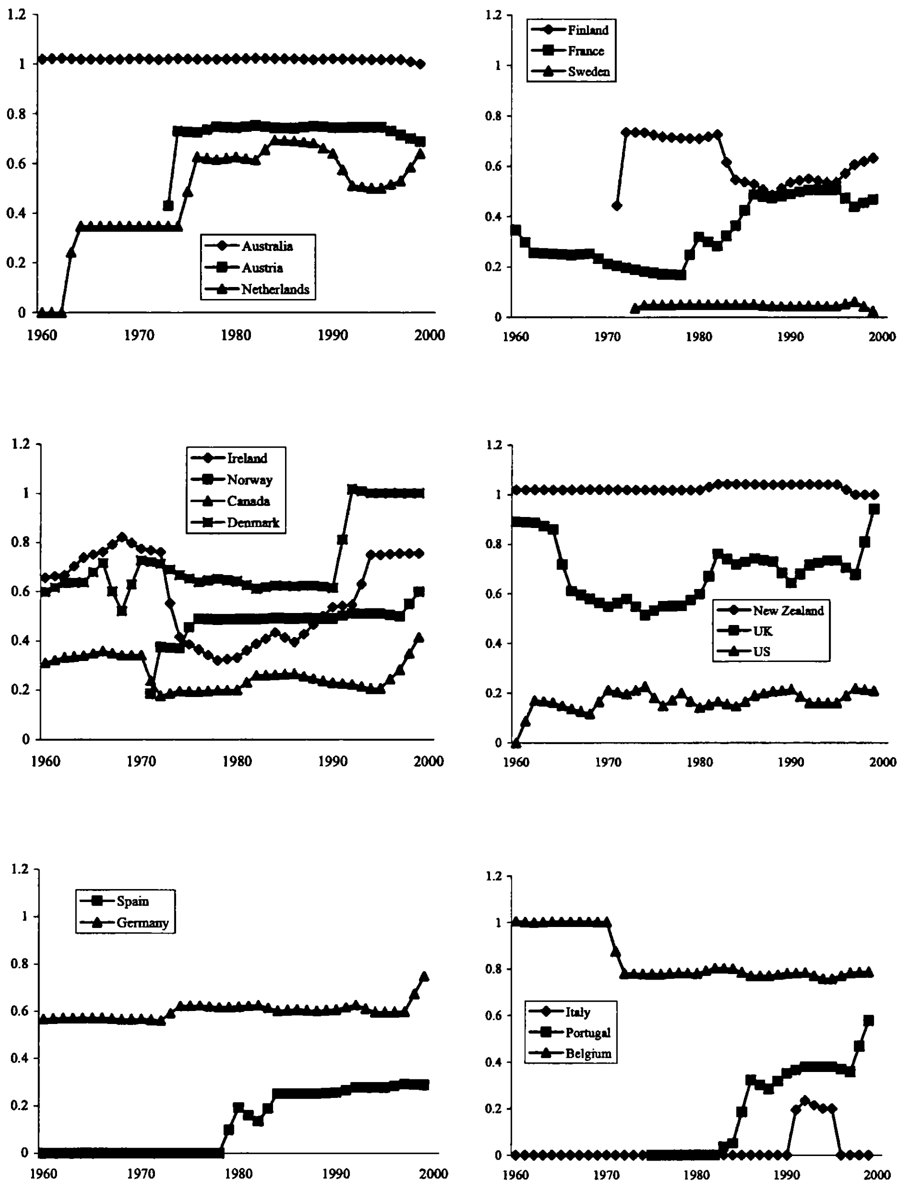

Figure 3.6: Benefit duration across OECD countries

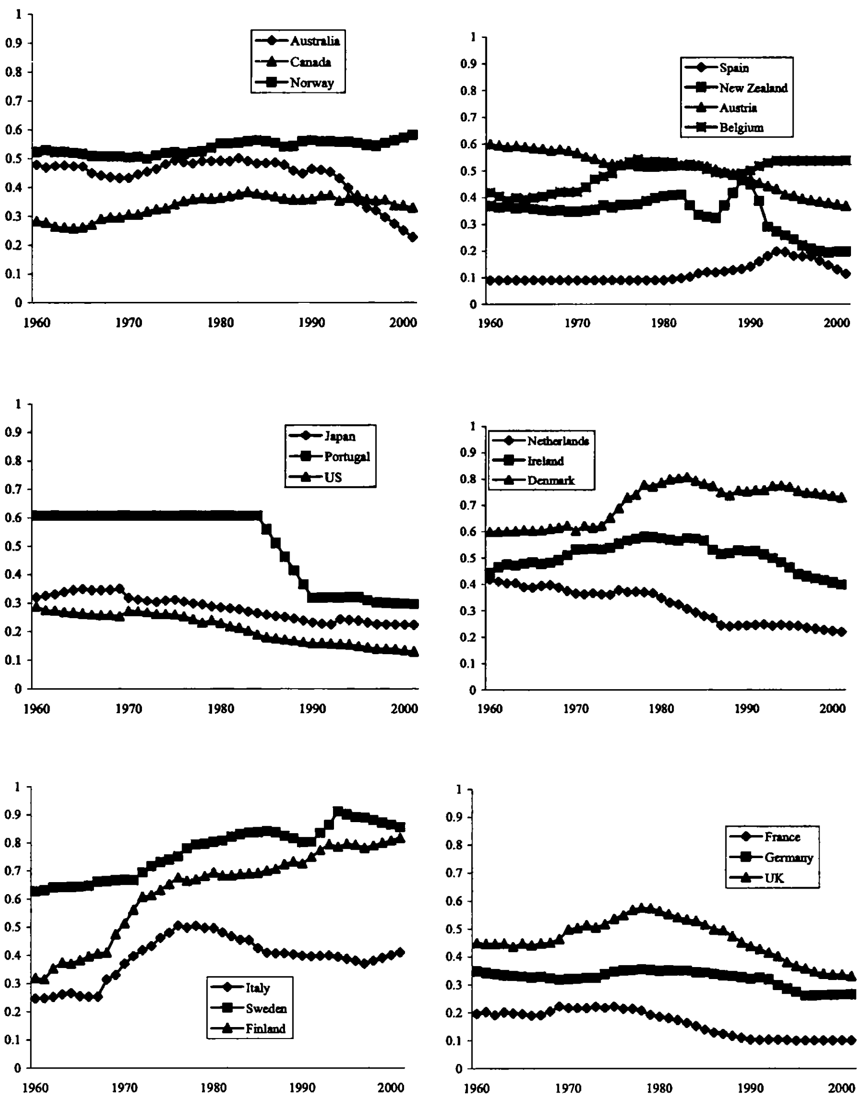

Figure 3.7: Union density across OECD countries

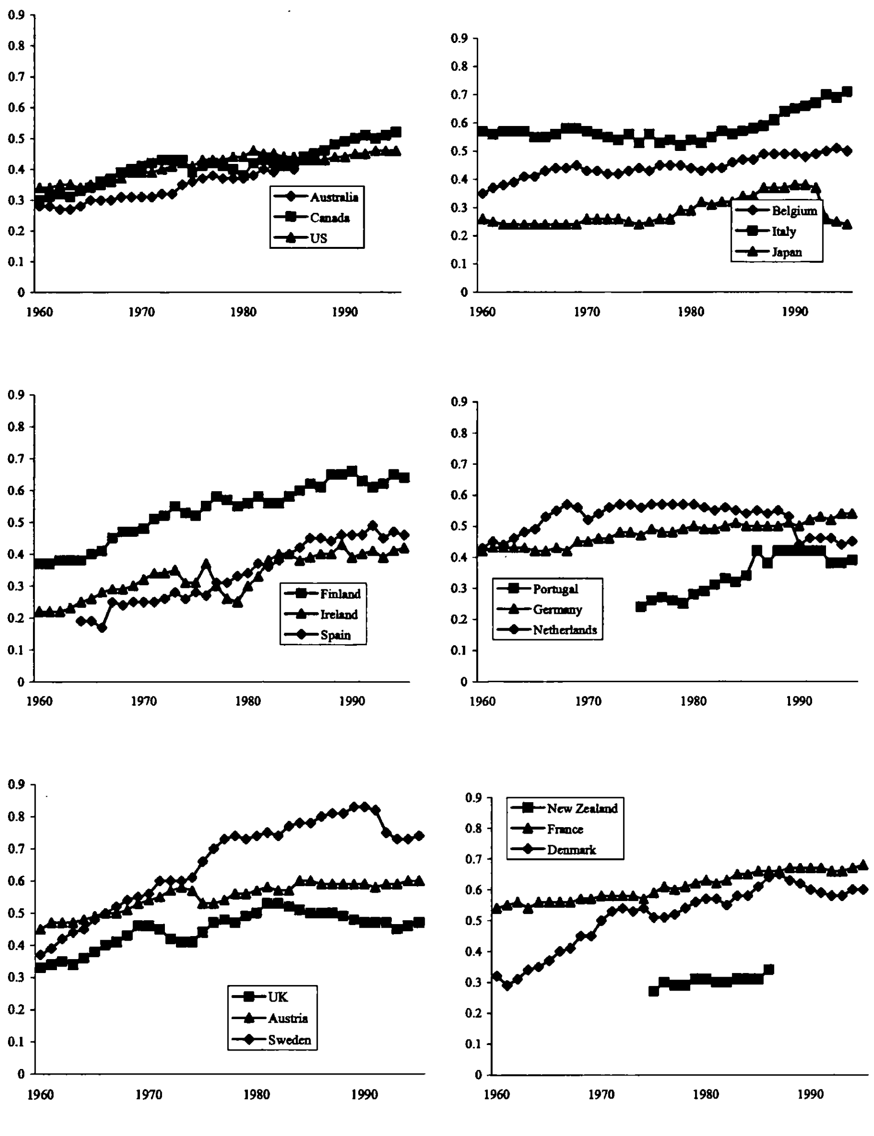

Figure 3.8: Tax wedge across OECD countries

Chapter 4

R&D, innovation and employment

4.1 Introduction

In this chapter we examine the dynamic effects of technological progress on employment. The persistence of high unemployment rates since the 1970s has motivated new theoretical models that predict a permanent effect of the rate of technological progress on equilibrium employment. This literature is reviewed below. We also incorporate in our analysis the vast literature on endogenous growth, in particular those models that describe innovation as a result of voluntary research activities of economic agents.

The empirical research on the effect of innovation on employment at the aggregate level is extremely scarce.[1] Traditional labour marked models (see e.g. Layard et al., 1991) have mostly ignored a potential long-run equilibrium link between unemployment and productivity growth: in conventional models, the long run equilibrium rate of unemployment is affected only by a limited number of factors like union bar-

[1] There are however a number of micro studies. See Acemoglu (2002) for a recent survey.

gaining power, the generosity of the unemployment benefit system or a measure of mismatch in the labour market. The possibility of a link between productivity and unemployment was dismissed on the basis that a steady rise in productivity would lead to continuous rise or fall in unemployment, and this fact seems at odd with the evidence. In other words, while productivity growth is probably unbounded, the unemployment rate is bounded between zero and one, and over the long run the two cannot be related. While this explanation seems plausible, there is no theoretical reason to reject the existence of a link between unemployment and the *rate of growth* of productivity, as both these variables are bounded.

The work which most closely relates to the analysis in this chapter is the paper by Pissarides and Vallanti (2003). They estimate a structural model of employment, wages and investment with exogenous technological progress and find positive long run effects of this on employment. Our analysis differs in various ways: first, we estimate a reduced form employment equation while they estimate a structural model with an employment and a wage equation. The main difficulty with structural estimation of labour market models is identification (Manning, 1993): estimating a reduced form avoid this difficulty.

The second difference is in the treatment of technological progress: we endogenise the rate of technical progress by estimating an equation derived from endogenous-type growth models, whereas in Pissarides and Vallanti (2003) technical progress is exogenous.

Finally, their model includes an investment equation and a vintage capital stock assumption, which is not included in the present work. Our results with respect to the impact of technolgical progress on employment, however, are consistent with that study.

Our findings confirm that investment in research and development is a fundamental driver of innovation. We also find that technological progress has a positive long run impact on employment, although in the short run the effect is negative.

This chapter is organised as follows. Sections 4.2 and 4.3 outline the theoretical motivations, Section 4.4 describes the empirical analysis and Section 4.5 summarises our conclusions.

4.2 Recent developments in the economic literature on R&D and growth: a survey

The economic consequences of the discovery of new ideas have recently received great attention in the theory of economic growth. Most of the "new growth theory" features technological progress as the engine of growth and emphasizes the importance of innovation for sustained economic development. This literature is rapidly increasing, motivated by finding – in the empirical studies - of positive and important effects of R&D activities on the level and growth rate of productivity. This survey describes the most important theoretical and empirical results that link investment in R&D, invention of new product and processes and economic growth.

The survey is organized as follows: Section 4.2.1 describes the "new growth" literature initiated by the pioneering works of Romer (1990), Grossman and Helpman (1991) and Aghion and Howitt (1992), while Section 4.2.2 describes the attempts to assess theoretically and empirically the validity of these models. In Section 4.2.3 the empirical research focusing on the effects of R&D on productivity is discussed. Section 4.2.4 summarises the research on the determinants of R&D expenditure at the firm level.

4.2.1 Theoretical models of innovation and growth

In the R&D based models of economic growth, the attention is focused on the central role of R&D as engine of growth. One of the premises of the work by Romer (1990) is that technological progress lies at the heart of economic growth, since it provides the incentives for continued capital accumulation. Economic growth is thus the result of innovative activity, but technological change arises because of intentional actions undertaken by agents who respond to market incentives. In these models, therefore, commercial research is treated as an ordinary economic activity: as such, it requires inputs of resources and it responds to profit opportunities. Technology is thus described as an entirely private product: an ordinary production function relates inputs for the innovation process to its output, new ideas or knowledge.

"Knowledge" is inherently different from other economic goods. It is typically characterized by the two features of non-rivalry and only partial excludability: the first attribute implies that its use by one firm or person in no way limits its use by another, the second that the owner cannot completely prevent others from using it.

Thus growth is driven by accumulation of a partially excludable, non-rival output. Therefore, an equilibrium with price taking cannot be supported: if non-rival input has productive value, it cannot be paid its marginal product, and output cannot be a constant return to scale function of all its input together. The way to reconcile the presence of this type of good is to explicitly introduce some degree of market power in the models.

Endogenous growth models thus depart from previous studies in which the presence of the non rival, non excludable input "knowledge" is either an exogenously provided public input (as, for example, in Solow, 1957) or the unintentional result or human capital accumulation (as in Lucas, 1988) or a public good provided by the government, which receives no compensation and that every individual can exploit freely.

In the R&D based models of endogenous growth, there exists a specific form of returns to R&D: monopoly rents in imperfectly competitive product markets. Product designs are assumed to be proprietary information, protected through a system of patents or by secrecy.

To understand the mechanism by which technological innovation drives economic growth, is useful to distinguish, as in Grossman and Helpman (1991), the output of industrial research as process or product innovation. Process innovation reduces the cost of producing known commodities, while product innovation consists of inventing entirely new commodities. Product invention can be further classified as vertical innovation, if new goods provide greater quality but perform similar functions of existing ones, or horizontal innovation, when the new goods serve entirely new functions, thus expanding the variety in consumption or the specialization in production. This taxonomy is useful to distinguish the characteristics of the different theoretical models of R&D-driven growth and, in particular, to identify the channels through which the innovative activity affects the growth process.

Models of product variety

A first type of model is characterized by a form of technological progress that shows up as an expansion in the number of varieties of producer or consumer goods: the change in this number is basic innovation. Discoveries of new types of goods, however, do not make existing types obsolete.

In this "model of producer good varieties" the production of a final good Y is obtained combining additively separable intermediate goods. Thus Y increases with N, the number of such specialized intermediate goods that are available in production at a given time.[2] Despite the tendency for diminishing returns to each intermediate individually, when the increase in intermediate inputs takes the form of increase in N, diminishing returns do not occur.

The expansion of the number of intermediate goods requires a technological

[2] This formulation makes the marginal product of the intermediate good i independent of the quantity employed of intermediate good j. Thus a new type of product is neither a direct substitute for, nor a direct complement with the types that already exist.

advance and thus an effort in the form of R&D investment. The benefit that accrues from research is the present discounted value of future net revenues from innovation.

This general framework includes the works by Romer (1990) and Grossman and Helpman (1991, ch. 3). The models differ, however, in the formulation of the research process.

In Romer (1990) invention requires human capital and existing stock of knowledge to produce new knowledge, in the form of designs for new producer durables: R&D is thus human capital and knowledge intensive. More precisely, let A be the level of knowledge in the economy and assume $A = N$, that aggregate knowledge is equal to the count of number of new designs. The output of the research sector is thus:

$$\dot{A} = \delta H_A A \tag{4.1}$$

Two assumptions are implicit in this formulation:

(a) devoting more human capital to research leads to a higher rate of production of new designs;

(b) the larger the total stock of designs and knowledge, the higher the productivity of a worker in the research sector.[3]

The growth in A by itself increases the productivity of human capital in research, making the cost of R&D proportional to $1/A$, and thus the cost of innovation declining as society accumulates more ideas: this is a form of positive spillovers from current research.[4]

The crucial feature of Romer's formulation is that knowledge enters into production in two distinct ways. First, it enables production of a new good that can be used to produce output and, second, it increases the total stock of knowledge and

[3] Linearity in A makes unbounded growth possible in this setting.

[4] This is due to the nonrival nature of A.

thereby increases the productivity of human capital in the research sector.

Grossman and Helpman (1991, ch. 3) present an alternative framework (the "consumer variety model") in which a variety of consumer goods (rather than producer goods) enter the utility function and the household cares about an index of these varieties. The formulation captures the idea that consumers like variety: let M be the number of types available: if M goes up, utility increases.

Invention of new products – increase in M – requires a certain research effort. The output of research has the form of blueprints for new consumer goods. Each new product substitutes imperfectly for existing brands and innovators exploit limited monopoly power in the product market.

The production function for blueprints is essentially the same as (4.1), in which R&D generates designs for new commodities, appropriable as stream of monopoly profits, but also adds to the stock of general knowledge capital, represented by a collection of ideas useful to future innovation. Because inventors cannot appropriate the returns to general information (which serves as input in the inventive activity), the process of endogenous innovation can be self-sustaining.

These models predict that the economy will grow faster the more productive its resources in research and the more patient its households. Some form of scale effect is present, by which the growth rate will be higher the larger the resource base of the economy.

Models of product quality

A typical feature of technological progress is that innovative products often displace completely earlier vintage goods from the marketplace. In the product variety models, new products substitute imperfectly for old ones and the process of obsolescence is not present. An alternative way of modelling industrial innovation is to feature endogenous product obsolescence as a result of continuing technological advancement. Thus the models described in this section identify growth with an increase in the average quality of a fixed set of commodities. This type of models have been proposed by Grossman and Helpman (1991, ch. 4) and Aghion and Howitt (1992).

A successful innovator creates the new "state of the art" product that captures the market share at the expense of a previous generation product. Innovative goods are better that older products simply because they provide more "product services" in relation to their cost of production.[5] Growth will be sustained if commercial R&D remains an economically viable activity so that the average quality of industrial products continues to rise.

The models are based on the notion of a "quality ladder": each product can be produced in an unlimited number of vertically differentiated varieties or "qualities", and each improvement causes a discrete jump in the level of services that the good provides.[6] Firms that manufacture state-of the art products earn positive profits in imperfectly competitive markets. Potential investors foresee these profit opportunities and compare them to the cost of research. But innovators realize that the profits are only temporary, since later technical improvements will render their own innovative product obsolete. This is the Shumpeterian (1934) process of "creative destruction": the more research is expected to follow the next innovation, the shorter the likely duration of the monopoly profits that will be enjoyed by the next innovator, and hence the smaller the payoff to innovating.

Technological spillovers play a different role in these models: when an innovation occurs and is brought to the market, rivals can study its attributes and begin their efforts to improve upon the new state of the art. Thus inventions contribute to create a stock of public knowledge that facilitates subsequent innovation, but now

[5]Each innovative good provides λ times the product services the previous type offered, with $\lambda > 1$.

[6]Note that these models could alternatively be interpreted as describing a series of process innovations: each technological breakthrough causes the cost of production of a specific good to fall by a factor of $1/\lambda$. Product and process innovations are similar in this framework as both provide greater services at a given cost.

flows to this stock come from particular product lines, rather than from any research effort.

Another difference with the previous models is that R&D entails uncertain prospects: a firm that invest resources in the research lab to develop the next generation product will succeed in its attempt only with a certain probability, proportional to the resource input; otherwise, the effort will fail. This formulation imposes constant returns to scale in the research effort. Also, R&D is a memoryless process: there is no benefit from cumulating unsuccessful research experience.

The equilibrium level of research, and thus the growth rate of the economy, will again depend on the size of the resource base (the labour market) and on the productivity of the research process.

4.2.2 Theoretical and empirical assessments of the R&D based models of economic growth

The endogenous growth literature described in the previous section has suggested models that explain long-run growth by focusing on technological progress and R&D. Technological progress results from the search for innovation, which raises productivity and long-term growth. The R&D equation that constitutes the heart of these models relates the growth rate of knowledge to the size of the labour force engaged in R&D. If one assumes that the size of the labour force is constant, the economy will be in steady state and follow a balanced growth path when the share of labour employed in R&D is constant. The key result is that subsidies to the R&D sector of the economy can increase the share of labour devoted to R&D and therefore increase the balanced path growth rate. In general, since in these models steady state growth rates depend endogenously on policy variables such as subsidies to R&D, one of the important predictions they generate is that permanent changes in variables that are potentially affected by government policy lead to permanent changes in growth rates.

One of the most pervasive criticisms to this approach came from Jones (1995a). He noticed that the growth rates of GDP per capita show, in fact, little or no persistent increase for the OECD economies in the post-World War II era: U.S. growth rates are well described, for example, by a process with a constant mean and very little persistence. This seem to imply that no government policy or other movement in the U.S. economy has had a large persistent effect on the growth rate, or that all persistent effects have been exactly offsetting. Thus the prediction of the endogenous growth models that permanent changes in policy variables have permanent effects on growth rates does not appear to be supported empirically. The implication of the scale effects present in these models is rejected by lack of persistent increase in growth rates: according to the model, the exponential trend in the level of the labour force should lead to an exponential trend in per capita growth rates. More specifically, the R&D equation (4.1) can be interpreted as saying that TFP growth is proportional to labour or human capital devoted to research. The OECD experience shows that TFP growth exhibits little or no persistent increase, but rather a negative trend for some countries, while the amount of labour devoted to research (as measured, for example, by the number of scientists and engineers engaged in R&D) exhibits strong exponential growth.

Although important, the conclusions of Jones' empirical investigation need to be compared with the results by Nelson and Plosser (1982) on US GDP per capita that provide evidence of permanent changes in the time series properties of income measures.

Eliminating the scale effects alters other implications of the R&D based growth models. An attempt is made by Jones (1995b), who generalizes R&D equation (4.1) to:

$$\dot{A} = \delta L_A A^{\phi} l_A^{\lambda-1} \tag{4.2}$$

where $l_A = L_A$ in equilibrium, but the presence of l_A captures the externalities occurring because of duplication in the R&D process. Moreover, ϕ measures the degree of externalities across time in the R&D process. If $\phi = 1$ and $\lambda = 1$, equation (4.1) obtains, but this restriction on ϕ is inconsistent with the empirical evidence. Jones assumes rather that $\phi < 1$: the rate of growth of technology is thus given by:

$$\frac{\dot{A}}{A} = \delta \frac{L_A^{\lambda}}{A^{1-\phi}}$$

An increase in labour devoted to R&D does not increase the rate of growth of technological process, provided L_A^{λ} and $A^{1-\phi}$ grow at the same rate. The model does not exhibit scale effects. Growth in the economy depends in steady state only on the growth rate of the labour force - not its level - and on the parameters ϕ and λ, the external return parameters in the R&D sector.

This model delivers Solow-type implications for long run growth, in the sense that long run growth depends only on parameters that are usually considered as exogenous. Growth is endogenous here in the sense that technological progress, which generates long run growth, results from R&D undertaken by profit-maximizing agents. However, long run growth is not endogenous, in the sense that policy changes have no long run growth effects: steady state growth is invariant to government policy, like investment tax credits and R&D subsidies. These features explain the definition of "Semi-endogenous R&D-based model of growth" attributed to this model by its author.[7]

Another attempt to remove the inconsistent feature represented by the scale effect is made by Young (1998). He modifies the conventional quality ladders model

[7] Kortum (1997) and Segerstrom (1998) present models similar to Jones'.

of product improvement to allow for the endogenous determination of the degree of product variety. This modification eliminates the prediction by endogenous growth models that a larger economy should grow faster.

In the rest of this section, the results of other studies aiming at testing empirically the validity and the predictions of the R&D-based models of endogenous growth are presented.

Kortum (1993) attempts to discriminate between the variety model and the quality ladder model. In the variety model, productivity growth is proportional to the growth of the stock of inventions, while in the quality model it is proportional to the flow of inventions. The latter captures the idea that the invention/R&D ratio is driven down by a rising value of inventions, which leads the research sector in equilibrium: the value of inventions rises because the output value of a percentage productivity gain rises as the economy grows. To discriminate empirically between the two types, he estimates the patent productivity relationship using a panel of U.S. manufacturing firms. More evidence is found (although not very strong) for the variety specification than for the quality ladder model.

Evans (1996) suggests that if countries have different trend growth rates as predicted by endogenous growth theories, the logarithms of their per capita outputs should wonder away from each other at positive rates and hence their cross-country variance should follow an upward quadratic trend. In his work, he considers four series of cross-country variances and none appears to trend upward quadratically, while the first series (relative to 13 industrial countries over the period 1970-1989) provides strong evidence of stationarity around a constant positive mean. Thus the author finds no evidence that growth rates differ endogenously. Instead, considerable evidence for parallel balanced growth paths is found.

These and other criticisms (in particular those expressed by Jones, 1995a,b) to the endogenous growth models described in section 1 are examined in Aghion and

Howitt (1998, ch. 12), who present a model without scale effects similar in spirit to Young's. The authors also suggest a more detailed series of empirical tests originated by their theoretical framework.

One of the most important studies in the tradition of the R&D-based models is that of Caballero and Jaffe (1993). The authors develop a model in the spirit of Grossman and Helpman (1991, ch. 4) and Aghion and Howitt (1992) that gives a simple relationship for the effect of new products on the value of existing ones. The process of research and development advances the technological frontier by increasing the quality of goods. Thus existing producers see their profit decline relative to those of the new leader: this rate of decline captures the endogenous process of creative destruction and it can be expressed algebraically by relating the rate of growth in a firm's' value relative to the industry to the firm's number of new ideas relative to the industry average. By relating the concept of new ideas to that of new patents, the empirical magnitude of creative destruction is estimated - using market value and patents on U.S. firms - to be about 4% per year.[8]

The two authors focus subsequently on a research process that uses as inputs private research effort and the public stock of existing ideas: a simple linear technology at the firm level maps these research inputs into output of new ideas. Two important features are considered: that it takes time for additional knowledge to diffuse in the economy and that old knowledge eventually becomes obsolete. The latter is termed "knowledge obsolescence" (and distinguished from the obsolescence in value represented by the creative destruction). The transmission of ideas in the research process is described by a "citation function" that takes into account both diffusion and obsolescence. This is then estimated using a sample of patents in the U.S. It is found that the rate of knowledge obsolescence rose from 2-3% per year early in the century to about 10-12% at the end of the 1980s. Also, the process

[8]This means that a firm that does not innovate sees its value relative to that of the industry erode on average by about 4% per year.

of knowledge diffusion is quite rapid. It is estimated that the usefulness of existing public knowledge has fallen (and it has driven down private productivity of research inputs) of about 30% from the late 1950s to the 1990s (for possible explanations of this slowdown, see Section 4.2.3 below).

Once an estimate of all important parameters is obtained, the model is calibrated to fit the average rate of growth of the U.S. during the postwar period. The behaviour of the model is found to be consistent with the productivity slowdown in the 1970s and with the stock market boom in the 1980s, and suggests that the optimal subsidy to private R&D expenditure is about 30%.

4.2.3 Empirical evidence on the relationship between R&D and productivity growth

This section summarizes the vast empirical literature that tries to assess the importance of cumulative domestic R&D in determining productivity at the industry and firm level. This literature also seeks evidence of diminishing returns to inventive activity.

Griliches (1995) distinguishes three types of studies on the contribution of R&D to economic growth: historical case studies,[9] invention counts and patent statistics (described below) and econometric studies relating productivity to R&D of similar variables. The last two types are discussed in more detail below.

Finally, many authors have focused on possible causes for the observed productivity slowdown in the OECD economies: except for Japan, the patent/R&D ratio has declined over the past three decades, suggesting a slowdown in innovation. This literature is also summarized in what follows.

[9] Despite the existence of a number of detailed case studies on particular innovations, these are difficult to generalize and not very representative.

Knowledge production: evidence from patent statistics

The output of research is neither well defined nor easily measurable: most studies postulate a "knowledge production function" which describes how new methods of production are discovered using specific resources. R&D expenditure is generally considered as input generating economically valuable knowledge, while patent statistics are often used as a quantitative indicator of the number of inventions.

There are a series of problems in both these measures of innovative activity: nonetheless, it is common to use the ratio of patents per unit of R&D expenditure or per unit of R&D personnel to assess the existence of increasing (decreasing) returns in knowledge production.

The conclusions of many studies, summarized in Griliches (1990), suggest that, in the cross sectional data, there is no evidence of diminishing returns to R&D, particularly for large firms. The average elasticity of patents with respect to R&D expenditures for large firms is about one, while for small firms it is about 0.4. This difference is partly due to sample selectivity and partly to the fact that small firms tend to do more informal R&D, which biases the patent/R&D ratio downwards.

The picture is different when the time series data are examined. The elasticity of patents with respect to R&D expenditures ranges from about 0.4 to 0.6, which suggests the possibility of diminishing returns.

Evidence on the relationship between R&D and productivity growth

Is there a significant relationship between R&D, output and productivity growth? And what is the rate of return on R&D investment at the firm and industry levels? This section will briefly summarize the results of numerous empirical studies in this area.[10]

The analytical tool employed to link productivity growth with research effort

[10]Nadiri (1993) and Griliches (1995) provide recent surveys.

is a Cobb-Douglas production function where output is a function of conventional inputs and the stock of R&D. Thus, in this framework, R&D investment is simply considered an alternative capital investment in a standard neoclassical model:

$$\log Y = a(t) + \beta \log X + \gamma \log K + u$$

where Y is some measure of output at the firm, industry of national level, X is a vector of standard economic inputs such as man hours, structures and equipment, energy use and K is a measure of cumulated research effort or "capital",[11] $a(t)$ represents other forces which affect output and change systematically over time, and u includes all other unsystematic random fluctuations in output. Estimated versions of this equation gave values for the elasticity of output with respect to R&D capital between 6% and 10% (Griliches, 1995).

In an alternative formulation, levels are replaced by growth rates and the above equation becomes:[12]

$$\frac{d \log Y}{dt} = a + \beta \frac{d \log X}{dt} + \rho \frac{R}{Y} + \frac{du}{dt}$$

where R is the net investment in K (that is R&D net of the depreciation of the previously accumulated R&D capital), and ρ is the rate of return to investment in K. In this form, the rate of growth of output or productivity is related to the intensity R/Y of the investment in R&D. Versions of this equation were estimated by many authors (for example by Griliches and Lichteberg, 1984, Scherer, 1982 and Terleckyj, 1980, using industry aggregates), who report estimated rates of return between 20% and 50%, with more recent estimates falling in the lower part of this range.

[11] R&D stock is computed as cumulative R&D expenditure, allowing for depreciation of the previously accumulated stock.

[12] The term $dlogK/dt$ is approximated by R/K and then transformed using the definition $\rho = dY/dK = \gamma Y/K$.

In conclusion, the empirical evidence supports the existence of strong correlation between R&D and productivity performance.

Explanations for the productivity slowdown

Part of the most recent literature on patents and innovation has focused on the productivity slowdown in the OECD countries. In most of the advanced economies, the patent/R&D ratio has declined steadily over the past three decades. At least three distinct explanations have been suggested for this phenomenon: *(i)* Kortum (1993) proposed that the expansion of markets has raised the value of patents and that competition in the research sector has resulted in greater R&D expenditure per patent; *(ii)* Evenson (1993) suggested that the exhaustion of technological opportunities has reduced the productivity of the research sector; *(iii)* Griliches (1989) pointed to the rising costs of dealing with the patent system, which has led researchers to patent fewer of their inventions.

Kortum (1993) tries to test formally the above explanations: to evaluate the sources of decline in the patent/R&D ratio, he constructs an equilibrium model of industry growth which is then used to test the competing hypotheses. To examine explanation *(i)* he allows for growth in the industry's market. The model predicts that industry will converge to a steady state with a patent/R&D ratio continually decreasing if there is sufficient growth in demand: this will raise the value of an invention and with decreasing returns to research at the industry level, it will lead to increase research expenditure per invention.

To examine explanation *(ii)* he allows for a decline in the productivity of the industry's research sector. In the model, the endogeneity of R&D weakens the link from declining opportunities to a declining invention/R&D ratio, because exhaustion will cause both input and output to fall. Thus the effect on their ratio is ambiguous.

Using data from 20 U.S. manufacturing industries, the author shows that growth of demand is not rapid enough to explain a substantial fraction of the decline in the patent/R&D ratio. He therefore concludes that explanation *(iii)* seems the most appropriate.

The evidence for R&D spillovers

It has long been recognized that externalities arise in the innovation process because of the inability of firms to capture all the benefits of their invention. More specifically, patent legislation, trade secrecy or other methods allow the firm to appropriate a sizable proportion of the benefits of inventions. Even if some form of property rights protects inventors' ability, however, appropriability is, in most cases, not perfect. In modelling the spillovers phenomenon it is thus assumed that the level of productivity achieved by one firm or industry depends not only on its own research efforts but also on the level of the pool of general knowledge accessible to it.

A simple model of within-industry spillover effects is given by (Griliches, 1992):

$$Y_i = B(X_i)^{1-\gamma}(K_i)^{\gamma}(K_a)^{\mu}$$

Where Y_i is the output of the i-th firm which depends on the level of conventional inputs X_i, its specific knowledge capital K_i and on the state of aggregate knowledge in the industry K_a. Under some assumptions[13] the individual production functions can be aggregated to yield:

$$\sum Y_i = B(X_a)^{1-\gamma}(K_a)^{\gamma+\mu} \tag{4.3}$$

The coefficient of aggregate knowledge capital $(\gamma + \mu)$ is higher than at the micro level (μ), reflecting not only the private but also the social returns to R&D.

[13] Namely that (1) the aggregate level of knowledge capital K_a is simply the sum of all firms' knowledge capital stocks, (2) resources are allocated optimally and (3) all firms in the industry face the same relative factor prices.

Equation (4.3), however, is based on restrictive assumptions and thus not very appropriate. Moreover, the industry under analysis in unlikely to be a closed entity. Rather, there are complex relationships in knowledge transmission across a wide array of industries and firms. The amount of knowledge a firm can receive from different sources depends on the economic and technological distance from that source.

Specifically, Griliches (1992) identifies two types of spillover effects: (a) knowledge spillovers, which refer to the effect of research performed in one industry in improving technology in a second industry; (b) inputs effects, by which inputs purchased by one industry from another industry embody quality improvements that are not fully appropriated by the selling industry.

According to Griliches, true spillovers are ideas borrowed by research teams of a given industry from the research results of another industry, thus those of type (a). It is not clear that this kind of borrowing is particularly related to input purchase flows. In practice, it is very difficult to distinguish between the two.

The econometric methodologies employed in the search for spillover effects are essentially of two types: the technology flow approach and the cost function approach. The technology flow approach is based on input-output or "technology matrices": patent data are used to position the firms or industries in a matrix of technological linkages. Spillover effects of R&D undertaken by one firm or industry on the remaining firms or industries are thus examined.

Regressing the total factor productivity of the industry on its own R&D and borrowed R&D, Terleckyj (1980) reported a 45% rate of return for borrowed R&D and about 28% for own R&D in the manufacturing sector. Other studies confirmed similar patterns, i.e. the rate of return on borrowed R&D was about twice that of own R&D.

Jaffe (1986, 1988) came closest in looking for the second type of spillovers, the disembodied kind. He used patent classification to position a firm in a technological space and included the proximity variable in the production function and in patent equations. His results indicate an elasticity of about one for patents and a positive relationship between a firm's own R&D and the size of the R&D pool in its technological space. Also, the firm's productivity growth varies positively with its own R&D as well as the R&D of its neighboring firms in the technological space. There is thus evidence of a technological spillover effect based on geographic proximity.

More recently, Jaffe (1989) also studied the effects of geographic proximity to university based research on the patenting of closely located firms with similar research objectives. His results suggest positive and strong spillover effects from university research on industry data. Jaffe, Trajtenberg and Henderson (1993) used patent citation frequencies to university based patents to assess the contribution of universities to industrial productivity.

Knowledge spillovers from universities are also documented in Adams (1990), Mansfield (1991), Acs, Audretsch and Feldman (1992), who all found that university research has substantial effects on innovative activity and performance.

The cost function approach (see Bernstein and Nadiri, 1989, 1991) estimates the effects of spillovers on the costs and structure of production of the receiving firms or industries. The basic econometric framework is to formulate a cost function which depends on output, relative factor prices for the variable inputs and quasi-fixed inputs such as stock of own physical capital and R&D capital but also the stock of R&D of other firms or industries. The latter variable captures the spillover of the research input of other firms or industries. The advantage of the cost function approach is that it is often more flexible in the functional form used and that it benefits from imposing more structure, considering the impact of R&D spillovers not only on total costs but also on the amount of labour and intermediate product demanded.

In summary, there has been a significant number of studies all pointing in the same direction: R&D spillovers are present, their magnitude may be quite large, and social rates of return remain significantly above private rates. The estimated elasticity of output with respect to aggregate outside R&D (μ) is between a half and double of the elasticity of output with respect to own R&D (γ).

Jones and Williams (1998) attempt to link the theoretical models of new growth theory to the empirical results in the productivity literature, providing a general method for computing social rates of return. Specifically, they derive an analytical relationship between the true social rate of return to R&D and the coefficient estimates from regressions of TFP growth on R&D investment. They show that common estimates represent a lower bound on the social rate of return to R&D, and that the optimal R&D spending as a share of GDP is two to four times larger than actual spending.

Coe and Helpman (1995) emphasize that in a world with international trade, foreign direct investment and international dissemination of knowledge, a country's productivity depends on its own R&D as well as on the R&D efforts of its trade partners. They use R&D expenditure as proxy for a stock of knowledge and, using a pooled times series cross-section sample of 21 OECD countries plus Israel over the period 1971 to 1990, they find that both domestic and foreign R&D capital stocks have important effects on total factor productivity. Some estimates suggest that foreign R&D capital stocks have stronger effects on domestic productivity the larger the share of domestic imports in GDP. It follows that more open economies derive larger productivity benefits from foreign R&D than less open economies. As mentioned in chapter 3, however, Kao, Chiang and Chen (1999) re-estimated Coe and Helpman's (1995) regressions by DOLS and found that this effect is not significant when the regressions are estimated by DOLS.

Keller (2001) also examines the existence of technological spillover effects and finds that about sixty percent of the total productivity effect on growth originates from domestic R&D and the remaining effect is due to international technology spillovers.

4.2.4 The determinants of R&D investment

This section outlines the most important studies by industrial organization economists to highlight the factors determining the level and rate of innovative activity and performance, in the tradition of Schumpeter's work. Schumpeter (1934) argued that the large firm operating in a concentrated market was the engine of technological progress: industrial organization economists became thus preoccupied with the effects of firm size and market concentration on innovation.

Firm size as determinant of innovative activity

Most of the empirical literature has interpreted Schumpeter's claim for a large firm advantage in innovation as a proposition that innovative activity increases more than proportionately with firm size.

Several justifications were put forward: capital market imperfections that confer advantage to large firms in financing risky R&D projects; scale economies in the R&D function itself; higher returns when the innovator has a large volume of sales over which to spread fixed cost of innovation; complementarities between R&D and other non manufacturing activities and so on.

Finding of empirical research on the relationship between firm size and innovation have been widely interpreted as indicating that, contrary to Shumpeter's idea, large size offered no advantage in the conduct of R&D. Several studies analyzing measures of innovative output, rather than input (i.e. R&D), reinforced the earlier consensus of no advantage of size.

A problem common to almost all the studies of R&D and firms size is, however, the endogeneity of firm size: central to Shumpeter's notion of creative destruction, this issue has been totally neglected in this type of studies.[14]

Market power and innovation

Shumpeter recognized that firms required the expectation of some ex-post degree of market power to have the incentive to invest in R&D. He also argued that an ex-ante oligopolistic market structure and the possession of market power also favoured innovation.

The empirical literature focused on the effects of ex-ante market concentration on innovative behaviour: the majority of studies that examined the relationship between market concentration and R&D found a positive relationship between the two. A few found evidence that concentration has a negative effect on R&D. Simple tests of the explanatory power of market concentration, however, find that it contributes little to an explanation of the variance in R&D intensity.

Recognizing the potential simultaneity between innovation and concentration, some investigators have used instrumental variables for the concentration variable in regression studies of the effects of market structure on innovative activity (see Levin et al., 1985). Others have used industry level data to estimate multi-equation models in which concentration and R&D are both treated as endogenous (see Levin and Reiss, 1988). Statistical tests reject the hypothesis that the concentration variables are orthogonal to the error term, suggesting that such techniques are appropriate.

Overall, the literature suggests that the direct influence of market concentration is small and it likely reflects the influence of other more fundamental determinants of technical advance, specifically technological opportunity and appropriability conditions.

[14] Although it has been recognized in some studies of the relationship between innovation and market concentration (see below).

Other firm characteristics

Only modest progress has been made in explaining inter-firm differences in R&D intensity by firm other characteristics. Cash flow, a measure of internal financial capability, is the most thoroughly examined firm characteristic. Many, but not all, the studies that have included this explanatory variable have found that a firm's cash flow is associated with higher levels of R&D intensity (see Hall, 1990 and Himmelberg and Petersen, 1992).

The other widely studied corporate attribute is diversification: the diversified firm possesses more opportunities for exploiting the new knowledge because the outcome of research tends to be unpredictable. Diversified firms can also better exploit economies of scope and complementarities among diverse activities. Results of this type of works have been mixed, though: moreover, measurement problems are pervasive in this literature.

Industry characteristics

Studies that address the importance of industry characteristics in explaining different R&D patterns have classified explanatory variables under three headings: (a) product market demand, (b) technological opportunities and (c) appropriability conditions.

As far as the role of demand is concerned, Schmookler (1962) claimed that the rate of technological progress could essentially be explained as the outcome of demand incentives. His work sparked a lively debate among economists concerning whether "demand pull" or "technology push" was the primary force behind technological change. His proposition that demand almost alone determined the rate and direction of technical change has not, however, survived the empirical analysis. Several case studies have documented examples in which a sequence of innovation were determined not by demand but by the state of knowledge in a particular industry.

Econometric studies have shown that variables representing demand conditions were statistically significant but less important than the technology variables.

To assess the importance of technological opportunities in R&D levels and performance, industries were classified on the basis of their scientific or technological field. Jaffe (1986, 1988) showed that technological opportunity clusters were significant in regressions that tried to explain inter-firm differences in R&D, patents, TFP, profits, and Tobin's q.

Levin et al. (1987) measured several variables thought to represent an industry's technological opportunity: a number of them have performed well in regression studies of innovative activity.

Cohen and Levinthal (1989) formulated and tested a model in which firms deliberately invest in R&D with two purposes: to generate new knowledge and to develop absorptive capacity. They found evidence suggesting that the degree to which outside knowledge is targeted to concerns of the firms influences own R&D spending. These ideas were also investigated empirically by Griffith et al. (2000, 2003).

Studies on appropriability conditions are motivated by the existence of spillovers due to the limited ability of inventors to capture the entire benefits from their inventive activity. Patents and other protection mechanisms (such as copyright and industrial designs) provide a solution to the problem of imperfect appropriability. However, industries differ widely in the extent to which patents are effective: the evidence suggests that patens are regarded as a necessary incentive for innovation in only a few industries. Also, there is evidence that patents are not perfectly enforced and many technologies are imitated very rapidly. Mansfield, (1984) estimates that about 60% of patented innovations are imitated within four years.

The Levin at al. (1987) survey revealed that firms in many industries tend to regard other mechanisms, such as costly imitation and investments in complementary assets, as quite effective in appropriating the returns from innovation. Head start and the ability to move quickly down the learning curve were also considered more effective means of appropriation than patents. Secrecy was viewed as more effective than patents in protecting process innovations.

Most empirical work in this area has focused on the mechanisms facilitating and constraining the ability of firms to capture the returns from new technology but -- partly because of difficulties in finding suitable data and formulating precise tests to distinguish among competing hypotheses – there is no clear empirical consensus about whether grater appropriability encourages innovative activity.

Access to R&D funding One of the most important factors that might affect firm's propensity to research and development could be access to long term funding for innovative research. Access to long term funds could lower the cost of R&D and thus encourage more investment in research. The magnitude of this effect would depend on the elasticity of firms' R&D demand to its price: Bloom et al. (2002) provide some evidence that these demand function are not totally rigid and show that fiscal incentives can have a significant impact in stimulating R&D.

4.3 Growth and unemployment: the theory

The next question we pose in this chapter is the following: is technological progress good or bad for employment? New technologies can destroy old jobs by making them unprofitable or, by creating new knowledge, they can stimulate demand and therefore the creation of new jobs. Petit (1995) suggests adopting an historical perspective and identifies four time epochs with different social and economic features that affected the relationship between technical progress and employment. The first, pre-industrial phase, was an epoch of strong complementarities between men and jobs and techniques were mainly created by users: technology had a local character and spillovers were not important. The effects of technological progress on employment received new attention during the industrialization phase, with the spreading of new machinery and productive processes. In the UK, at the beginning of the nineteen century, substitution of labor with machines led to the so called "Luddite riots": workers worried about their occupational prospects protested destroying the new machines. A third historical period can be identified with the rapid economic growth following World War II until the 1970s. In the 1950s, thanks to the diffusion of innovations occurred in the previous decades, full employment was reached and attention focused on the problem of labour shortage. This is the spirit of the Solow (1957) growth model: in this pioneering study into the determinants of growth, unemployment is absent and wages adjust such that all available labour force is employed as input in the production process. Employment is equal to the labour supply and an increase in the labour force simply reduces physical capital per worker. Technological progress in this framework is an exogenous, constant force.

With the economic crisis of the 1970s, the paradigm shifted, and technological progress became a new, endogenous process subject to uncertainties. The presence of interdependent economies, rapid innovation in the information technologies and the persistence of unemployment brought new attention to the relationship between technological progress and jobs.

The economic models of endogenous innovation summarised in the previous section describe economies in which growth arises explicitly from technological advances that result from intentional actions of economic agents motivated by profit. What are the effects of the implementation of new technology on the rate on unemployment? In Aghion and Howitt (1994, 1998) and Mortensen and Pissarides (1994, 1998) two competing effects of growth on employment are uncovered: on the one hand, an increase in growth raises the capitalized value of a firm and thus the incentive to create jobs: this effect is called "capitalization effect". On the other hand, technological progress has a "creative destruction" effect whereby it increases the rate at which workers are separated from their jobs and it discourages the creation of new job vacancies. Which one of the two effects prevails depends on the parameters of the model and is ultimately an empirical issue, which we discuss and develop in the next section. We now examine in more detail the theoretical framework of the existing models of growth and unemployment.

In an exogenous growth model, Pissarides (2000, chapter 3) shows the effect of growth on unemployment in presence of frictions in the job market. When technological progress is disembodied,[15] labour productivity grows at the exogenous rate of technological progress and the search model of unemployment becomes a neoclassical Solow growth model with a constant unemployment rate that depends negatively on the rate of growth. If the interest rate is fixed, faster rate of technological progress implies lower rate or unemployment and higher vacancies: this is precisely what Aghion and Howitt (1998) term the capitalization effect: the growth rate affects the effective discount rate at which firms discount all future income flows, thus making more profitable to create a vacancy today.

If the interest rate is allowed to be determined endogenously, for example from a Ramsey-type growth model with optimizing consumers, the result is reversed for reasonable values of the parameters, and faster growth rate leads to higher unemployment, as shown by Eriksson (1997). This is because the capital stock depends on savings and faster growth reduces the amount of capital available per efficiency unit of labour.

The other main reference in this field is Aghion and Howitt (1994, 1998, ch.4). They model the effects of growth on unemployment in an economy where the leading edge technology grows at some exogenous rate g while productivity of each plant of vintage t remains fixed; therefore, in steady state, firms become unprofitable and close down, making their workers unemployed. An inverse relationship between the

[15] That is, all existing and new jobs benefit from the higher labour productivity without the need to replace their capital stock.

growth rate and duration of a plant is derived; this is the result of frictions in the labour market. Three effects are present: (a) a direct creative destruction effect of growth on unemployment through job destruction at a constant vacancy rate, (b) an indirect effect through the job creation rate: growth reduces the lifetime of a production unit and causes faster decrease in profits, which reduces the number of vacancies, (c) a capitalization effect: if firms can upgrade their technology with positive probability, an increase in g reduces the net discount rate of expected future income thus encouraging entry and creation of new jobs. The net effect on the unemployment rate depends on the values of the parameters of the model. But, as the authors emphasize, these effects do not represent the popular belief that technology increases demand and thus new jobs: this is obtained by introducing in the model complementarities across firms and sectors. Low substitutability across sectors reverses the indirect creative destruction effect: an increase in g reduces unemployment even without capitalization effect. When the final output is produced by a continuum of distinct, imperfectly substitutable intermediate inputs, growth in the rest of the economy raises the output price of any intermediate plant: this growth generates an increase in demand and therefore the revenue from a plant increases over time at a rate proportional to g. The overall effect of an increase in g on the capitalized value of a plant, therefore, will not be automatically negative, but might increase with g if there is enough intersectoral complementarity. As a consequence, the indirect effect of growth will be to increase job creation.

Aghion and Howitt (1994, 1998) also examine a framework in which growth is the result of innovation intentionally pursued by economic agents. There is a continuum of research facilities in the economy each of which generates a stream of innovations. Research firms are forward looking, and they evaluate the entire stream of innovations when deciding whether to enter the market. The capitalization effect is reintroduced: an increase in g reduces the net discount rate of future profits thus encouraging entry of research facilities: growth is made endogenous and g depends on innovation. The effect on unemployment is positive (i.e. the unemployment rate increases with g) if the size of innovation increases, while if the frequency of innovation increases, unemployment is unaffected.

Mortensen and Pissarides (1998) propose an encompassing model in which technological progress is embodied in new capital and thus productivity of existing jobs does not grow, unless the firm decides to update a job's technology at some fixed implementation cost. If they are not updated, old jobs become obsolete, and job destruction takes place. This effect is named "creative job destruction". Job creation, in turn, depends on the value of new jobs. As the implementation cost falls, more firms will destroy old jobs and adopt the new technology. In the limit, as the implementation cost goes to zero, technology is updated continuously. On the other hand, as the implementation cost increases, technology is updated less frequently, and, if it becomes sufficiently large, new technology is never implemented. It is thus shown that the effect of innovation on employment can be positive, with the capitalization effect prevailing when the implementation cost is small. Conversely, for large implementation cost, the creative destruction effect dominates.

One of the earliest contributions that emphasised the possibility of an effect of productivity growth on unemployment is due to Manning (1992). His view is that the slowdown in productivity growth and the fall in the rate of growth of real wages which occurred in most OECD countries in the 1970s could have a role in explaining the long-run rise in OECD unemployment in that decade. He presents a dynamic version of the traditional union bargaining model in which the link between unemployment and productivity growth is introduced. In his model, the more valuable a job is relative to unemployment in the future, the lower the level at which current wages will be set: this allows workers to maximise their probability of employment today and enjoy rents in the future. Economic growth raises future rents relative to current wages and thus encourages current wage moderation, which in turn is associated with a lower equilibrium rate of unemployment.

Hoon and Phelps (1997) study the effects of faster technical progress in a labour-turnover model of the natural rate of unemployment. They show that in a closed economy, as the steady-growth rate is approached, the increase in the rate of technical progress is neutral for the natural unemployment rate and its effects are completely offset by an increase in the interest rate. However, of two small open economies having the same technology level at some data, the one where technical progress is faster will have a lower natural rate of unemployment.

Other studies on the effects of economic growth on unemployment include Eriksson (1997), who shows that, with endogenous growth, the positive association between growth and employment is restored; Ball (1999), who includes demand effects in a model with hysteresis in unemployment; Saint-Paul (1996), who shows that increases in unemployment may be due to asymmetric effects on skilled and unskilled labour, and Acemoglu (1997), who shows how interactions of skills and technology adoption may lead to multiple equilibria.

In Section 4.2.2, one of the implications of endogenous growth models with scale effects was that subsidies to R&D could increase the share of labour devoted to R&D and therefore increase the balanced path growth rate. In this case, unemployment would also fall in a model of unemployment and growth. It can be assumed, however, that growth is generated by a semi-endogenous model, in which R&D subsidies and in general policies that increase technological progress could have no long run effect on unemployment.

4.4 Empirical investigation

In this section we discuss the results of our empirical investigation into the effects of endogenous technological progress on employment. First we investigate the existence of causality links highlighted by the theoretical studies summarised in the two previous sections. We then estimate a model of employment were the rate of growth of technological progress affects the equilibrium employment rate and where productivity growth is the outcome of investment in research and development activities.

4.4.1 Data description

The empirical analysis is performed on a sample of 19 OECD countries over the period 1970-1999. The countries in the sample are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, the U.K. and the U.S. The data come from a number of sources (see Appendix C for details).

Data on output, labour and capital are obtained from the OECD National Accounts. To measure R&D we use real gross domestic expenditure on research and development (GERD) from the OECD Main Science and Technology Indicators. Following the existing literature, the variable we include in our regressions is R&D intensity, that is the ratio of R&D expenditure to real GDP $\left(\frac{R}{Y}\right)$. Table 4.1 reports average R&D intensity across our sample countries for the periods 1970-79, 1980-89 and 1990-99: in all countries, investment in research and development as fraction of GDP has increased during these three decades.

Data on labour market institutions come from Nickell et al. (2003) and was described in the previous chapter.

We measure technical efficiency by total factor productivity (TFP), computed as Solow residual (details on the procedure are contained in Appendix C). Table 4.2 gives the mean annual growth rate of TFP for the periods 1970-79, 1980-89 and 1990-99. It appears that most European countries experienced a productivity slowdown in the past decade. Few countries (Australia, Canada and Denmark)

Table 4.1: Average R&D intensity

	1970-79	1980-89	1990-99
Australia	0.6	1.1	1.5
Austria	0.6	1.2	1.6
Belgium	0.9	1.6	1.8
Canada	0.7	1.4	1.7
Denmark	0.6	1.2	1.8
Finland	0.5	1.5	2.4
France	1.1	2.1	2.3
Germany	1.5	2.4	2.4
Ireland	0.3	0.7	1.2
Italy	0.4	1.0	1.1
Japan	1.4	2.6	2.9
Netherlands	0.7	1.9	2.0
New Zealand	0.6	0.9	1.0
Norway	0.8	1.6	1.7
Portugal	0.1	0.3	0.6
Spain	0.1	0.5	0.8
Sweden	1.0	2.6	3.3
UK	1.0	2.2	2.0
US	1.6	2.6	2.6

performed poorly in the second decade of our sample, whereas some economies, notably Finland, Ireland, Norway, Sweden and the US experienced increasing rates of TFP growth throughout our sample period.

In this study we are also interested in capturing possible spillover effects across countries: for this reason we follow Griffith et al. (2000, 2003) and include in our models the distance of a country from the technological frontier.[16] This distance is measured by relative TFP, computed as follows: first, we compare the level of TFP in each year and country relative to the geometric mean of all the other countries. We then define the "frontier" country in each period as the country with the highest value of TFP relative to the geometric mean. The relative TFP measure is thus given by the difference between relative TFP in each country and year and the

[16]Griffith et al. (2000, 2003) study the effects of R&D expenditure on TFP at the industry level: we use a specification similar to theirs and apply it to aggregate data across OECD countries.

Table 4.2: Mean annual growth rate of TFP

	1970-79	1980-89	1990-99
Australia	1.2	0.6	2.0
Austria	2.5	2.0	1.8
Belgium	2.8	2.3	1.3
Canada	0.8	-0.1	1.0
Denmark	1.7	0.9	2.0
Finland	2.9	3.1	3.8
France	2.3	2.0	1.0
Germany	3.2	1.8	-0.9
Ireland	3.3	3.5	4.9
Italy	3.3	2.2	1.5
Japan	2.4	2.4	0.2
Netherlands	2.9	1.6	1.2
New Zealand	0.4	1.3	0.8
Norway	2.7	2.1	4.3
Portugal	2.8	2.5	0.7
Spain	2.6	2.5	0.6
Sweden	0.8	1.7	2.6
UK	1.9	1.9	1.6
US	0.8	1.0	1.2

relative TFP of the frontier country (see Appendix C). Relative TFP across our sample is depicted in Figure 4.1. What is the identity of the frontier country in each period? In our sample, the country with highest TFP level relative to the geometric average for each year apart from 1999 were the USA. In the last period the position of technological leader was occupied by Ireland, as the top left panel of Figure 4.1 shows.

4.4.2 Testing for causality

The aim of this section is to carry out a preliminary investigation on the predictions of the theory summarized in Sections 4.2 and 4.3: we therefore examine the impact of R&D expenditure on productivity growth, and of this on employment. Traditionally, this type of preliminary investigation is carried out by means of a series of Granger

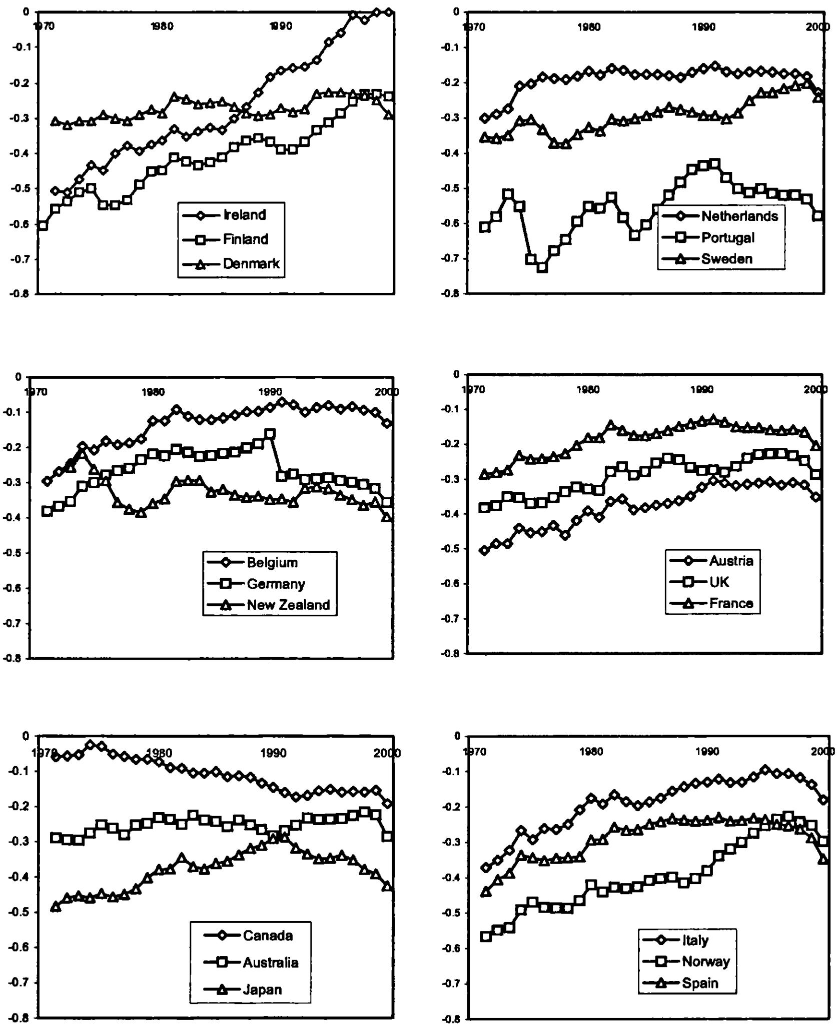

Figure 4.1: TFP relative to the frontier

causality tests. Although initially designed for a time series setting (Granger, 1969 and Sims, 1980) these tests have been also adapted to a panel data context.

Following Holtz-Eakin et al. (1988) consider a bivariate time stationary VAR model in a panel data framework:

$$y_{it} = \alpha_0 + \sum_{j=1}^{m} \alpha_j y_{it-j} + \sum_{j=1}^{m} \beta_j x_{it-j} + f_i + \varepsilon_{it} \tag{4.4}$$

where f_i are meant to capture individual-specific heterogeneity and the lag length m is sufficiently large to ensure that ε_{it} is a white noise error term. Conditional on the assumption that the lag length m is correctly specified, the variable x is said not to Granger-cause the variable y if the history of x does not improve the prediction of y, given the history of y. More formally, x is said not to Granger-cause y if $\beta_j = 0$ for $j = 1, ...m$, i.e. all the coefficients of the lagged x in equation (4.4) are not significantly different from zero.

Equation (4.4) is characterized by the presence of the lagged dependent variables y_{it-j} $(j = 1, ...m)$ among the regressors. Two sources of persistence are thus present in this specification: autocorrelation due to the presence of the lagged dependent variable and individual-specific heterogeneity. It is clear that the lagged dependent variables are correlated with the time-invariant individual-specific terms f_i : an estimation based on the least squares dummy variable (LSDV) approach would therefore yield biased and inconsistent estimates in a finite sample (Nickell, 1981). Several methods for dealing with the inconsistency of the fixed effect estimator have been proposed in the literature on dynamic panel data. The usual approach is to first difference the data to remove the fixed effects:

$$\Delta y_{it} = \sum_{j=1}^{m} \alpha_j \Delta y_{it-j} + \sum_{j=1}^{m} \beta_j \Delta x_{it-j} + u_{it} \tag{4.5}$$

where $u_{it} = \varepsilon_{it} - \varepsilon_{it-1}$. The model can then be estimated using the instrumental variables method to remove the residual correlation between the first lagged dependent variable and the MA(1) error term.

This procedure was first introduced by Anderson and Hsiao (1981), who suggested using Δy_{it-2} or simply y_{it-2} as instrument for the lagged dependent variable.[17] More efficient sets of instruments in a generalized method of moments (GMM) setting have been proposed by Arellano and Bond (1991), Ahn and Schmidt (1995), Arellano and Bover (1995), Blundell and Bond (1998) and others.[18]

Common to these studies is the main focus on micro-type panel data set, where the dimension of the cross section N is large relative to the time series dimension T. As mentioned in the previous chapter, however, the properties of these micro-level panels differ from the datasets normally encountered by macroeconomists, where the time series dimension tends to dominate the cross-sectional one. Therefore, in presence of macro-type panel data sets with a relatively large T, different estimation techniques than those used on micro panels might be required. In this setting, it has been shown that the bias of the LSDV estimator becomes less severe as the time dimension of the panel increases, as long as the error terms are not serially correlated (Nickell, 1981). Judson and Owen (1999) on the other hand, show that the bias can be considerably large even with $T = 20$. They perform a Monte Carlo study that compares four different estimators for a dynamic fixed effect model and conclude that when $T = 30$ the LSDV estimator performs just as well or better than the viable alternatives.[19] For $T < 30$, they suggest using the Anderson-Hsiao (1981) instrumental variable estimator.

In the remainder of this section we perform Granger causality tests to establish

[17] Arellano (1989) recommends the use of instruments in levels, i.e. y_{it-2}, because the estimator that uses the differences Δy_{it-2} for instruments has a singularity point and very large variances over a significant range of parameter values.

[18] A thorough discussion of the literature is outside the scope of this study. See Baltagi (2001) for a review of the latest developments on dynamic panel data estimators.

[19] The alternative estimators examined by Judson and Owen are the Anderson-Hsiao (1981) estimator, the Arellano and Bond's one-step estimator and their two-step estimator (Arellano and Bond, 1991), and a corrected LSDV estimator proposed by Kiviet (1995).

the existence of causality links between R&D expenditure and the rate of growth of TFP. We also investigate the relationship between TFP growth and the employment rate. The tests are performed on a panel dataset comprised of observations for 19 OECD countries over the period 1970-1999. The sample size of 30 time periods is large enough for the estimation of model (4.4) by LSDV methods to achieve consistency. For the purpose of Granger causality tests, however, the choice was made to employ an instrumental variable estimator on the differenced model (4.5).[20]

To test for Granger non-causality between R&D expenditure and technical progress, we considered a bivariate VAR model where the endogenous variables were R&D intensity ($R\&D$) and the TFP growth rate (ΔTFP):

$$\Delta TFP_{it} = \alpha_0 + \sum_{j=1}^{m} \alpha_j \Delta TFP_{it-j} + \sum_{j=1}^{m} \beta_j R\&D_{it-j} + f_i + \varepsilon_{it} \qquad (4.6)$$

We took first differences of model (4.6) and estimated the first equation by the instrumental variables method suggested by Anderson and Hsiao (1981). We performed several specification tests whose results are presented in Table 4.3. We initially specified the model as a $VAR(4)$ in differences.[21] We then performed (sequential) Wald tests for the choice of the appropriate lag length. At each step, we also performed a Sargan test of over-identifying restrictions to verify the appropriateness of the instruments chosen.

The lagged dependent variable was instrumented using two of its lagged levels: the Sargan test reported in Table 4.3 does not reject the validity of the instruments. After establishing the validity of the instruments, we performed a Wald test of the

[20] The reason for this choice was precautionary: estimation of a VAR model requires an initial choice of lag lenght which should be large enough to ensure the residuals are uncorrelated: this process might thus reduce the sample size significantly and introduce biases in the LSDV estimator.

[21] This corresponds to a $VAR(5)$ in levels. An LM serial correlation test confirmed the choice of maximum lag produced uncorrelated residuals ($\chi^2(1)$=1.819, p-value=0.18).

Table 4.3: Specification and causality tests for the TFP growth equation

Dependent variable: *TFP* growth	(ΔTFP)
	Lag length: m=4
Wald (m=3)	7.35
	(0.025)
Sargan	0.109
	(0.741)
Granger non-causality test	10.74
	(0.029)

Note. All tests based on Anderson and Hsiao (1981) first-differenced instrumental variable estimates. The p-values are reported in parenthesis.

joint hypothesis that the fourth lags of the R&D and TFP growth variables were jointly zero. The restriction was rejected at conventional statistical levels, thus we settled for a lag length of four in the TFP growth equation.

Once the lag specification was chosen, a Granger non-causality test was performed for the TFP growth equation. The null hypothesis that the history of the R&D intensity does not improve the prediction of the TFP growth rate was tested using an F test of the joint hypothesis:

$$H_0 : \beta_1 = \beta_2 = \beta_3 = \beta_4 = 0 \tag{4.7}$$

in equation (4.6).

The results of the Granger non-causality test of hypothesis (4.7) is shown at the bottom of Table 4.3. The hypothesis that R&D intensity does not Granger-cause TFP growth is rejected at the 5% significance level.

To investigate the possibility that the TFP growth rate Granger-causes employment, we estimated a bivariate VAR with endogenous variables the employment/population ratio (E/P) and the TFP growth rate:[22]

[22]The choice of the employment/population ratio rather than the unemployment rate could in principle deliver different results as the employment/population ratio tends to be influenced by those social and cultural factors that affect the labour market participation of married women (Nickell, 1997). However, we performed all the empirical analysis of this chapter using the unemployment rate as well as the employment/population ratio and found very similar results.

$$\left(\frac{E}{P}\right)_{it} = \alpha_0 + \sum_{j=1}^{m} \alpha_j \left(\frac{E}{P}\right)_{it-j} + \sum_{j=1}^{m} \beta_j \Delta TFP_{it-j} + f_i + \varepsilon_{it} \qquad (4.8)$$

Table 4.4 presents the results of the specification tests for the first equation in model (4.8) – the employment equation – which we initially specified as $VAR(4)$ in first differences and estimated by instrumental variable methods, using as instruments for the lagged dependent variable two of its lagged levels.[23]

Table 4.4: Specification and causality tests for the employment equation

Dependent variable: E/P	
	Lag length: m=4
Wald (m=3)	1.21
	(0.546)
Sargan	0.700
	(0.403)
	Lag length: m=3
Wald (m=2)	5.31
	(0.070)
Sargan	0.076
	(0.782)
Granger non-causality test	31.44
	(0.000)

Note. All tests based on Anderson and Hsiao (1981) first-differenced instrumental variable estimates. The p-values are reported in parenthesis.

Based on the appropriate instrument specification, we performed a Wald test of the joint hypothesis that the fourth lags of the variables are jointly zero. The restriction could not be rejected at conventional statistical levels, thus we re-estimated the employment equation with three lags of the right hand side variables. Again, the Sargan test did not reject the validity of the instruments, but the redundancy of the third lag was rejected according to the Wald test. We thus settled for a lag

[23] Again, the choice of $VAR(5)$ in levels was not rejected by an LM serial correlation test on the residuals (($\chi^2(1)$=0.491, p-value=0.48).

length of three in the employment equation. We then performed an F test of the null hypothesis that all the lags of the TFP growth in the employment equation are equal to zero: the results are reported at the bottom of Table 4.4. The hypothesis was strongly rejected by the Granger causality test.

One problem with equation (4.8) is that, if the Solow residuals are cyclical, the estimation may be biased and the relationship spurious. We adjusted the Solow residual using procedure for correcting for cyclicality suggested by Hall (1988). Results of the Granger causality tests did not change when computed using the adjusted TFP growth series.

4.4.3 Estimation results

The results in the previous section confirmed the existence of causality links in the direction predicted by the economic theory: first, expenditure in research and development is found to Granger-cause TFP growth; moreover, there is evidence indicating the existence of a causality effect from TFP growth to the employment/population ratio.

In this section we investigate this set of relationships in more detail, and estimate a model of equilibrium employment where the rate of growth of technological progress is endogenously determined as a result of investment in research and development.

To motivate the empirical analysis that follows, consider, as a starting point, the model of endogenous growth from Aghion and Howitt (1998, ch. 12):

$$\Delta \ln A_t = \sigma\lambda\phi\left(\frac{R_t}{A_t^{\max}}\right), \phi' > 0, \phi'' < 0$$

where A_t represents technological progress (its log-difference is measured by the TFP growth rate), and its growth rate is proportional to σ, the innovation size and λ, the probability of innovation, and is a function ϕ of research and development:

R_t is real expenditure in R&D and $A_t^{\max}$ the leading-edge productivity at time t. This model does not contain scale effects and implies a relationship between R&D *intensity*, rather than expenditure, and productivity growth. More precisely, in a steady-state, technology and output grow at the same rate, thus the properties of $\left(\frac{R_t}{A_t^{\max}}\right)$ and R&D intensity $\left(\frac{R_t}{Y_t}\right)$ will be similar. A test of the endogenous growth theory based on a model of R&D induced growth can therefore be performed by regressing productivity growth on lagged levels of R&D intensity, as described in Section 4.2 and presented, e.g., in Zachariadis (2004). Following Griffith et al. (2000, 2003), we also include TFP relative to the frontier country to allow for the possibility of spillover effects.

The equation for technological progress has the form:

$$\Delta \ln A_{it} = \rho \left(\frac{R}{Y}\right)_{it-1} + \mu \ln \left(\frac{A_F}{A_i}\right)_{t-1} + \beta X_{it} + \varepsilon_{it} \tag{4.9}$$

where X_{it} contains other control variables (see below).

The employment equation can be derived as a reduced form from the theoretical models of Mortensen and Pissarides (1994, 1998).[24] Employment is determined in equilibrium by technological progress and a set of labour market institutions. To account for the persistency of the series, we include two lags of the dependent variable. The employment equation has the form:

$$\left(\frac{E}{P}\right)_{it} = \gamma_0 \left(\frac{E}{P}\right)_{it-1} + \gamma_1 \left(\frac{E}{P}\right)_{it-2} + \sum_{j=0}^{p} \delta_j \Delta \ln A_{it-j} + \phi Z_{it} + \nu_{it} \tag{4.10}$$

where Z_{it} contains a set of labour market institutions.

What are the time series properties of the TFP growth and the employment rate? Changes in (the log of) TFP are likely to be stationary, although the TFP

[24] See e.g. Pissarides and Vallanti (2003).

level is not.[25] The employment/population ratio is also expected to be stationary, since it is naturally bounded between zero and one. The labour market institutional variables both contain unit roots, as emerged in Chapter 3.[26]

The structure of the model is thus that of an equation for technical progress (4.9) and a recursive one for employment (4.10).

The first equation in the model contains only exogenous variables, We thus first estimated equation (4.9) by fixed-effect methods. Results from different specifications are reported in Table 4.5. Each specification contains country dummies, time dummies as well as country specific time trends and a lagged dependent variable. As discussed in section 4.4.2, the fixed effect method delivers consistent parameter estimates even in presence of the lagged dependent variable, provided the error term is serially uncorrelated: we perform panel serial correlation LM tests on the residuals and find no evidence of autocorrelation.

For the purpose of comparison with the work of Griffith et al. (2000, 2003), we begin by investigating the role of R&D expenditure in productivity growth. In column (1) of Table 4.5 we report estimates of a TFP equation where the lagged level of R&D intensity (R/Y) enters as determinant of productivity growth. The coefficient estimate is positive and statistically significant. We also include the relative TFP term ($RTFP$) to our specification. This term is expected to enter the equation negatively, since countries that are further behind the technological frontier experience higher rates of productivity growth. The coefficient has the expected sign and is highly significant.

Next, in column (2), we experiment with interacting the R&D intensity level and the productivity gap as in Griffith et al. (2000, 2003): this is meant to capture the second role or "face" of R&D (Cohen and Levinthal, 1989). The coefficient, however, does not appear to be significantly different from zero at conventional

[25] IPS tests confirm this expectation.

[26] Technically, we should require them to be stationary for the equation to be balanced.

Table 4.5: The TFP growth equation: single equation estimation

Dependent variable ΔTFP_{it}	(1)	(2)	(3)	(4)
ΔTFP_{it-1}	0.221	0.224	0.222	0.223
	(5.05)	(5.10)	(5.03)	(5.08)
$(R/Y)_{it-1}$	2.595	2.915	2.581	2.517
	(3.63)	(3.59)	(3.58)	(3.46)
$RTFP_{it-1}$	-0.310	-0.337	-0.311	-0.321
	(-8.17)	(-6.71)	(-7.95)	(-7.59)
$(R/Y * RTFP)_{it-1}$		2.116		
		(0.83)		
$(IMP/Y)_{it-1}$			-0.019	
			(-0.17)	
$(RTFP * IMP/Y)_{it-1}$				0.226
				(0.61)
N	19	19	19	19
NT	570	570	570	570
Serial Correlation LM test	0.090	0.102	0.091	0.107
p-value	0.76	0.75	0.76	0.74
Heteroskedasticity LM test	23.62	22.84	23.57	23.24
p-value	0.16	0.19	0.17	0.18
Country dummies	✓	✓	✓	✓
Year dummies	✓	✓	✓	✓
Country-specific time trends	✓	✓	✓	✓

Note. Estimation method is fixed effect (within). Numbers in brackets are the t-statistics. Serial correlation LM test (Baltagi, 2001) distributed as a χ^2 under the null hypothesis of no serial correlation. Heteroskedasticity is a groupwise LM test, distributed as a $\chi^2(N-1)$ under the null (given $v_{it} = c_i + \lambda_t + \epsilon_{it}, H_0 : \epsilon_{it}$ is homoskedastic).

statistical levels.

We also experiment, in column (3), including a measure of international trade: imports from the frontier country relative to GDP (IMP/Y). This variable, which measures the extent to which trade with the frontier country contributes to innovation, does not appear to have a significant effect in our regression.

Finally, we experiment with interacting trade with the distance from the frontier country: again, we fail to identify a significant effect of this variable on the rate of growth of technological innovation (column (4)).

In conclusion, there is strong evidence on the positive effect of R&D on innovation and on the existence of spillovers in technology.

We then estimate the model described by equations (4.9) and (4.10) as a simultaneous equation system: results are presented in Tables 4.6 and 4.7; the estimation method is two stage least squares. Although the TFP equation is independent from the employment equation, the model is estimated as a system rather than equation by equation to exploit the common structure of the error term.[27]

Results for the TFP equation should not differ markedly, but estimation of the employment equation seems to gain efficiency. The preferred specification for the TFP growth equation is that in column (1) of Table 4.5 and the coefficient estimates are very similar.

Table 4.6: The TFP growth equation: system estimation

Dependent variable ΔTFP_{it}	
ΔTFP_{it-1}	0.244
	(5.11)
$(R/Y)_{it-1}$	2.895
	(3.41)
$RTFP_{it-1}$	-0.372
	(-8.26)
N	19
NT	507
Country dummies	✓
Year dummies	✓
Serial Correlation (LM)	1.76
p-value	0.18
Heteroskedasticity (LM)	20.80
p-value	0.29
Poolability test	36.37
p-value	0.99

Note. Estimation method: two stage least squares. Numbers in brackets are the t-statistics. Serial correlation LM test (Baltagi, 2001) distributed as a χ^2 under the null hypothesis of no serial correlation. Heteroskedasticity is a groupwise LM test, distributed as a $\chi^2(N-1)$ under the null (given $v_{it} = c_i + \lambda_t + \epsilon_{it}, H_0 : \epsilon_{it}$ is homoskedastic). Poolability test distributed as a χ^2 under the null hypothesis of common slopes.

We now turn to the employment equation (4.10), whose estimation results are reported in Table 4.7. The equation contains country dummies as well as time

[27] The SURE method could have been used instead. When we experimented with SURE estimation we obtained similar results.

dummies and two lagged values of the dependent variable. A panel LM test confirms that there is no presence of autocorrelation in the residuals, thus allowing the use of the LSDV estimation method (Judson and Owen, 1999).

Table 4.7: The employment equation: system estimation

Dependent variable $(E/P)_{it}$	
$(E/P)_{it-1}$	1.314
	(25.18)
$(E/P)_{it-2}$	-0.408
	(-8.18)
ΔTFP_{it}	-0.070
	(-2.03)
ΔTFP_{it-1}	0.104
	(6.48)
ΔTFP_{it-2}	0.032
	(2.04)
$union_{it}$	-0.021
	(-2.66)
tax_{it}	-0.030
	(-2.36)
N	19
NT	507
Country dummies	✓
Year dummies	✓
Serial Correlation LM test	0.097
p-value	0.75
Heteroskedasticity LM test	17.40
p-value	0.49
Poolability test	117.86
p-value	0.94

Note. See notes for Table 4.6.

To assess the effect of TFP growth on employment, both contemporaneous and lagged levels of the TFP growth rate were included in the equation. The coefficient on the contemporaneous TFP growth variable has a negative sign and appears to be significantly different from zero. A t-test confirms that the hypothesis of a negative contemporaneous effect of TFP growth on the employment rate cannot be rejected at the 5% significance level.

The long run effect, however, is the opposite. The coefficients of the TFP growth variable lagged once and twice are significantly positive at conventional statistical level. The sum of the three coefficients of TFP growth is positive, thus indicating the existence of a positive long-run effect of innovation on employment.

Therefore, on impact, higher technological progress destroys jobs: this is the "creative destruction" effect of innovation on jobs. In the long run, the effect is reversed and innovation encourages job creation. The long run multiplier of TFP growth on the employment rate is 0.62: a 1% increase in the TFP growth rate increases the employment rate by 0.62% in the long run.

Of the labour market institutional variables included in the model, union density and the tax wedge have the expected negative sign and their effect on the dependent variable appears significant in both cases.

We also experimented including the benefit replacement ratio and benefit duration, but they did not appear to have a significant impact on the employment rate thus they were omitted in the final estimation.[28] To explain this possibility, it has been suggested (Nickell and Layard, 1999) that benefits might have a weaker impact on employment/population ratios than on unemployment because the negative effect on unemployment tends to be offset by a positive effect on labour force participation.

To investigate further the role of labour market institution, we run a two step analysis following Phelps (1994): in the first step, we estimated the employment equation allowing for country-specific constant terms and productivity growth coefficients. We ther regressed the productivity growth coefficients on the institutional variables. These variables were averaged across time, while in Phelps they are time-invariant. None of the institutional coefficients appeared to be significantly differently from zero.

[28] Their omission did not affect the coefficients on the other variables, which remained unchanged.

We also estimated equation (4.10) with dependent variable employment over the labour force, rather than the employment/population ratio. The results were very similar to the intial specification and are reported in Table 4.9 at the end of this Chapter. The only difference is in the contemporaneous TFP growth coefficient, which is now very small and insignificant.

How well does the model explain the patterns of employment/population ratios across our sample? To get a measure of the goodness of fit we run a dynamic simulation of the basic employment model: the results are depicted in Figures 4.2 and 4.3 at the end of the chapter. The model does a good job in explaining employment in some countries, namely those depicted in Figure 4.2, for which changes in employment are not very large: these are Australia, Austria, Belgium, Canada, France, Italy, Norway, Portugal, the UK and the US. The model performs less well for those countries (reported in Figure 4.3) which exhibit large changes in the employment population ratio, namely Denmark, Finland, Germany, Ireland, Japan, the Netherlands, New Zealand, Spain and Sweden.

To assess the magnitude of the estimated effects we present in Figures 4.4 and 4.5 a dynamic simulation of the model keeping technological progress fixed. Table 4.8 reports, for each country in the sample, the fraction of the change in the employment/population ratio between 1970 and 1999 attributable to technological progress. In some countries, patterns of technological progress explain a significant part (more than 45%) of the evolution of the employment/population ratio: these countries are Australia, Finland, Ireland, Italy, Norway, Sweden and the UK. For some countries, i.e. Austria, Canada, France, Germany, Japan, Portugal and Spain the effect is much smaller (around or less than 25%).

Overall, it appears that technological progress, driven by investment in research and development, is a significant factor in explaining changes in employment/population rates across OECD countries in the past 30 years. The effect of

Table 4.8: Percentage of the employment/population ratio explained by technological progress

Australia	51%*
Austria	26%
Belgium	41%
Canada	21%
Denmark	42%**
Finland	70%
France	19%
Germany	2%
Ireland	80%
Italy	53%
Japan	12%
New Zealand	33%
Netherlands	29%
Norway	47%
Portugal	25%
Spain	6%
Sweden	84%
UK	47%
US	33%

Note. * since 1991; ** since 1980.

innovation is, however, very different across countries, and ranges between eighty percent for Ireland to two percent for Germany.[29]

4.5 Concluding remarks

This chapter presented a series of empirical investigations motivated by theoretical models of innovation and equilibrium employment. The results are strongly in favour of endogenous growth models where technological progress arises as a consequence of research activity. A dynamic model of employment was estimated and it was found that technological progress negatively impacts on employment in the short run, but has more than compensating positive effects on job creation in the long run.

[29] In the case of Germany, the effect of the reunification in 1991 is likely to be important. We included a dummy variable for the post-reunification years in all our regressions.

Table 4.9: The employment equation: system estimation

Dependent variable $(E/P)_{it}$	
$(E/P)_{it-1}$	1.252
	(25.45)
$(E/P)_{it-2}$	-0.394
	(-8.49)
ΔTFP_{it}	0.001
	(0.02)
ΔTFP_{it-1}	0.089
	(6.17)
ΔTFP_{it-2}	0.038
	(2.74)
$union_{it}$	-0.024
	(-3.45)
tax_{it}	-0.028
	(-2.55)
N	19
NT	507
Country dummies	✓
Year dummies	✓

Note. See notes for Table 4.6.

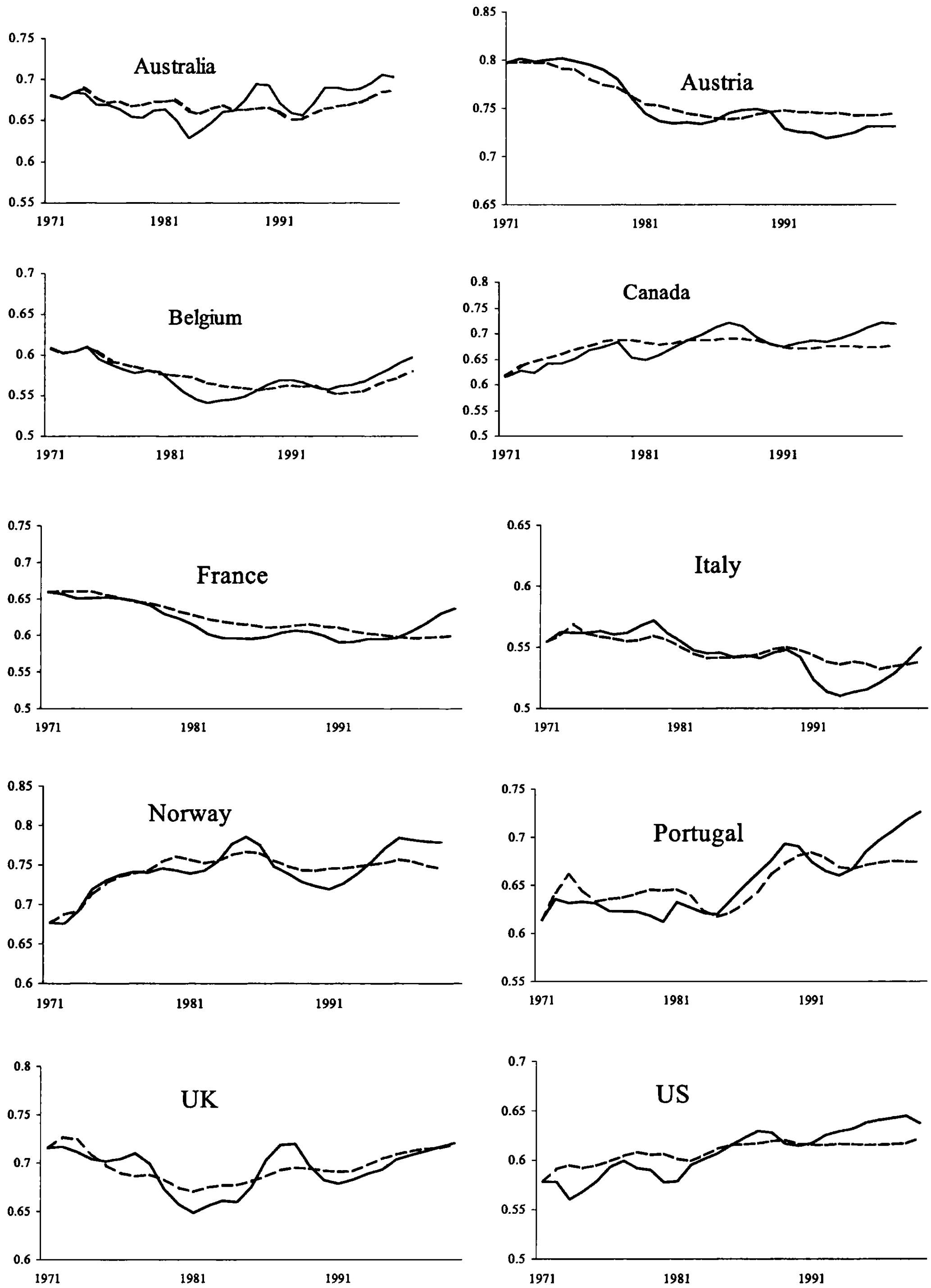

Figure 4.2: Dynamic simulation of the baseline employment model

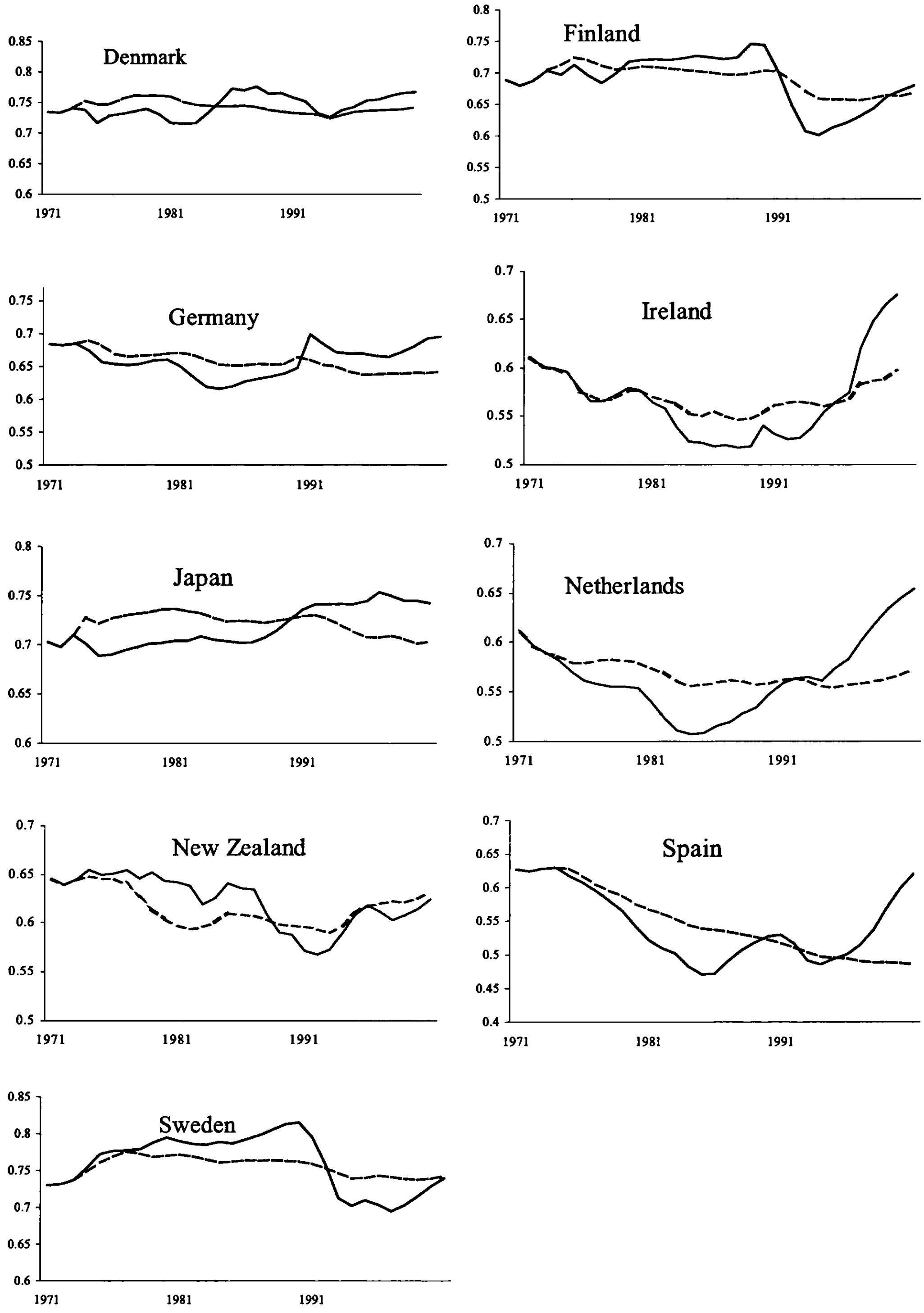

Figure 4.3: Dynamic simulation of the baseline employment model (cont.)

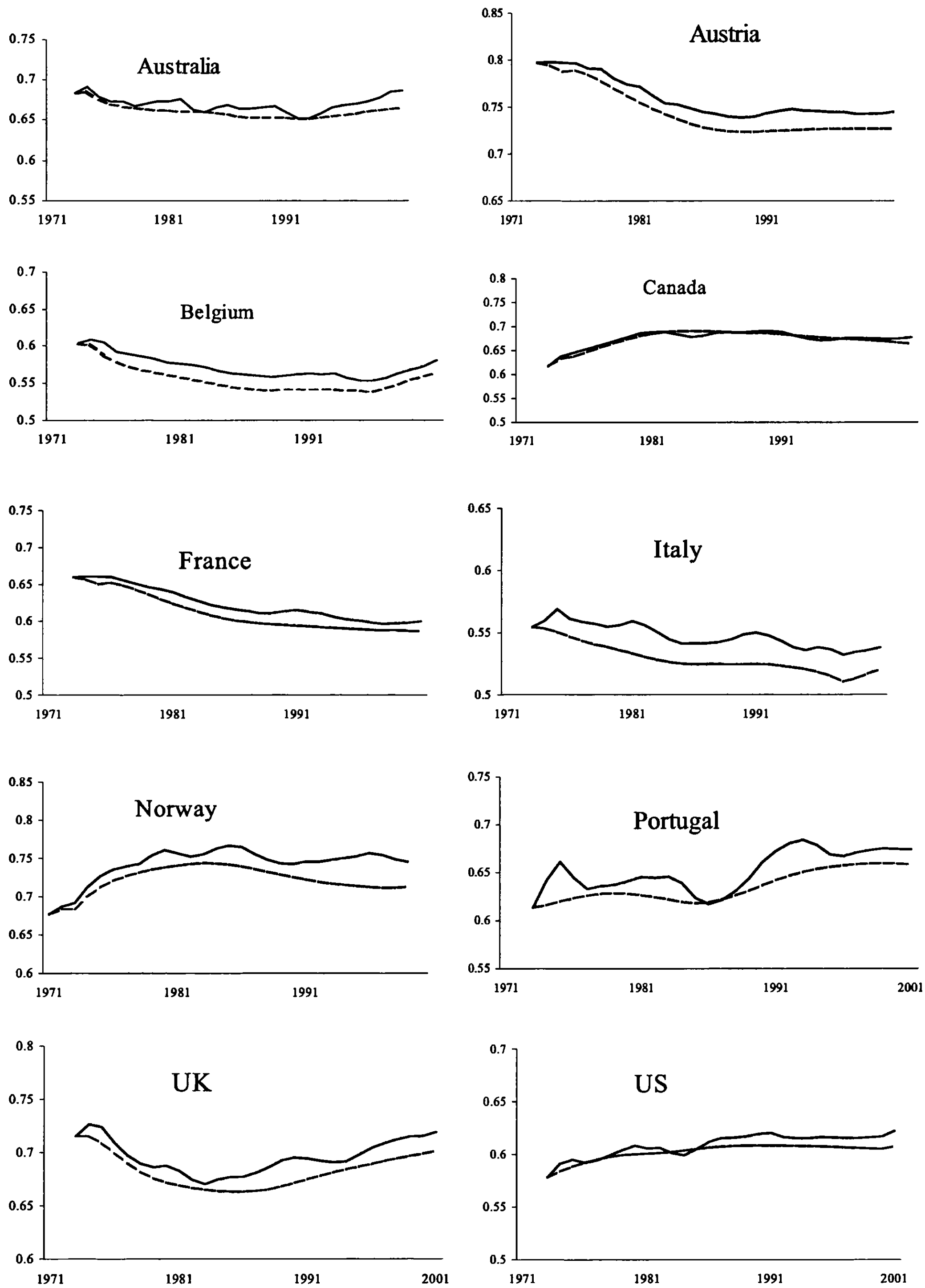

Figure 4.4: Dynamic simulation with technological progress fixed

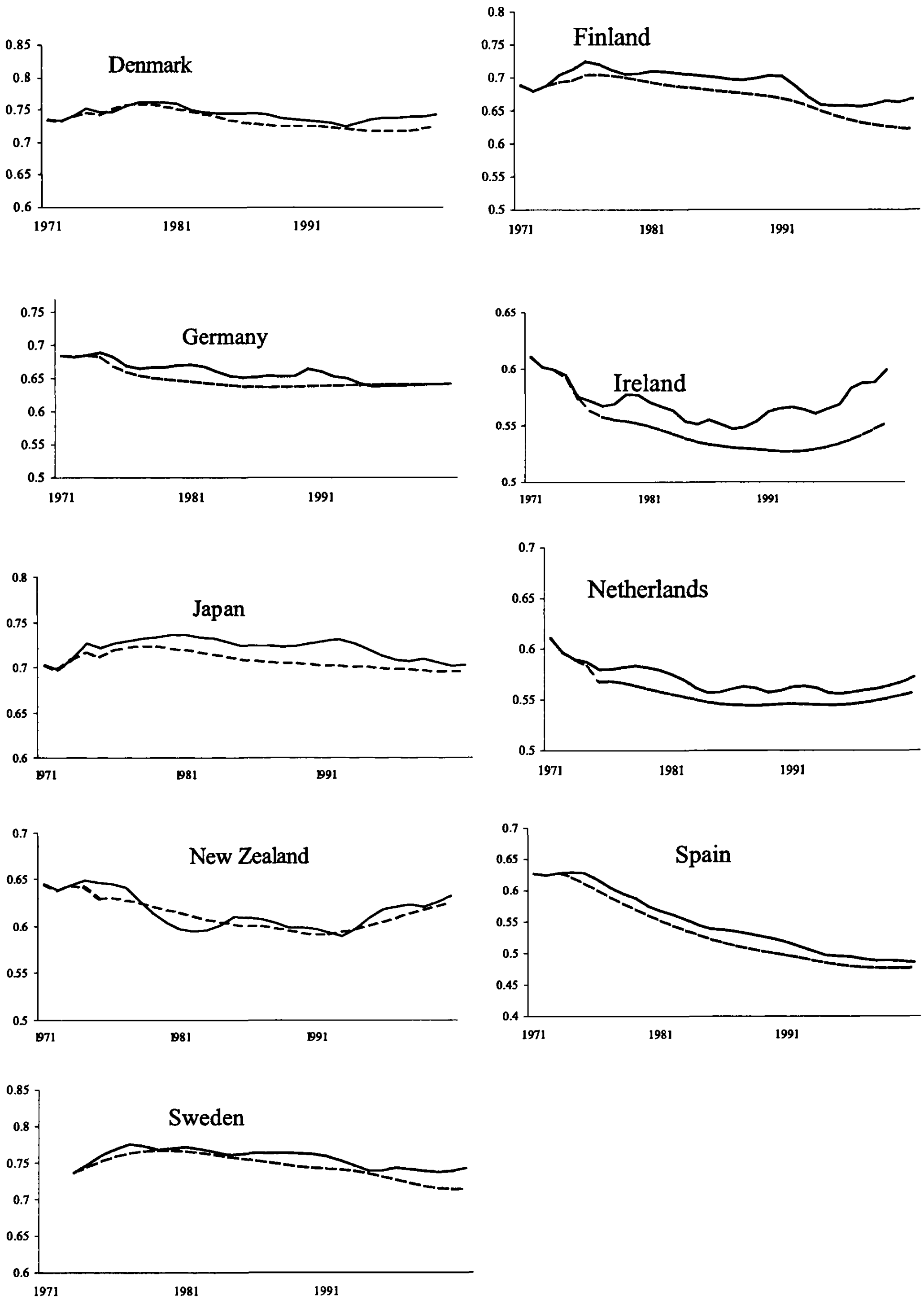

Figure 4.5: Dynamic simulation with technological progress fixed (cont.)

Appendix A

New developments in the theory of non stationary panels

This Appendix summarises the main results in the recent literature on nonstationary panel datasets used in chapter three: it describes new panel unit root tests and cointegration tests and new methodologies for estimating cointegrating regressions with panel data.

A.1 Panel unit root tests

Consider a sample of N cross sections observed over T time periods: the stochastic process y_{it} generated by a first order autoregressive process can be written:

$$\Delta y_{it} = \alpha_i + \beta_i y_{i,t-1} + \varepsilon_{it} \qquad i = 1, ..., N, \quad t = 1, ..., T. \tag{A.1}$$

Im, Pesaran and Shin (IPS, 2003) propose a unit root test procedure for panels based on averaging individual unit root test statistics. In particular, they propose a test based on the average of augmented Dickey- Fuller (Dickey and Fuller, 1979) statistics computed for each group in the panel and call it t-bar test. The test allows for residual serial correlation and heterogeneity of the dynamics and of the error variances across groups in the panel. They establish that the (standardized) t-bar statistic converges in distribution to a standard normal variate sequentially, as $T \to \infty$ followed by $N \to \infty$.The IPS t-bar test considers the null hypothesis that all individual units have unit roots, against the alternative that some units do not have a unit root. In terms of the parameters of equation (A.1) this implies:

$$H_0 : \beta_i = 0 \ for \ all \ i$$

against the alternative that $\beta_i < 0$ for at least one i.

A.2 Panel estimation

Consider the following model:

$$\begin{aligned} y_{it} &= \alpha_i + x'_{it}\beta + u_{it} \qquad i = 1, ..., N \quad t = 1, ..., T, \\ x_{it} &= x_{i,t-1} + \varepsilon_{it}. \end{aligned} \tag{A.2}$$

where y_{it} are 1×1, β is an $M \times 1$ vector of the slope parameters, α_i are the intercepts and u_{it} are the stationary disturbance terms. We assume that the x_{it} are $M \times 1$ integrated processes of order one for all i. Under these specifications, equation (A.2) describes a system of cointegrated regressions, i.e. y_{it} is cointegrated with x_{it} with the assumption that y_{it} and x_{it} are independent across cross-sectional units and $(1, -\beta')$ is a cointegrating vector that is identical across individuals. The pooled OLS estimator of β is[1]:

[1] This is the traditional "within" estimator . In the literature on nonstationary panels, this estimator is called "pooled OLS" estimator and this convention will be followed here.

$$\hat{\beta}_{OLS} = \left[\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it}-\bar{x}_i)(x_{it}-\bar{x}_i)'\right]^{-1}\left[\sum_{i=1}^{N}\sum_{t=1}^{T}(x_{it}-\bar{x}_i)(y_{it}-\bar{y}_i)'\right] \tag{A.3}$$

where $\bar{x}_i = (1/T)\sum_{t=1}^{T} x_{it}$ and $\bar{y}_i = (1/T)\sum_{t=1}^{T} y_{it}$. Let the innovation vector be $w_{it} = (u_{it}, \varepsilon_{it}')'$.The long run covariance matrix of $\{w_{it}\}$ is given by:

$$\Omega = \sum_{j=-\infty}^{\infty} E(w_{ij}w_{i0}') = \begin{bmatrix} \Omega_u & \Omega_{u\varepsilon} \\ \Omega_{\varepsilon u} & \Omega_{\varepsilon} \end{bmatrix}$$

Define the one-sided long-run covariance:

$$\Delta = \sum_{j=0}^{\infty} E(w_{ij}w_{i0}') = \begin{bmatrix} \Delta_u & \Delta_{u\varepsilon} \\ \Delta_{\varepsilon u} & \Delta_{\varepsilon} \end{bmatrix}$$

Also define:

$$\Omega_{u.\varepsilon} = \Omega_u - \Omega_{u\varepsilon}\Omega_{\varepsilon}^{-1}\Omega_{\varepsilon u}$$

It can be shown (Kao and Chiang, 2000 and Phillips and Moon, 1999) that the pooled OLS estimator is $\sqrt{N}$ consistent or $\sqrt{N}T-$ consistent depending on whether or not there exists serial correlation in the time series component of $(u_{it}, \Delta x_{it})$. More formally:

$$T(\hat{\beta}_{OLS} - \beta) \xrightarrow{p} -3\Omega_{\varepsilon}^{-1}\Omega_{\varepsilon u} + 6\Omega_{\varepsilon}^{-1}\Delta_{\varepsilon u}$$

and

$$\sqrt{N}T(\hat{\beta}_{OLS} - \beta) - \sqrt{N}\delta_{NT} \Rightarrow N(0, 6\Omega_{\varepsilon}^{-1}\Omega_{u.\varepsilon})$$

where δ_{NT} is a bias term due to the endogeneity of the regressor x_{it} and the serial correlation in the errors. Thus in the panel case this bias is serious enough to alter the rate of convergence of the estimator. To address the problem, some specialized estimation procedures have been suggested.

A bias-corrected OLS can be computed based on a consistent estimate of the bias:

$$\hat{\beta}_{OLS}^{+} = \hat{\beta}_{OLS} - \frac{\hat{\delta}_{NT}}{T}.$$

A fully-modified OLS estimator (FMOLS) was also suggested (Phillips and Moon, 1999), as extension of the time series estimator originally suggested by Phillips and Hansen (1990). The FM estimator is constructed by making corrections for endogeneity and serial correlation to the OLS estimator in (A.3):

$$\hat{\beta}_{FM} = \left[\sum_{i=1}^{N} \sum_{t=1}^{T} (x_{it} - \bar{x}_i)(x_{it} - \bar{x}_i)' \right]^{-1} \left[\sum_{i=1}^{N} \left(\sum_{t=1}^{T} (x_{it} - \bar{x}_i) \hat{y}_{it}^{+} - T \hat{\Delta}_{\varepsilon u}^{+} \right) \right]$$

where the endogeneity correction is achieved by transforming the variable y_{it}:

$$\hat{y}_{it}^{+} = y_{it} - \hat{\Omega}_{u\varepsilon} \hat{\Omega}_{\varepsilon}^{-1} \Delta x_{it}$$

while the serial correlation correction is obtained through the term:

$$\hat{\Delta}_{\varepsilon u}^{+} = \hat{\Delta}_{\varepsilon u} - \hat{\Delta}_{\varepsilon} \hat{\Omega}_{\varepsilon}^{-1} \hat{\Omega}_{\varepsilon u}.$$

Phillips and Moon show, under certain assumptions, that this estimator is $\sqrt{N}T$ consistent for β and has a normal distribution: $\sqrt{N}T(\hat{\beta}_{FM} - \beta) \Rightarrow N(0, 6\Omega_{\varepsilon}^{-1}\Omega_{u.\varepsilon})$.

Kao and Chiang (2000) suggested a panel version of the dynamic OLS (DOLS) estimator proposed for time series by Sarkkonen (1991) and Stock and Watson (1993). In the DOLS estimator, the endogeneity correction is obtained adding leads and lags of the differenced regressors to the cointegrating equation. More precisely, the DOLS estimator $\hat{\beta}_D$ is obtained running the following regression:

$$y_{it} = \alpha_i + x'_{it}\beta + \sum_{j=-p_1}^{p_2} c_{ij}\Delta x_{it+j} + v_{it}.$$

This estimator has the same limiting distribution of the FM estimator. Kao and Chiang (2000) showed that the DOLS estimator can outperform both the OLS and the FM estimators in finite samples.

A.3 Panel cointegration tests

Kao (1999) and Pedroni (1995) suggest panel cointegration tests under the hypothesis that β is the same across all units, but the analysis can be generalized to allow for heterogeneous β_i.

Kao (1999) presents two types of cointegration tests in panel data, the Dickey-Fuller (DF) and augmented Dickey-Fuller (ADF) type. The DF-type tests can be calculated from the estimated residuals as:

$$\hat{e}_{it} = \rho\hat{e}_{it-1} + \nu_{it}$$

where $\hat{e}_{it}$ are the residuals from the cointegrating equation estimated by OLS. The null hypothesis of no cointegration can be written as $H_0 : \gamma = 1$. The OLS estimate of γ is:

$$\hat{\rho} = \frac{\sum_{i=1}^{N}\sum_{t=2}^{T}\hat{e}_{it}\hat{e}_{it-1}}{\sum_{i=1}^{N}\sum_{t=2}^{T}\hat{e}_{it}^2}$$

Four DF-type tests are constructed: while DF_ρ and DF_t are based on assuming strict exogeneity of the regressors with respect to the errors, whereas DF_ρ^* and DF_t^* are for cointegration with endogenous regressors.

For the ADF test, the following ADF regression is run:

$$\hat{e}_{it} = \gamma \hat{e}_{it-1} + \sum_{j=1}^{p} \delta_j \Delta \hat{e}_{it-j} + \nu_{it} \tag{A.4}$$

The *ADF* test is constructed as normalization of the *t*statistics of γ in equation (A.4). Pedroni (1995) also suggest two tests based on linear transformations of $\hat{\rho}$ in the framework of homogenous cointegration.

Appendix B

Data definitions and sources for Part I

Data for Part I come from the Penn World Tables Mark 5.6, a revised and updated version of the dataset compiled by Summers and Heston (1991). The tables include observations for 152 countries listed in Table B.1. Observations range from 1950 to 1990 for most of the countries, but for some countries data only start in 1960 and ends before 1990. We used observations on the variable "real GDP per worker" from 1960 to 1989 (30 years).

The complete sample was available for only 120 of the 152 countries, therefore the following countries were dropped from the sample: Djibouti, Ethiopia, Liberia, Sierra Leone, Sudan, Tanzania, Bahamas, Belize, Dominica, Grenada, St. Kitts & Nevis, St. Lucia, St. Vincent & the Grenadines, Bahrain, Bhutan, Iraq, Kuwait, Laos, Mongolia, Nepal, Oman, Qatar, United Arab Emirates, Yemen, Bulgaria, East Germany, Hungary, Poland, Solomon Islands, Tonga, Vanuatu, Western Samoa.

Table B.1: Penn tables mark 5.6: list of countries

1	Algeria	2	Angola	3	Benin
4	Botswana	5	Burkina Faso	6	Burundi
7	Cameroon	8	Cape Verde Is.	9	Central Afr. Rep.
10	Chad	11	Comoros	12	Congo
13	Djibouti	14	Egypt	15	Ethiopia
16	Gabon	17	Gambia	18	Ghana
19	Guinea	20	Guinea Bissau	21	Ivory Coast
22	Kenya	23	Lesotho	24	Liberia
25	Madagascar	26	Malawi	27	Mali
28	Mauritania	29	Mauritius	30	Morocco
31	Mozambique	32	Namibia	33	Niger
34	Nigeria	35	Reunion	36	Rwanda
37	Senegal	38	Seychelles	39	Sierra Leone
40	Somalia	41	South Africa	42	Sudan
43	Swaziland	44	Tanzania	45	Togo
46	Tunisia	47	Uganda	48	Zaire
49	Zambia	50	Zimbabwe	51	Bahamas
52	Barbados	53	Belize	54	Canada
55	Costa Rica	56	Dominica	57	Dominican Rep.
58	El Salvador	59	Grenada	60	Guatemala
61	Haiti	62	Honduras	63	Jamaica
64	Mexico	65	Nicaragua	66	Panama
67	Puerto Rico	68	St Kitts&Nevis	69	St Lucia

Table B.1: (continued)

70	St Vincent&Gre	71	Trinidad&Tob.	72	U.S.A.
73	Argentina	74	Bolivia	75	Brazil
76	Chile	77	Colombia	78	Ecuador
79	Guyana	80	Praguay	81	Peru
82	Suriname	83	Uruguay	84	Venezuela
85	Bahrain	86	Bangladesh	87	Bhutan
88	China	89	Hong Kong	90	India
91	Indonesia	92	Iran	93	Iraq
94	Israel	95	Japan	96	Jordan
97	Korea, Rep.	98	Kuwait	99	Laos
100	Malaysia	101	Mongolia	102	Myanmar
103	Nepal	104	Oman	105	Pakistan
106	Philippines	107	Qatar	108	Saudi Arabia
109	Singapore	110	Sri Lanka	111	Syria
112	Taiwan	113	Thailand	114	United Arab E.
115	Yemen	116	Austria	117	Belgium
118	Bulgaria	119	Cyprus	120	Czechoslovakia
121	Denmark	122	Finland	123	France
124	Germany, East	125	Germany, West	126	Greece
127	Hungary	128	Iceland	129	Ireland
130	Italy	131	Luxembourg	132	Malta
133	Netherlands	134	Norway	135	Poland
136	Portugal	137	Romania	138	Spain

Table B.1: (continued)

139	Sweden	140	Switzerland	141	Turkey
142	U.K.	143	U.S.S.R.	144	Yugoslavia
145	Australia	146	Fiji	147	New Zealand
148	Papua N. Guinea	149	Solomon Is.	150	Tonga
151	Vanuatu	152	Western Samoa		

Appendix C

Data definitions and sources for Part II

The data for Part II consist of observations for 19 OECD countries over the period 1960-1999. The countries are Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Portugal, Spain, Sweden, the U.K. and the U.S. We combined various OECD datasets (the OECD National Accounts, the Main Science and Technology Indicators, the OECD Bilateral Trade Database) with information on labour market institutions from Nickell et al. (2003).

C.1 Macroeconomic variables

E Total employment (*source*: OECD National Accounts).

U Standardised unemployment rates (*source*: OECD National Accounts).

L Labour force (*source*: OECD National Accounts).

P Total population (*source*: OECD National Accounts).

A Total Factor Productivity (TFP). This is computed as Solow residual using the formula: $d \ln A = \frac{1}{1-\bar{\alpha}} [d \ln Y - (1-\bar{\alpha}) d \ln L - \bar{\alpha} d \ln K]$, where Y is gross domestic output at constant price (*source*: OECD National Accounts), $(1-\bar{\alpha})$ is a smoothed share of labor following he procedure described in Harrigan (1997), L is total employment as defined above, K is real capital stock. This is computed according to the Perpetual Inventory Method: $K = (1-\delta)K_{-1} + \left(\frac{I}{def_{INV}}\right)$, where I is the gross fixed capital formation at current prices (*source*: OECD National Accounts) and δ is the depreciation rate, assumed to be constant and equal to 8 percent. Initial capital stock is calculated as: $K_0 = \frac{I_0}{g+\delta}$, where g is the average annual growth on investment expenditure and I_0 is investment expenditure in the first year for which data are available. For comparability of the TFP measure across countries, both Y and K were converted to US dollars using the GDP and gross fixed capital formation Purchasing Power Parities (1999) respectively (*source*: OECD National Accounts).

$\frac{A_F}{A_i}$ TFP relative to the frontier country ($RTFP$). This is defined as: $RTFP_{it} = MTFP_{it} - MTFP_{Ft}$ where $MTFP_{it}$ is the level of TFP in country i at time t relative to the geometric mean of all the other countries: $MTFP_{it} = \ln\left(\frac{Y_{it}}{\bar{Y}_t}\right) - \tilde{\sigma}_{it} \ln\left(\frac{L_{it}}{\bar{L}_t}\right) - (1-\tilde{\sigma}_{it}) \ln\left(\frac{K_{it}}{\bar{K}_t}\right)$, where Y_{it}, L_{it}, K_{it} are defined above, $\bar{Y}_t$, $\bar{L}_t$, $\bar{K}_t$ are the geometric means of output, labour and capital across countries at time t respectively, and the variable $\tilde{\sigma}_{it} = \frac{1}{2}(\bar{\alpha}_{it} + \tilde{\alpha}_t)$ is the average of the (smoothed) labour share in country i and the geometric mean (smoothed) labour share. The "frontier" country is the country with the highest value of TFP relative to the geometric mean at time t and is denoted $MTFP_{Ft}$.

$\frac{R}{Y}$ R&D intensity: ratio of real gross domestic expenditure on research and development (GERD) (*source*: OECD Main Science and Technology Indicators) to real GDP (*source*: OECD National Accounts).

$\frac{IMP}{Y}$ Imports from the frontier (*source*: OECD Bilateral Trade Database) over real GDP (*source*: OECD National Accounts).

C.2 Labour market institutions

brr Benefit replacement ratio: unemployment benefits as percentage of wages. The data refers to the first year of unemployment benefits, averaged over family types of recipients (*source*: Nickell et al., 2003 constructed from OECD data sources).

bd Benefit duration: index constructed as weighted average of two fractions: the first is the fraction of benefit replacement ratio received in the second and third year to that received in the first year, while the second fraction is between the benefit replacement ratio in the fourth and fifth year to that in the first year (*source*: Nickell et al., 2003).

union Net union density: percentage of employees who are union members (*source*: Nickell et al., 2003).

tax Tax wedge calculated as the sum of the employment tax rate, the direct tax rate and the indirect tax rate (*source*: Nickell et al. 2003).

coord Bargaining coordination: this is an index constructed as interpolation of OECD data on bargaining coordination and is increasing in the degree of coordination in the bargaining process on both the employers' and unions' side (*source*: Nickell et al., 2003).

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