DOES ECONOMIC GROWTH EXHIBIT A DIFFERENT IMPACT ON JOB CREATION AND JOB DESTRUCTION?

by

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Abstract

The two main implications of the literature on endogenous growth are a unique equilibrium rate of unemployment for a given rate of economic growth, and an identical number of exits and entries from unemployment. This paper tests these two hypotheses against a neoclassical theory of growth and unemployment on the one hand and a theory of endogenous growth and unemployment augmented with intersectoral shifts on the other hand, using microeconomic panel data for the United Kingdom. We find a significant and negative relation between unemployment and economic growth, using fixed effects panel regression methods. Moreover, chi-square-tests on parameter equality in logistic panel regressions for both job creation and destruction reveal that the impact of economic growth differs between exits and entries, hence confirming the sectoral shifts model. (JEL-Codes: J63, O41, O52, C23)

Keywords

Sectoral Shifts, Endogenous Growth, Structural Unemployment, Panel Data Estimation.

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SUMMARY

The endogenous growth literature claims that economic growth is driven by structural change. The cost associated with economic growth is structural unemployment, as structural change destroys jobs in one firm and creates jobs in another, leading to structural unemployment. The theory makes the strong prediction that the number of jobs created equals the number of jobs destroyed for any rate of economic growth, thus resulting in a constant rate of unemployment. By contrast, neoclassical growth theory suggests that exogenous productivity gains are incorporated in the factor labor, hence changes in economic growth should leave unemployment unaffected. This paper presents a simple theoretical framework of intersectoral and intrasectoral change. The economy comprises two sectors. The engine of growth is labor augmenting technical progress in the first sector, and intrasectoral structural change in the other sector. Thus it contains both the neoclassical growth model and the endogenous growth model as special cases. The general model implies that economic growth exhibits a different impact on job creation and job destruction, depending on the relative size of the two sectors, leading to changing rates of unemployment for given rates of economic growth.

This paper then tests these two implications, using microeconomic panel data for the United Kingdom. We find a significant and negative relation between unemployment and economic growth, using fixed effects panel regression methods. This implies that faster sectoral change, driven by higher rates of innovation and therefore by higher rates of economic growth, would foster structural unemployment. The test of this first hypothesis rejects the neoclassical growth model in favor of a framework which includes sectoral shifts.

If the increase in unemployment would be driven entirely by intrasectoral change, we would find that the exit from employment must equal the entry to employment for every rate of economic growth. Chi-square-tests on parameter equality in logistic panel regressions for both job creation and destruction reveal that the impact of economic growth differs between exits and entries, hence rejecting the pure intrasectoral shifts hypothesis in favor of a framework based on both inter- and intrasectoral shifts.

1 Motivation

The economy is permanently exposed to structural change, both within sectors and between sectors. The literature of intersectoral change finds that both employment and consumption have continuously shifted towards the service sector (Clark, 1957, Kuznets, 1957, and Chenery, 1960). Echevarria (1997) attributed these facts to demand shifts due to non-homothetic preferences. By contrast, Kongsamut, Rebelo, and Xie (1997) attribute the sectoral shifts to exogenous changes in productivity. Changes in productivity can account for changes in nominal and real shares of output for wide classes of preferences. In order to obtain intersectoral shifts in both employment and output, potentially leading to a transitory, but rather persistent relation between economic growth and unemployment, they have to deviate from homothetic preferences, too.

However, the employment dynamics is not mainly due to shifts between sectors, but due to shifts within sectors of the economy (Davis and Haltiwanger, 1999). The endogenous growth literature claims that economic growth drives this intrasectoral structural change, i.e. a change within the sectoral composition of the economy (Romer, 1990). The introduction of new modes of production, which allow for a more efficient allocation of resources, or the innovation of a new product line itself, which augments the value of the product, form the essence of the growth process, but necessitate the decline of existing products or production techniques alongside. In that respect, differentiated products and markets will be more exposed to intrasectoral structural change than traditional homogenous markets and goods.

The cost associated with economic growth is structural unemployment, as structural change destroys jobs in one firm and creates jobs in another (Aghion and Howitt, 1994). Firms producing a product in a declining market will lay off workers. Workers specializing in a particular mode of production will loose their jobs as new modes of production make their qualifications redundant. Until these workers requalify and are matched to new jobs in an expanding product segment or adopt to a new technology, these workers will suffer through periods of unemployment. The source of unemployment is the rate of intrasectoral structural change associated with faster economic growth. Hence the model predicts a constant unemployment rate for a given rate of economic growth. The unemployment rate would reach its lowest bound in a static economy, described by a static matching model (Mortensen and Pissarides, 1999). Higher growth induces larger structural shifts, and therefore fosters unemployment. Once we include intersectoral change, this no longer needs to be the case.

Depending on the size of the traditional sector with respect to the innovative sector, the degree of job creation and destruction may differ, and hence the unemployment rate may change over time, even controlling for economic growth (Zagler, 2000a).

This view on unemployment and economic growth can, in principle, be tested. Whilst conventional theories of economic growth (Solow, 1956) and unemployment (for a survey, cf. Layard, Nickell, and Jackman, 1991) find that neither unemployment influences economic growth, nor that long-run economic growth effects equilibrium unemployment (Blanchard, 1997; Zagler, 2000b). The endogenous growth and unemployment literature concludes that economic growth plays a significant role in the determination of equilibrium unemployment. This is the first hypothesis, which shall be tested in this paper. In order to account for differences between individuals, sectors, and over time, a panel structure, where we can control for both observable and unobservable components between groups, is adopted to estimate the impact of growth on unemployment.

The literature on endogenous growth and unemployment furthermore predicts a constant unemployment rate, and hence an equal number of job exits and entries, for a given rate of growth. The second hypothesis therefore is whether the coefficient for the growth rate is statistically equivalent for both exits and entries.

The paper uses the Juvos cohort data of individual labor market exits and entries (Lawlor, 1990), and matches the cases with regionally and sectorally differentiated growth rates taken from the ONS Regional Database.

The paper proceeds as follows. The next section will describe a simple theoretical framework of the effect of economic growth on intersectoral and intrasectoral change and unemployment. It contains both the neoclassical growth model and the Aghion and Howitt model, and is largely based on Zagler (2000a)[1]. We will discuss the related empirical literature in chapter 3, describe the data in chapter 4, and finally present the empirical results in chapters 5 and 6.

2 A Simple Theoretical Framework

Consumers devote an increasing share of their nominal spending on differentiated products. Assume that agents devote a share α_t of their total spending on differentiated products, and a

[1] The emphasis here is on simplicity rather than rigor. For a more precise and rigorous exposition, see Zagler (2000a).

share ($1 - \alpha_t$) on traditional homogenous goods. Consumer spending is then divided between the two sectors according to,

$$p_t x_t/\alpha_t = q_t y_t/(1 - \alpha_t), \tag{1}$$

denoting the price[2] of a typical bundle of differentiated products by p_t, aggregate demand of the innovative sector (all differentiated products) by x_t, demand for traditional goods by y_t, and their price by q_t. We can interpret a change in the differentiated product consumption share α_t as a change in consumer preferences. If relative prices reflect changes in relative productivities, the above formulation contains both the preference shifts hypothesis (Echevarria, 1997) and the technology hypothesis (Kongsamut, Rebelo, and Xie, 1997) of intersectoral change. We shall argue later on that it also contains the neoclassical growth model (Solow, 1956) as a special case with $\alpha_t = 0$, and the endogenous growth model (Aghion and Howitt, 1992) as a special case with $\alpha_t = 1$.

Whilst traditional goods are widely standardized, differentiated products are by definition provided in a heterogeneous variety. We argue that it is the increase in variety, indexed by n_t, which induces the shift in consumer preferences, or equivalently,

$$\alpha_t = \alpha(n_t), \tag{2}$$

with $\alpha(0) = 0$, $\alpha(\infty) = 1$, and $\alpha'(n_t) \geq 0$. Consumer demand for a particular differentiated product $x_{i,t}$ depends inversely on the products relative price, with a price elasticity of demand equal to ε, and positively on aggregate demand,

$$x_{i,t} = (p_{i,t}/p_t)^{-\varepsilon} x_t. \tag{3}$$

This demand function contains a powerful implication for productivity driven sectoral change. Multiplying both sides by the price for the particular product $p_{i,t}$, and aggregating over all n_t different differentiated products, we find that the aggregate innovative sector price index p_t declines for given individual product prices $p_{i,t}$. Hence variety increases productivity in the innovation sector irrespective of productivity gains by individual differentiated product suppliers. As nonstandardization implies that differentiated products exhibit little productivity gains, we shall ignore them altogether and assume that one unit of labor in the innovative sector, $e_{i,t}$, produces one unit of output, $x_{i,t}$. Substituting these assumptions into the demand function (3), taking time derivatives and rearranging terms, yields,

$$\hat{x}_t = \hat{e}_t + \tfrac{1}{\varepsilon - 1}\hat{n}_t, \tag{4}$$

[2] To be discussed below.

where e_t is aggregate innovation sector employment to be defined below (8). Growth in the innovative sector is driven by an 'extensive' term, the change in employment, and an 'intensive' term, the increase in heterogeneity of differentiated products.

The creation of a new differentiated product, the process of innovation, is costly, and that providers of differentiated products pay for these costs by incurring monopoly profits. They therefore set a price equal to a mark-up over costs, which is inversely related to the elasticity of demand,

$$p_{i,t} = \frac{\varepsilon}{\varepsilon - 1} w_t \,, \tag{5}$$

where w_t is the wage per unit of labor. The total profit $\pi_{i,t}$ of a firm in the innovative sector is equal to revenue minus costs,

$$\pi_{i,t} = \frac{1}{\varepsilon - 1} w_t e_{i,t} \,. \tag{6}$$

Given the importance of new innovations for innovation sector productivity, we shall formalize the process of innovation in a very simple manner. Suppose that s_t workers innovate a new product variety with productivity ϕn_t, then the growth rate of innovations is equal to,

$$\hat{n}_t = \phi s_t \,. \tag{7}$$

Assuming that all profits (6) are reinvested, then employment in the creation of new products will be a constant share of total employment in the innovative sector,

$$e_t = n_t e_{i,t} + s_t = \frac{\varepsilon}{\varepsilon - 1} n_t e_{i,t} = \varepsilon s_t \,. \tag{8}$$

As opposed to differentiated products, traditional goods are widely standardized. This standardization implies that productivity gains can be realized much easier, and that it is easier to enter this market. For simplicity, we shall assume that manufacturers produce one unit of output with labor, l_t, as the only input, and technology a_t, under perfect competition, implying that the price q_t will equal marginal costs, w_t/a_t, and hence all revenue will go to the workers,

$$q_t y_t = w_t l_t. \tag{9}$$

Apart from capital, the traditional sector in this economy represents very well the competitive single-good economy as described in Solow (1956), whereas the heterogeneous monopolistically competitive innovative sector captures all essential features of the endogenous growth literature (Aghion and Howitt, 1992).

Substituting traditional goods expenditure (9), the mark-up (5), and innovation employment (8) into consumption shares (1), we find that as consumers shift demand towards differentiated products, employment must follow this shift, whereas mere productivity induced changes in relative prices, holding α constant, would not have this consequence, as

$$(1 - \alpha_t)e_t = \alpha_t l_t. \tag{10}$$

Defining the unemployment rate as one minus the employment rate, eliminating the traditional sector labor force from condition (10) above, and innovative sector employment through conditions (8) and (7), we find an inverse relation between the rate of innovation, which itself determines economic growth (4), and unemployment,

$$u_t = 1 - \frac{\varepsilon}{\phi \alpha_t} \hat{n}_t . \qquad \textbf{(H 1)}$$

This structural form equation is the first testable hypothesis. Note already that this formulation contains both the Solow and the Aghion-Howitt model as special cases. In a Solow type economy, economic growth is entirely driven by exogenous changes in factor productivity, a_t, which is equivalent to a purely traditional economy in our model, represented by a share of traditional goods in consumption $(1 - \alpha_t)$ equal to unity. In that case employment in the innovative sector will be zero due to equation (10), and therefore innovation growth will be zero due to equation (7). Therefore, as α_t converges to zero, the unemployment rate defined in (H 1) will be constant and independent of the rate of economic growth. By contrast, in an Aghion-Howitt framework economic growth is entirely driven by innovation, equivalent to a pure innovative economy, where the differentiated product share in consumption α_t equals unity. Unless the rate of substitution ε and productivity in innovation ϕ change persistently and systematically over time, unemployment rates should be identical for a given rate of economic growth. The inclusion of intersectoral shifts - where α_t evolves according to equation (2) - breaks the sharp prediction. The impact of new innovations on unemployment, captured by the derivative of unemployment with respect to innovation growth, becomes weaker as the level of innovation increases, as the cross derivative of uenmployment with respect to innovation and innovation growth is negative, $\delta^2 u_t / \delta n_t \delta \hat{n}_t < 0$.

The model exhibits rich flow dynamics of workers in and out of employment, which are of particular interest, as they allow more efficient empirical estimates due to a higher volatility. Workers are driven out of jobs due to intersectoral shifts, leaving jobs in the traditional sector and eventually finding employment in the innovative sector. The larger part of employment fluctuation happens within the innovative sector due to intrasectoral shifts, however. New innovations create new jobs, but at the same time destroy existing jobs, not only in the traditional sector, but also in incumbent innovation sector firms. Job creation in this economy happens primarily in new innovation sector firms, which each employ an average of $e_{i,t}$ employees. In addition, as the innovative workforce the differentiated product sector, s_t, grows proportionally with the rest of the sector (8). Job creation in terms of total employment, c_t, therefore equals,

$$c_t = (\dot{n}_t e_{i,t} + \dot{s}_t)/(e_t + l_t) = \tfrac{\alpha_t}{\varepsilon}\hat{e}_t + \tfrac{(\varepsilon-1)\alpha_t}{\varepsilon}\hat{n}_t \,, \qquad \textbf{(H 2a)}$$

where dots denote the total number of changes over time. The creation of new jobs makes exiting jobs redundant at the margin, thus leading to the creative destruction of existing jobs,

$$n_t \dot{e}_{i,t} /(e_t + l_t) = \alpha_t (n_t e_{i,t})\hat{e}_{i,t} = \tfrac{(\varepsilon-1)\alpha_t}{\varepsilon}[\hat{x}_t - \hat{n}_t - \tfrac{1}{\varepsilon-1}\hat{n}_t] = \tfrac{(\varepsilon-1)\alpha_t}{\varepsilon}(\hat{e}_t - \hat{n}_t)\,. \qquad (11)$$

Note that under the assumption $\alpha_t = 1$, equation (10) implies that employment is constant on a balanced growth path. The change in employment in the last expression of equation (11) therefore vanishes, rendering the creative destruction effect unambiguously negative. The third expression in equation (11) is however more intuitive. It captures all three effects of creative destruction as discussed in Aghion and Howitt (1994). The second term in the square brackets is the direct effect of creative destruction. As new firms enter, the share of aggregate demand served by each firm declines. The third term in the square brackets is the indirect creative destruction effect. As new firms enter, aggregate prices decline faster than individual prices, thus reducing demand, and therefore indirectly destroying jobs. The first term in the square brackets represents the counteracting capitalization effect, which is due to the fact that lower aggregate prices increase aggregate demand and thus partially defer the creative destruction of jobs in incumbent firms.

As opposed to the Aghion-Howitt framework, innovation sector employment can change over time in a model, which includes intersectoral shifts for two reasons. First, the impact of growth on unemployment may differ according to the current level of innovations, hence total employment may change over time. Second, shifts from the traditional sector into the innovative sector can change innovation sector employment for a given rate of unemployment. In terms of employment flows, we need to incorporate the flow of workers which are driven out of the traditional sector, hence the exit rate from employment, d_t, changes to,

$$d_t = (n_t e_{i,t} + l_t)/(e_t + l_t) = (\tfrac{\alpha_t}{\varepsilon} + 1)\hat{e}_t - [\tfrac{(\varepsilon-1)\alpha_t}{\varepsilon} + \tfrac{\partial \alpha_t}{\partial n_t}\tfrac{n_t}{\alpha_t}]\hat{n}_t \,, \qquad \textbf{(H 2b)}$$

making use of equations (10) and (2). The first term merely expresses that an increase in total employment increases the number of workers who may be hit by structural change. The second term is the creative destruction effect as noted by Aghion and Howitt (1993). The third term, which is the elasticity of the innovative sector's share in total output with respect to the number of innovations, captures an indirect creative destruction effect. As the number of new innovations increases, a larger share of jobs in the traditional sector becomes redundant.

Finally, note that the direct and the indirect effect of economic growth on job creation and destruction are identical if $\alpha_t = 1$, hence the Aghion-Howitt hypothesis, $c_t = d_t$, can be considered a special case of a model consisting of both intersectoral and intrasectoral structural change.[3]

3 Related Empirical Literature

Much of the empirical literature on the effect of economic growth on unemployment has focused on aggregate time series. The evidence on the choice of the correct underlying model is mixed. Topel (1999) finds time series evidence of a positive association of growth on unemployment within the Solow-framework, whereas Altissimo and Violante (forthcoming) find results favoring an association which would support an endogenous growth setting. As economic growth may influence unemployment both through the business cycle and through its impact on the creative destruction of jobs, authors have turned attention to panel data methods. Both Blanchard and Wolfers (2000), and Bulli (2000) use international panel data evidence, the former to test a neoclassical model, and the later to test endogenous growth models. Both find empirical support for their respective estimates, thus not enabling us to distinguish between the two hypotheses. Time series currently available are too short to distinguish between an neoclassical growth framework with a lot of persistence, and an endogenous growth model which generates a unit root. We will therefore use microeconomic data of individual unemployment experiences, where we can control for business cycle effects, as many individuals are hit by identical shocks, in order to capture the long-run impact of economic growth on equilibrium unemployment.

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[3] Indeed, an even less stringent condition, $\alpha' = 0$ is required to obtain equality of job creation and destruction. Hence a mixed economy with homothetic preferences (as in Kongsamut, Rebelo, and Xie, 1997) is in that respect analytically equivalent to Aghion and Howitt (1994).

The idea to use microeconomic panel data is not completely new to growth models. Harberger (1998) has been able to assess the significance of human capital investment and innovation on the long-run growth rate of revenues of US companies, thus confirming many of the arguments within the theoretical literature on endogenous growth.

Panel data have received a much wider attention within the empirical labor market literature. Bailey, Hulten, and Campbell (1992) use plant level data to estimate the effect of labor reallocation on productivity growth on the plant level, finding that faster changes in the labor force result in higher rates of productivity. Foster, Haltiwanger, and Krizan (1998) have decomposed the impact of factor reallocation on productivity growth between exiting, entering and surviving firms, finding a similar impact of labor reallocation on productivity throughout. This has two implications for the following analysis. First, „reallocation plays a significant role in labor productivity growth via net entry" (Davis and Haltiwanger, 1999, p. 2767), and hence for output growth. Second, the type of firm seems irrelevant, and hence we need not necessarily control for it, allowing us to focus on panel data evidence which captures employment flows.

Using UK microdata on unemployment, Layard, Nickell, and Jackman (1991, p. 286ff) summarize the reasons for being unemployed. First, they find that the usual occupation and the geographical region of the unemployed exhibit a significant impact on the workers chance to be unemployed. As some jobs and some regions are exposed to stronger structural change, it is quite evident that the process of creative destruction would lead to such a pattern. Indeed, economic growth may be the driving force behind differences in regional and occupational unemployment rates. Second, they find that a number of personal characteristics play an important role, in particular age, race, and gender.

As the former and the latter are typically associated with additional detriments to occupational change and regional flexibility (Böheim and Taylor, 1999), we shall control for these factors explicitly. Moreover, we shall include stable relationships, such as marriages and partnerships, for the same reason, in our panel.

4 The Data

The core of the econometric investigation in this paper is based on the Joint Unemployment and Vacancies Online System (Juvos) database. It randomly generates a 5 % sample of all entries and exits into unemployment, alongside with some other statistical information, for a total of 3.398,223 UK cases over a period from October 1982 to December 1999, based on daily information supplied by the Employment Service local offices (ONS, 1997). The database is longitudinal, as it assigns a code to each individual (generated to replace the National Insurance Number), and can hence be transformed into a panel structure, reporting every exit and entry to the pool of unemployed over time (Ward and Bird, 1995).

The panel contains 319,057 men and 163,555 women, with 338,082 living in a stable relationship (marriage and partnerships), and 144,530 living alone. On October 1, 1982, 4,202 individuals were over fifty, 49,987 were over forty, 79,860 were over thirty, 92,424 were over twenty, 148,707 were older than ten, and 107,432 younger than ten at the beginning of the sample.

The econometric analysis, which follows, uses as dependent variables the time series of exits, the time series of entries, and a self-generated series, labeled the individual unemployment rate. The latter captures the number of days a person spends being unemployed over the entire year, and therefore represents the closest individual correspondence to the aggregate unemployment rate.

The best individual representation of a growth rate would probably be individual wage growth. Three arguments speak against the use of this series. First, individual wage growth does not account for total value added by the individual, unless we assume perfect competition and constant returns to scale in production. Second, as high wage claims by individuals will certainly lead to a higher risk of unemployment, we will face a sample selection bias. Third, individual wage data cannot yet be matched with individual unemployment spells. Therefore, we have used the closest available proxy to individual value added growth, which is the GDP growth rate of the region and the sector in which the individual is occupied. The Juvos data provide the individuals unemployment benefit office number, which can be transformed into the 11 standard statistical regions (SSR) of the United Kingdom.[4] They provide both usual (in the past) and sought (wanted) occupational codes for 1.028,396 cases or 482,612 individuals, which have been matched to the 12 industry sectors and 13 manufacturing classes as defined by the European System of Accounts (ESA 95)

[4] These are the North, North West, Yorkshire and Humberside, East Midlands, West Midlands, East Anglia, South East, South West, Wales, Scotland, and Northern Ireland.

classification (Sweeney, 1996a).[5] GDP growth rates, taken from the ONS Regional Accounts, for these 264 observations per annum were then assigned to the individuals in the Juvos panel. The growth rates have been assigned in three different ways, by region only, by region and sought occupation, and by region and usual occupation.

Unemployment is driven by the business cycle. In order not to capture effects of the business cycle, but of economic growth, we will instrumentalize the average growth rate with the two period lagged growth rate, which exhibits the highest correlation with the current growth rate, and therefore seems an appropriate instrument.

5 Does Economic Growth Determine Unemployment?

This chapter presents estimation results and the test of the first hypothesis (H 1), which predicts a negative correlation between unemployment and economic growth, based on the empirical data presented in chapter 4. The innovation here is clearly the use of microeconomic panel data in testing this hypothesis. As discussed in chapter 2, unemployment can be viewed as the difference between flows of workers into unemployment, and flows of workers out of unemployment. Evidently these flows are in part driven by the willingness of a particular worker to accept a job, and by the willingness of firms to hire a particular type of worker. As each worker is different from another, we would like to control for these individual characteristics. Panel data allow us to control for both observable and unobservable time

[5] Note that we have eliminated all individual cases which are still seeking employment (53,464 cases), as well as all individuals which have not returned to work for some reason or another. This leaves us with a sample of 238,036 cases, or about 40 % of the unemployed, who return to job (Sweeney, 1996b), whereas the remaining 60 % cannot be termed structurally unemployed in the spirit of Mortensen (1986) or Pissarides (1990). The industries are agriculture, hunting, forestry and fishing; mining and quarrying including oil and gas extraction; manufacturing (see footnote below); electricity, gas and water supply; construction; wholesale and retail trade, repairs, hotels and restaurants; transport, storage, and communication; financial intermediation, real estate, renting and business activities; public administration, national defense and compulsory social security; education, health, and social work; and other services, including sewage and refuse disposal. The manufacturing industry can be divided into manufacturing classes, which are food, beverages, and tobacco products; textiles and leather products; wood and wood products; pulp, paper and products, printing and publishing; solid nuclear fuels, oil refining; chemicals and man-made fibers; rubber and plastic products; other non-metallic mineral products; basic metal and metal products; machinery and equipment; electrical and optical equipment; transport equipment; and other manufacturing.

invariant individual characteristics. As the first hypothesis (H 1) should hold in every period and for every sector, we can restate it in matrix notation,

$$U_{i,t} = N_{i,t}\gamma + X_{i,t}\beta + Y_i\theta + Z_i\delta t + v_{i,t}\ , \tag{12}$$

where $U_{i,t}$ is the dependent series, which corresponds to the individual unemployment rate, $N_{i,t}$ is the assigned growth rate, $X_{i,t}$ are other time varying regressors and the time varying individual characteristics, Y_i are the observable time invariant dependent variables, Z_i are time variant dependent variables, which may reflect underlying unobservable components which change continuously over time, γ, β, θ, and δ are the associated parameters, and $v_{i,t}$ is the error term. In principle, we are faced with two types of biases in our estimation, non-stationarity and measurement errors due to unobserved components, which are correlated with the dependent variable, and we shall address these issues in turn.

Clearly, at least one regressor is non-stationary. More importantly, there may be non-stationarity in the dependent series as well, due to hysteresis in unemployment. This holds for aggregate data, where the fact that there is unemployment today is good indicator that there will be unemployment tomorrow, but even more true in individual data, where the fact that someone is unemployed today implies that she will most likely be unemployed tomorrow. This implies that lagged unemployment will be absorbed in the error term of equation (12), $v_{i,t} = v'_{i,t}\beta + U_{i,t-1}\rho$, where the autocorrelation coefficient ρ measures the persistence of unemployment. The unemployment rate will then exhibit persistence if $\rho < 1$, and full hysteresis, or a random walk, if $\rho = 1$. When regressing equation (12), this implies that the residual is correlated with the error term, and thus that all estimators are biased. We can eliminate persistence by taking first differences of equation (12)[6], resulting in

$$\Delta U_{i,t} = \Delta(N_{i,t}\gamma) + \Delta(X_{i,t}\beta) + \Delta(Y_i\theta) + \Delta(Z_i\delta t) + \Delta(U_{i,t-1}\rho) + \Delta v'_{i,t}\ , \tag{13}$$

which still does not eliminate the bias. However, as the time invariant dependent variables are equivalent to their average, the third term in expression (13) vanishes. Moreover, as time only directly influences the time variant dependent regressors, the fourth term simplifies to $Z_i\delta$. In order to eliminate the bias, we follow Arellano and Bond (1991), who suggest that we can instrument for the lagged change in the dependent variable with the twice lagged level of the

[6] Note this the following procedure is invalid in the presence of a unit root, $\rho = 1$. We shall therefore present a unit root test together with the results in table 1, to show the validity of the estimation procedure.

dependent variable as a valid instrument. The first stage instrumental variable (IV) estimation the equals,

$$\Delta U_{i,t-1} = U_{i,t-2}\varphi + \xi_{i,t}, \qquad (14)$$

where $\xi_{i,t}$ is the error term. Substituting the deterministic part of the first stage IV-estimation (14) into equation (13), we obtain the second stage IV-estimator,

$$\Delta U_{i,t} = \Delta N_{i,t}\gamma + \Delta X_{i,t}\beta + Z_i\delta + U_{i,t-2}\varphi\rho + \Delta v'_{i,t}. \qquad (15)$$

Unless φ equals unity, which we can test for in equation (14), this equation provides us with a simple unit root test for the hysteresis hypothesis of individual unemployment rates. Whilst this procedure eliminates the bias due to non-stationarity of the series, we still have to deal with the measurement error due to unobservable components which are associated with the dependent variable.

In contrast to pure time series or cross sectional analysis, panel data allow us to eliminate some of the measurement error. The measurement error appears, as independent regressors may be correlated with unobserved individual characteristics. To give an example, it may well be the case that some workers are more mobile than others, and therefore exhibit a higher search intensity. This can be the case of individuals in stable relationships, which are bound to seek work in the vicinity of their partner. Estimating equation (15), the unobserved individual search intensity will be absorbed in the error term, $\Delta v'_{i,t} = Z_i\varphi + \Delta v''_{i,t}$. Substituting this into equation (12), we find that the OLS estimator will be biased upwards by φ (Angrist and Kruger, 1999). Substituting the same information into the fixed effect panel estimator (13), we find that,

$$\Delta U_{i,t} - \overline{\Delta U_i} = (\Delta N_{i,t} - \overline{\Delta N_i})\gamma + (\Delta X_{i,t} - \overline{\Delta X_i})\beta + (\Delta Z_i - \overline{\Delta Z_i})(\delta + \varphi) + \Delta v''_{i,t} - \overline{\Delta v''_i}, \qquad (16)$$

which is unbiased due to the elimination of the fixed effects, as the third term on the right hand side is zero by definition. Therefore, if we estimate (16), which is a fixed effect estimation, it does not matter whether we can observe the time invariant fixed components or not (Baltagi, 1995, p. 10ff). Moreover, as the error terms are zero by definition, the very last term in expression (16) vanishes. In this respect, the error structure remains MA(1), and the double differentiation (first differences and then deviations from mean), do not alter the error structure, and thus statistical properties of the model remain valid. Denoting deviations from average changes by tildes, the estimated fixed effects (FE) instrumental variable panel regression ultimately equals,

$$\widetilde{U}_{i,t} = \widetilde{N}_{i,t}\gamma + \widetilde{X}_{i,t}\beta + \Delta v''_{i,t}, \tag{17}$$

The following table summarizes the results of the empirical estimation of the above equation for three different methods of assigning growth rates to individual workers, equivalent to the test of hypothesis one (H 1). We could not reject hypothesis one if the coefficient on the growth rate is significant and negative.

(Table 1 about here)

The reported estimations can explain a remarkably large part in the variation of the dependent variable, with the relevant R^2 above 30 %. The F-test reveals that all regressors taken together are significant, and we find that indeed all regressors taken individually are significant at least at the 1 % significance level.

This implies that we find a statistically significant impact of economic growth on unemployment at the microeconomic level. The sign is negative, as predicted by hypothesis one (H 1).

The three estimated coefficients on economic growth cannot be directly compared. Whilst the first scenario has only 11 different regional growth rates attributed in every year, the later two scenarios attribute both regionally and sectorally differentiated growth rates to each individual. The growth rates in the first column therefore contain more averaging than the later two, thus explaining the higher coefficient of scenario 1. If we would account for this fact, the coefficient of the first column would be much closer to the other two.

The effect is also economically significant. Given an average individual unemployment rate of 12,5 % in our sample[7], a one percentage point increase of a particular regional and sectoral growth rate would reduce unemployment by 5 percent, or the equivalent of one working week per employee.

All time invariant individual characteristics, such as date of birth, race, and gender have been implicitly accounted for by the fixed effect estimation. We could however explicitly control for all time varying effects. We find, in particular, that both a regional migration and a change

[7] The individual unemployment rate is higher than the national aggregate for the period in question. The difference is due to the measurement of intramonthly unemployment spells, which are omitted in national aggregates, and the fact that national unemployment statistics have a different (and much stricter) definition of unemployment compared to claimant counts.

of occupation increase the individual unemployment experience. Evidently, as agents are forced to leave there region to find a job elsewhere, they will be more reluctant to move, thus prolonging the duration of unemployment. As agents loose a job in a declining sector, employers in other sectors will be less inclined to offer them a new job, hence their probability to remain unemployed increases by the same token.

Whilst most personal characteristics are time invariant, we can explicitly account for changes in the marital and partnership status of individuals. We find that people entering a stable relationship will see their unemployment experience on average increasing, which may be due to the fact that regional flexibility in the search strategy on the labor market declines. By contrast, we find that people who break up with their relationship are more likely becoming unemployed as well. This can be explained both from individual characteristics - people who are in the process of splitting up will be less focused on their job and are therefore likely to be fired - and from employer characteristics. Employers may be less likely to hire divorced people, with only the increased regional flexibility to offset these two psychological factors.

Finally, note that the level of the twice lagged dependent variable, the individual unemployment rate, exhibits a positive impact on the current unemployment experience. As we are using this variable as an instrument for the lagged change in the individual unemployment rate, we can conclude that there is indeed some hysteresis in the time series. However, the unit-root test derived from this series, which we obtain by splitting the coefficient into the autocorrelation coefficient ρ and the coefficient of the first stage IV estimation φ, rejects the hypothesis of a unit root in the individual unemployment rate. This implies that the estimation procedure adopted is valid, and not subject to spurious results.

Fixed effects estimation is based on the idea that each individual has particular time invariant observable and unobservable characteristics, and therefore relies entirely on the information obtained from variation within each individual observation. Evidently, this leads to a loss of degrees of freedom, and therefore to a inefficient estimators. In our analysis, we have suggested that it is the fact that we cannot observe important individual characteristics, such as search intensity, therefore a fixed effect model is appropriate. The most popular alternative is a random effect model, where we treat our missing knowledge over a particular individual as individual ignorance with respect to that individual (and assume some distribution over that lack of knowledge). We can test whether it is indeed individual ignorance, by testing whether the error terms are indeed not systematically correlated, following a test procedure as described by Hausmann (1978). The Hausmann-tests rejects the null hypothesis that the difference in coefficients is not systematic. Therefore, we would have to reject the random effect specification in favor of something else, which gives additional support for the fixed effects modeling choice pursued here.

Summarizing, we can conclude that economic growth exhibits a significant and negative impact on unemployment. Whilst this rejects the Solow model, it confirms both the intrasectoral shifts Aghion-Howitt framework and the intra- and intersectoral shifts framework presented in chapter 2. The estimation is rather robust with respect to the particular attribution of growth rates to individuals, hence we shall pursue by only using the last representation, by usual occupation and region.

We have seen both in the theoretical chapter 2 and here, that it is important to look at flows of workers into employment and out of employment rather than at the aggregated series, which will be done in the following.

6 Does Economic Growth Exhibit a Different Impact on Exits and Entries?

In chapter two, we have found that the impact of economic growth on entry and exit from employment need not be identical, which lead to the formulation of hypothesis two. As our data provide information on both exits and entries into the labor market, we can in principle test the two equations (H 2a) and (H 2b) separately, and then test for parameter equality, which is our second hypothesis.

The econometric procedure is equivalent to the previous chapter, substituting entries $C_{i,t}$ and exits $D_{i,t}$ for the individual unemployment rates $U_{i,t}$ of the previous chapter. There is, however, with one important distinction. As agents can either be entering a new job or not, or either be leaving a job or not, both dependent variables are binary, which implies that the variance of the error term varies systematically, or that the error terms are heteroscedastic (Mofitt, 1999). We therefore estimate the model using logistic regressions, estimating the probability of an individual to find a job or to loose her job, but otherwise remain to follow the fixed effects panel data estimation procedure described in the previous chapter. As logit is a nonlinear estimation procedure, we have to take care in interpreting the results. In particular, note that the coefficients in table 2 below represent the marginal effect of a unit change in independent variable from the baseline scenario, which is assumed to be $X_{i,t} = 0$.

The first two columns in table 2 are the diseggregated equivalents to the last column in table 1. We note from the likelihood ratio test that the model performs better than the simplest alternative, or that all coefficients taken together are highly significant[8]. Indeed, every coefficient is again significant at the 1 % significance level. The coefficient on the twice lagged level of the dependent variable, which is used as an instrument for the lagged dependent variable, is negative. This implies that once you have been hired or fired yesterday, you are not very likely to be hired or fired again today, which is a reasonable result. Separating the coefficient into the autocorrelation coefficient ρ and the coefficient of the first stage IV estimation δ, we can again reject the hypothesis of a unit root in the individual unemployment rate.

(Table 2 about here)

The principal result is that we again find that economic growth exhibits a significant association with the probability to enter or leave employment. Both signs are positive, as predicted by theory, equations (H 2a) and (H 2b). However, the coefficients are different, and a formal χ^2-test rejects the null hypothesis of parameter equality. We may therefore conclude that economic growth exhibits a different impact on job creation than job destruction, thus rejecting the pure intrasectoral change model as proposed by Aghion and Howitt (1993), in favor of a broader approach including both intra- and intersectoral change.

According to the two equations, which form hypothesis 2, exits and entries to employment both depend on the growth rate and the change of the innovative sector's employment share. Omitting this variable could lead to a bias in the estimation, which may be stronger in one of the two regressions, thus leading to a biased estimator of the impact on growth on job creation and destruction.

Instead of directly including sectoral employment shift variables in the estimation, we note from equation (12) that a share α_t of total employment will work in the innovative sector. As the employment rate equals $1 - u_t$, we can substitute the employment share of the innovative sector, e_t, into equation (H 1), to find that employment in the innovative sector is proportional

[8] As the result is derived using maximum likelihood methods, we cannot give a coefficient of determination. The log likelihood is presented instead, but it only allows us to differentiate between different models, but does not reveal an overall goodness of fit.

to economic growth. This is equivalent to stating that the change in the innovative sectors employment share, the second explanatory variable in both equations of hypothesis 2, is equal to the change in the rate of economic growth.

The later variable has been included in columns 3 and 4 of table 2. We find that both the rate of economic growth and the change in the rate of economic growth exhibit a positive and significant impact both on job creation and job destruction. The Hausmann test reveals again that a random effect specification for the same variables would have to be rejected. The likelihood ratio test indicates all coefficients together are significant. The model performs slightly worse than the simpler alternative, excluding the change in the economic growth rate.

Comparing the two coefficients describing the impact of growth on job creation and destruction, they seem closer together than in the previous model, columns 1 and 2 of table 2. However, in order to ensure that the impact of economic growth on the creation and the destruction of jobs offset each other, we must have that both coefficients together cannot be significantly different to zero. We can test this hypothesis with a standard Wald test, presented in the last line of table 2. We find again that the null hypothesis of parameter equality has to be rejected, thus leading to a rejection of a pure model of intrasectoral change in favor of a model of both intersectoral and intrasectoral change.

Finally, note that the change in economic growth exhibits a positive impact on both job creation and job destruction. As stated before, this implies that as the total employment rate increases, a larger number of workers are subject to the reallocation process of labor resources in the economy. Therefore, both the number of exits and entries to employment increases.

This result is closely related to a completely different set of evidence on the asymmetries of job creation and destruction over the business cycle. Caballero and Hammour (1996) suggest that an efficient economy would concentrate its job creation and job destruction efforts during cyclical downturns. Their hypothesis has first been confirmed empirically by Davis, Haltiwanger, and Schuh (1998).

The economic intuition is similar to the one presented in chapter 2. During a recession, just like during the process of intersectoral and intrasectoral structural change, labor reallocation is more efficient for two reasons. First, a lower number of employees have to be fired in order to compensate for changes in the demand structure. Second, a larger pool of unemployed facilitates hiring for firms. Therefore, the results are observationally equivalent to our findings on the positive impact of the change in economic growth on job creation and destruction, presented in table 2, as the change in the economic growth rate is largest during a recession and lowest during a boom. The intuition is as follows. Both at the height of a boom and in the depth of a recession, the change in output is zero by definition. Shortly afterwards, economic growth is negative in the case of a fading boom and positive in an ending recession. The change in the economic rate of growth is therefore approaching minus infinity at the height of a boom and plus infinity in the depth of a recession. Therefore, the change in the economic growth rate presented in table 2 captures the extent of the recession in the economy.

7 Conclusions

The aim of this paper was to test three hypothesis of the impact of economic growth on unemployment, due to sectoral change. Chapter 2 has presented a model of both intersectoral and intrasectoral change in an endogenous growth framework with unemployment. One particularity of this approach was the fact that the model nested two other competing frameworks, the neoclassical Solow-model and the model of intrasectoral change of Aghion and Howitt (1994). In the theoretical framework, we were able to derive two hypotheses on the impact of economic growth on unemployment, which allowed us to discriminate between the theories.

This paper has presented tests of these two hypotheses, using microeconomic panel data for the United Kingdom. The results show a significant and negative relation between unemployment and economic growth, using fixed effects panel regression methods. This implies that faster sectoral change, driven by higher rates of innovation and therefore by higher rates of economic growth, would foster structural unemployment. This test rejects the neoclassical Solow-model in favor of a framework, which includes sectoral shifts.

If the increase in unemployment would be entirely driven by intrasectoral change, we found that the exit from employment must equal the entry to employment for every rate of economic growth. Chi-square-tests on parameter equality in logistic panel regressions for both job creation and destruction revealed that the impact of economic growth differs between exits and entries, hence rejecting the pure intrasectoral shifts hypothesis in favor of a framework based on both inter- and intrasectoral shifts.

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Appendix

Table 1: Change in Individual Unemployment Experiences due to Economic Growth

Dependent Series: Individual Unemployment Rate in First Differences (FE IV - estimation)	Scenario 1	Scenario 2	Scenario 3
Lagged Unemployment Rate (in Levels)	0.1234 (0.0039)	0.1183 (0.0039)	0.1181 (0.0039)
GDP Growth Rate (assigned by Region only)	- 0.8866 (0.0362)		
GDP Growth Rate (by Region and Sought Occupation)		- 0.0601 (0.0050)	
GDP Growth Rate (by Region and Usual Occupation)			- 0.0569 (0.0053)
Regional Change	0.0425 (0.0037)	0.0433 (0.0037)	0.0433 (0.0037)
Occupational Change	0.0996 (0.0019)	0.1007 (0.0019)	0.1008 (0.0019)
Entering Stable Relationship	0.0967 (0.0114)	0.0983 (0.0114)	0.0987 (0.0114)
Breaking up of a Stable Relationship	0.0691 (0.0132)	0.0694 (0.0132)	0.0693 (0.0132)
Constant	- 0.0713 (0.0007)	- 0.0708 (0.0007)	- 0.0707 (0.0007)
R^2 (between)	31.84 %	31.43 %	31.48 %
F-test	860.77 (0.0000)	782.34 (0.0000)	777.68 (0.0000)
Unit-root-χ^2-test	282 511.99 (0.0000)	281 359.80 (0.0000)	281 285.17 (0.0000)
Hausmann-test for the equivalent RE-model	16 648.27 (0.0000)	16 343.21 (0.0000)	16 326.02 (0.0000)

Remarks: The columns differ only in the way the regionally and sectorally different growth rates are assigned to individuals. Standard errors for coefficients and p-values for test statistics are given in parenthesis. The reported Hausmann-test corresponds to the equivalent random effect model. The quasi-unit root test corresponds to a χ^2-test of the coefficient of the lagged dependent variable equaling unity. Due to endogeneity, the change in the lagged dependent variable is instrumentalized with the twice lagged level of the dependent variable, following Arellano and Bond (1991).

Table 2: Change in Exits and Entries to Employment due to Economic Growth

Dependent Variables in First Differences FE IV Logit Estimation	Entry to Employment	Exit from Employment	Entry to Employment	Exit from Employment
Lagged Entry (in Levels)	- 2.1194 (0.01540)		- 2.1289 (0.0141)	
Lagged Exits (in Levels)		- 2.2409 (0.0154)		- 2.2489 (0.0155)
GDP Growth Rate	0.4005 (0.0436)	0.2565 (0.0510)	0.3543 (0.0444)	0.2234 (0.0520)
Change in the GDP Growth Rate			0.0065 (0.0009)	0.0049 (0.0011)
Regional Change	- 1.2855 (0.0377)	- 1.3167 (0.0410)	- 1.2816 (0.0378)	- 1.3127 (0.0411)
Occupational Change	- 2.0232 (0.0185)	- 2.0440 (0.0207)	- 2.0259 (0.0186)	- 2.0487 (0.0208)
Entering Stable Relationship	- 1.7723 (0.1033)	- 1.6790 (0.1222)	- 1.7671 (0.1036)	- 1.6785 (0.1224)
Breaking up of a Stable Relationship	- 2.5036 (0.1471)	- 2.8675 (0.1686)	- 2.5337 (0.1478)	- 2.9043 (0.1698)
Log Likelihood	- 41 801.80	- 30 924.88	- 41 596.73	- 30 770.48
LR-χ^2-test	48 216.35 (0.0000)	44 609.34 (0.0000)	48 029.01 (0.0000)	44 449.57 (0.0000)
Quasi-unit-root-χ^2-test	3 010.92 (0.0000)	4 191.57 (0.0000)	3 033.14 (0.0000)	4 182.03 (0.0000)
Hausmann-test for the equivalent RE-model	6 167.25 (0.0000)	23 234.90 (0.0000)	7 166.70 (0.0000)	36 921.33 (0.0000)
χ^2-Test of parameter equality between job creation and destruction		25.26 (0.00)		47.67 (0.00)

Remarks: The coefficients represent the marginal effect of a unit change in independent variable from the baseline scenario, which is $X_{i,t} = 0$. Standard errors are given in parenthesis. The reported Hausmann-test corresponds to the equivalent random effect model. The quasi-unit root test corresponds to a χ^2-test of the lagged dependent variable equaling unity. Due to endogeneity, the lagged dependent variable is instrumentalized with the twice lagged level of the dependent variable, following Arellano and Bond (1991).