DISCUSSION PAPER SERIES

No. 3848

AGGREGATE GROWTH AND THE EFFICIENCY OF LABOUR REALLOCATION

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LABOUR ECONOMICS

Centre for Economic Policy Research

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Available online at: **www.cepr.org/pubs/dps/DP3848.asp**

ISSN 0265-8003

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March 2003

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CEPR Discussion Paper No. 3848

March 2003

ABSTRACT

Aggregate Growth and the Efficiency of Labour Reallocation*

We consider the potential importance of labour market efficiency for aggregate growth. The idea is that efficient labour markets move workers more quickly from low to high productivity sites, thereby raising aggregate productivity growth. We define a measure of labour market efficiency as a structural parameter from a matching function. Using labour market data on 15 OECD countries, we estimate this and show that it has a significant effect on growth. The results are robust to a number of different estimation techniques. The quantitative impact of market efficiency is not trivial.

JEL Classification: J63 and O40
Keywords: growth, labour efficiency and labour market institutions

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*This Paper is partly based on Mawson's Ph.D. Chapter 5, written at the University of Bristol. We gratefully acknowledge ESRC funding for Mawson's Ph.D. Many thanks to Tito Boeri and Jonathan Wadsworth for data. We are also very grateful for comments from Rachel Griffiths, John Haltiwanger, Jonathan Haskel, Jon Temple and others at a CEPR seminar.

Submitted 07 March 2003

1. Introduction

Much of the literature on growth has taken a representative agent approach. The focus is therefore on what happens within firms (production, innovation, and invention), on the activities of workers (acquiring human capital), and on macroeconomic interactions (savings and investment). Recent work has produced a considerable advance in both theory and empirical work[1]. This paper examines a different factor that matters in the growth process – the reallocation of resources, and in particular, labour. This has been studied both on a large (sectoral) scale and on a micro (plant) scale[2]. The latter perspective moves away from representative agents to highlight the heterogeneity now recognized to characterize labour and product markets. New empirical evidence derived from longitudinal micro datasets shows that economies exhibit vast amounts of heterogeneity and dynamics at the firm or plant level. High rates of job creation and destruction[3] and worker churning[4] are evidence of high rates of labour reallocation; these are accompanied by high rates of firm turnover[5] and substantial dispersion in productivity[6]. This paper contributes to our understanding of the importance of this reallocation process to growth.

Intuitively, the faster an economy can move resources around from less to more productive uses, the better use is made of the labour force[7]. But what affects the ability of an economy to reallocate its resources quickly? Economists have discussed this question, but more in relation to unemployment and the business cycle. In this paper, we examine how an economy's ability to reallocate resources affects its growth rate. We estimate a measure of labour market efficiency based on a matching approach for a set of OECD

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[1] See recent surveys by Durlauf and Quah (1999) and Temple (1999)
[2] See for example, Temin (1999) and Foster, Haltiwanger and Kirzan (1998), discussed more fully below.
[3] See Davis and Haltiwanger (1992), Davis, Haltiwanger and Schuh (1997).
[4] See Burgess, Lane and Stevens (2000).
[5] See the survey in Caves (1998).
[6] Surveyed by Bartelsman and Doms (2000).
[7] It may be implausible that countries will grow indefinitely at different rates on the basis of labour market institutions. It may be that the reallocation affects the level of income, rather than having a permanent effect on growth. The interpretation of what follows then is that conditional on the initial level of income, reallocation does affect the conditional rgowth (convergence) rate. We thank Jon Temple for this view.

countries. We include this measure in a standard growth regression. This goes beyond calculating the growth accounting contribution of reallocation in two ways. First the amount of reallocation actually achieved is endogenous, and so its interpretation in growth accounting is not straightforward. We estimate a structural parameter from the labour market. This will depend on structural and institutional features of the labour market, but not business cycle or growth effects. Second, by adding this to a growth regression we are partialling out other related effects.

We find that inefficient labour markets do indeed reduce aggregate growth, and the effect is quantitatively significant. The relatively small set of countries with available labour market data means that the estimates are not very precise, but the evidence is suggestive and supports further work on the topic. Microeconomic evidence is clearly needed to support these aggregate results.

This paper is organized as follows. The next section reviews some background – briefly reviewing the related literature and setting out a modelling framework. Section 3 describes the data and section 4 estimates the measure of labour market efficiency. In section 5 we estimate baseline growth regressions, and section 6 introduces the labour market efficiency measure. Section 7 concludes.

2. Background

Literature

The reallocation of labour at a sectoral level has long been thought to be an important part of the growth process. In particular, the timing of the move out of agriculture into manufacturing has had a significant impact on growth rates (see for example Kaldor, 1966, Kindleberger, 1967, Denison, 1967; and more recently Temin, 1999, and Temple, 2001). Recently, the availability of longitudinal micro data has shown that labour reallocation is very high and pervasive in the OECD countries. This labour reallocation takes place in the context of very substantial productivity differences among firms and plants (see the survey of this evidence in Bartelsman and Doms, 2000). The two facts together suggest an important role for reallocation in accounting for aggregate productivity growth: "The manufacturing sector is characterized by large shifts in employment and output across establishments every year – the aggregate data belie the tremendous amount of turmoil underneath. This turmoil is a major force contributing to [aggregate] productivity growth, resurrecting the Schumpeterian idea of creative-destruction" (Bartelsman and Doms, 2000, p. 571).

Two recent papers focussing on this are Baily, Bartelsman and Haltiwanger (1996) and Foster, Haltiwanger and Krizan (1998). They propose an accounting decomposition of aggregate productivity growth (TFP) in manufacturing into a within-plant element and across-plant, entry and exit elements. The within-plant component accounts for about half the total. Baldwin (1995) further relates a productivity decomposition to market share dynamics. This approach has established some very useful facts on the importance of taking a micro-level and dynamic view of productivity growth. Note that the accounting decomposition necessarily relies on the realized amount of reallocation achieved to calculate the importance of reallocation. In this paper, we take the approach further by estimating a structural measure of labour market frictions, and hence the potential for reallocation. This will not suffer from the same endogeneity problems.

This perspective suggests a different list of factors to think of in growth economics[8]: what determines the efficiency of reallocation? First, labour market and capital market institutions differ considerably between countries and will generally affect the efficiency of resource reallocation. We look briefly at one set of labour market institutions below. Second, a search and matching approach suggests that thick market effects may be important in affecting the efficiency of labour markets. In this case, the spatial organization of a country will matter for growth. Third, product market institutions can also potentially play a role; this is emphasized by Nelson (1981) and Bartelsman and Doms (2000). On a different tack, Nickell (1993) examines whether competition affects productivity growth *within* (large manufacturing) firms.

[8] Another related issue is the relationship between growth and unemployment. Many studies consider the affect of one on the other – see for example, the work by Aghion and Howitt (1992), and Mortensen and Pissarides (1995). The perspective that is taken here is that both growth and unemployment are jointly influenced by labour and product market institutions.

Modelling Framework

The central idea explored in this paper is that labour market frictions may inhibit aggregate growth. This seems like a rather general idea that could arise in different models. The appropriate context is one with a huge amount of heterogeneity and rapid churning of firms, establishments, jobs and workers. Elsewhere, one of us has developed a model capturing some of this intuition (Mawson, 2001). This extends work by Aghion and Howitt (1992) formalizing a model of 'creative destruction' and Laing, Palivos and Wang (1995) focussing on human capital acquisition in a matching context. The basic idea of the model adopted here is as follows. The setting is a matching framework, with a manufacturing sector and a research sector. Labour market efficiency has a direct and an indirect effect on growth. Higher labour market efficiency is manifested in increased speed by which the labour market redistributes labour from old sectors to newer more productive ones. The direct effect incorporates the idea that by improving the utilization of labour resources the rate of economic growth can be increased. It is the reallocation from old technologies to newer ones which is the prime driver behind increased growth. Thinking of productivity as a 'bow wave' which is moving out over time to higher and higher levels of output, the optimal outcome would be to allocate as much labour as possible into the higher productivity workplaces. A more efficient market allows a smaller pool of unemployed to supply the needs of the manufacturing sector, thereby freeing more workers for the research sector, generating more innovations. A more sophisticated argument employed by Aghion and Howitt also allows for development of a technology through a form of learning by doing; this can be incorporated in the model also.

The indirect efficiency effect follows the work of Laing Palivos and Wang (1995) and captures the idea that by reducing the time workers spend in unemployment or sub-optimal jobs, an increase in labour market efficiency raises the value of workers' human capital investments. This induces them to invest in more education and so raises the overall level of human capital in the economy, increasing the rate of growth.

Thus we expect that a more efficient labour market will, *ceteris paribus*, imply a faster rate of aggregate growth. Related ideas have been pursued by King and Levine (1993), studying capital market efficiency.

3. Data

Ideally, we would want to use the sort of longitudinal microdata described above, deriving measures of reallocation for all industries within a country and then for a wide variety of countries on a comparable basis. Unfortunately, this possibility seems remote. There are immense challenges to setting up an internationally comparable dataset on job flows and productivity. In the meantime, it seems worthwhile not to pass up the opportunity to consider what can be learnt from more aggregated data.

The dataset is constructed from a variety of sources. The basic growth data were taken from the Penn World Tables covering the period 1960 to 1990 across 15 OECD nations. These are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Japan, Netherlands, New Zealand, Norway, Sweden, UK, USA[9]. The data are recorded quintennially providing a total of 90 observations in all. Data on educational attainment from Barro and Lee (1997) are merged in. These are given separately for primary, secondary and tertiary education. The choice of countries to include was largely driven by the availability of labour market data. The labour market data (series for unemployment and vacancy stocks) were drawn from an updated data set based on that compiled by Jackman, Pissarides and Savouri (1990) along with a series of comparable unemployment duration statistics compiled by Boeri[10].

4. Measuring Labour Market Efficiency

There are potentially a number of different dimensions to labour market efficiency. The approach that we follow here is to focus on the efficiency of *matching* of workers and jobs. Matching functions are now a mainstay of labour and macroeconomics and

[9] One notable absentee from this list is Italy, due to lack of labour market data. This is unfortunate as Italy would have been an interesting case – tight employment protection (at least *de jure*) and yet a reasonable growth performance.

[10] Many thanks to Jonathan Wadsworth for the former and Tito Boeri for the latter.

represent one way of characterizing simply the process whereby millions of workers and jobs are paired each quarter in the OECD economies[11]. Rather than use a measure of actual matching (for example, job or worker reallocation) achieved – which would clearly be endogenous – we use a structural measure of matching. That is, conditional on demand and supply in the labour market, we examine how many new matches are formed[12]. We estimate a coefficient measuring this matching efficiency.

Specification

We assume the following standard form for matches in country *i* at time *t*:

$$M_{it} = m(\mu_{it}, U_{it}, V_{it}) \qquad (1)$$

where *M* is the number of new matches made involving unemployed searchers, *U* the number of unemployed and *V* the number of vacancies. The parameter μ is a measure of matching efficiency. Dividing through by the unemployment stock gives the hazard rate out of unemployment; this in turn is approximately equal to the inverse of the average unemployment duration (*dur*).

The specification of country heterogeneity is important. Given the limited scope of the duration data available, full estimation country-by-country was not a viable option, and so we pooled the data and allowed some of the coefficients to vary across countries. We originally allowed the effect of U and V to vary, but could accept the hypothesis that they were common across countries. Consequently, we parameterize the country heterogeneity in terms of a fixed country effect and country time trends. We adopt the usual log linear formulation (though we did experiment with a variety of other functional forms):

$$\log\ \log(dur_{it}) = \alpha_{0i} + \alpha_{1i} t + \alpha_2 \log u + \alpha_3 \log v + \varepsilon_{it} \qquad (2)$$

where *u* and *v* have been normalized by the labour force to give unemployment and vacancy *rates*.

Note that all factors that might generally be thought to affect unemployment duration beyond labour market tightness will be absorbed into the country effects. This includes

[11] See Petrongolo and Pissarides, 2001, for a recent survey.

demographic factors and dimensions of labour mismatch. This seems appropriate – they are factors affecting the efficiency of the labour market in moving workers around from low to high productivity sites.

Results

Equation (2) was estimated for our 15 countries over the maximal period 1967 – 1997, though actual data points were fewer than 31 due to missing data (principally duration). The results are in Table 1. The coefficients on unemployment and vacancies are broadly in line with previous findings, though not well determined. While the coefficient on vacancies is insignificantly different from zero, it is also insignificantly different from a constant returns to scale assumption – this restriction (not imposed) is close to acceptance at 5% (the value of the $F(1, 255)$ test is 3.81, with a p-value of 0.052). Our main interest is in the country dummies. Taking the natural value of the country factors (note that the dependent variable is in logs), the interpretation of these figures is that unemployment duration is on average 1.69 months longer in Japan than in the USA holding all other things equal (the natural values are 4.7635 (USA) and 6.4572 (Japan)). The pattern described by these coefficients is in line with the accepted stylized facts concerning labour market efficiency with the high turnover labour markets such as the USA having lower conditional unemployment durations and higher estimated efficiency levels than the more rigid European ones. In fact, the estimated country dummies are not *statistically* significantly different from one another. However, we persevered with them and the results below show that they are sufficiently *quantitatively* different to generate significant effects at the second stage regressions.

In addition given that the time trend terms capture changes in efficiency over time, we also calculated the mean value of $\alpha_{0i} + \alpha_{1i}*t$ for each country.

Comparison with institutional factors

[12] Data constraints force us to consider only new matches involving unemployed searchers. This is unfortunate as job to job moves are an important component of reallocation. We hope to return to this in later work.

Lying behind our measure of labour market efficiency are institutional differences between countries, among other things. One commonly cited such difference is the strictness of employment protection legislation (EPL). While this is hard to measure, the OECD has produced such a measure (OECD, 1999). This is graphed against our measure α_{0i} in Figure 1. There is clearly a relationship with tighter EPL regimes being associated with less efficient labour markets (in the sense used here). This gives us some confidence that our measure is picking up some elements of real differences between labour markets.

5. Baseline Growth Regression

Running aggregate growth regressions has been a very active pursuit in recent years and there are a number of well-established facts (see surveys by Temple, 1999, and Durlauf and Quah, 1999; also Barro and Sala-i-Martin, 1995). In this section, we set up the specification of our growth model and establish some baseline regressions before adding measures of labour market efficiency to the specification.

Specification

The starting point for this analysis lies in the following general specification of a standard growth regression:

$$g_{it} = \alpha \ln y_{it-1} + \beta H_{it} + \gamma X_{it} + \eta_i + u_{it} \qquad (3)$$

The conditional growth rate of output *per capita*, g_{it}, depends on initial *per capita* income $\ln y_{it-1}$, a vector of human capital variables H_{it}, a vector of exogenous determinants X_{it}, a country effect η_i, and an error term u_{it}. This framework is analogous to the cross sectional approach employed by Barro and Sala-i-Martin (1995), extended to a panel context. We allow for convergence effects ($\ln y_{it-1}$), human capital effects (H_{it}) and use investment and population growth as our other variables (X_{it}).

Human capital stocks are assumed to be proportionate to the average levels of educational attainment in the economy as measured in terms of years of schooling; a range of measures were considered including breakdowns by gender and level of education. Models developed by Nelson and Phelps (1966) and others suggest that the rate of convergence will be increasing in the average level of human capital in an economy. Consequently an interaction term of $devy_{it-1}$ and *School* is included, where $devy_{it-1}$ is the deviation from the period mean of initial income across the sample and *School* is the average number of years of education per person. If these theories are correct one would expect there to be a negative coefficient on this interaction term. The Solow-Swan and Ramsey models imply a positive relationship between the level of investment and growth. As the share of investment in GDP, denoted *invsh*, increases then so too will the rate of capital accumulation and ultimately growth. These same models also negatively link the rate of population growth denoted *gpop* to output growth. In principle, there is a wide range of additional control variables which could also have been included in this study[13], however given our relatively small sample size it seems prudent to keep their number to a minimum.

Econometric Issues

The main econometric issues to consider are the treatment of heterogeneity and endogeneity. First, heterogeneity: the simplest treatment for the country specific effect is to assume a common effect ($\eta_i = \eta$) and run pooled OLS. We report the results of this. The use of random effects allows us to identify the effect of labour market efficiency using cross-sectional variation, and we also report the results of this. This technique of course relies on the assumption of orthogonality of the error term and the included regressors. Using fixed effects means we cannot directly include labour market efficiency, unless we rely on time series variation only for identification. As we explain below, relying purely on time series variation in efficiency and its correlation with time series variation in growth is unlikely to be persuasive. But (in the following section) we do estimate fixed effects, and graphically compare the estimated country effects with the labour market efficiency measure. We test for the appropriateness of random and fixed effects using the Hausman specification test and the Breusch-Pagan test, but the results were inconclusive. The Hausman test could not reject the hypothesis of no correlation between the regressors in three of the four equations considered (only two of which are

[13] See for example, Barro and Sala-i-Martin (1995) and Levine and Renelt (1992).

detailed below), while the Breusch-Pagan test rejected the hypothesis of random effects in all cases.

Second, there are concerns over the endogeneity of initial income, population growth and the investment share. We also therefore report instrumental variables (IV) results, using lagged values of the regressors as instruments where appropriate.

Third, we tested for heteroskedasticity in the disturbance term (using the Breusch-Pagan-Godfrey test) and could not reject the null of homoskedasticity across the range of regressions considered. However, given that the tests were not entirely conclusive, the results are reported using the White correction for standard errors (White, 1980).

Finally, two timing issues. In order to consider the possibility that five yearly intervals are too short to capture meaningful results about growth all the above was repeated using decade time intervals instead. The two stage nature of our estimation[14] is forced on us by the frequency mismatch of the datasets – growth data at 5-yearly intervals, labour market data annually.

Results

The results are in Tables 2 (5 year spans) and 3 (10 year spans). They generally fit the pattern set by previous studies. Initial income is significant with a coefficient of around -0.03 to -0.04, yielding an average speed of convergence to steady state of around 3% to 5%. This is considerably higher than that found by Barro and Sala-i-Martin (1995) and similar studies, but lower than the rates found by Caselli, Esquivel and Lefort (1996) who employed panel data techniques in their paper on convergence. The investment ratio is also robust to the model specification with an average coefficient of 0.0006 to 0.0007. Taking account of the difference in units this is again slightly higher than that reported by Barro and Sala-i-Martin, but lower than that found by Caselli *et al*. In contrast the population growth variable is almost never significantly different from zero. This result mirrors that found by other studies and again in the case of OECD countries is unsurprising.

[14] This means that the standard errors at the second stage are not correct.

Turning to the results for the human capital variables, we experimented with a variety of breakdowns of years of schooling by gender and by educational level. In the end we settled on a breakdown by level: primary, secondary and higher. We report results for this and for the combined variable. Some of the coefficients are initially surprising. Primary and higher schooling are found to be significantly negative and positive influences respectively on growth when schooling is broken down by level of schooling. In part these findings may be due to the nature of the data involved: one can argue that the OECD nations are sufficiently alike in terms of years of education that the differences in human capital between nations are primarily explained by differences in the quality not quantity of education. As yet a comprehensive quality adjusted dataset for human capital is not available, although some effort is now being made in that direction[15]. A simple explanation for this result is that in the developed nations primary and secondary education is common across the vast majority of the populace. In such circumstances increasing the average years of such education across the population is difficult, and amongst the OECD nations improvements in the quantity of schooling can only be made at the higher levels.

6. Labour market efficiency and growth

We are now in a position to introduce our measure of labour market efficiency into the growth equation. We adopt the version of the equation with human capital broken down by level, and again report results for OLS, RE and IV, and for 5- and 10-year spans. We also estimate and graphically present fixed effect results.

What is the source of variation that we believe identifies this effect? We rely principally on cross-section variation to identify the relationship between growth and efficiency. There is likely to be a time series correlation between labour market efficiency and aggregate growth overall since we know that growth slowed down and U-V curves started to shift out in many countries at about the same time – the early 1970s. We therefore do not want to use that co-movement as that may well arise from mutual correlation with omitted variables. We argue that independent variation in labour market

[15] See Kim and Hanushek (1995) and Barro and Lee (1997).

efficiency can arise from legal and institutional frameworks for example, and that these have been found to be correlated with differences in other macroeconomic outcomes such as unemployment (recall the relationship with employment protection legislation in Figure 1, for example).

The raw data (plotted in Figure 2) show little obvious relationship between the mean growth rate over the entire period for each country and the market efficiency measure. Even excluding the outlier Japan there is little correlation. However, if we consider the adjusted variable plot[16] in Figure 3, the picture is much more encouraging. Note that Japan is no longer an outlier, its low initial income and high investment share explaining its high growth rate.

The regression results presented in Tables 4 (5-year spans) and 5 (10-year spans) confirm this picture. To reiterate, we expect a positive relationship between labour market efficiency and growth, and therefore a negative relationship between our measure α_{0i}, which measures inefficiency, and growth. This is indeed what we find. Across all the three estimation methods and both time spans, the estimated coefficient on α_{0i} is always negative, and consistent in size (apart from the IV estimation when it is twice as large). The coefficient is generally significant at the 5% level in the RE and IV estimation and close to this under OLS. We also report results for the mean value of the version incorporating the time drift in the matching function. Similarly, this also shows a relationship with growth.

We also estimate a fixed effect model[17], extract the country effects and plot them against the labour market efficiency measure – see Figure 4. Given that these are capturing a multitude of factors influencing growth, the relationship with market efficiency is pleasing – the correlation among these 15 data points is –0.191 (with a p-value of 0.71).

We can provide a partial check on our results by taking an externally-given measure of labour market efficiency. We construct (0,1) dummies *High Flow* and *Low Flow* which characterize respectively high turnover/low duration labour markets (Canada, USA and Australia) and low turnover/high duration labour markets (Austria, Belgium, Denmark,

[16] Adjusted for the variables in the regressions reported in Table 4.
[17] Coefficients not reported here but available from the authors.

France, Germany, Netherlands, UK and New-Zealand). This categorization is taken from Jackman, Pissarides and Savouri (1996). It should be re-emphasized that our own measure is to be preferred as it is (an estimate of) a summary parameter of a structural relationship within the economy, rather than an outcome measure that may be endogenous. There is a clear correlation between this dichotomous characterization, and our continuous measure. The results in Tables 4 and 5 suggest that the low flow/high duration economies do indeed grow more slowly than the rest of the sample.

The coefficient on our measure of labour market inefficiency is quantitatively significant. A country reducing its α_{0i} score by 0.3 (equivalent to the difference between Germany at 1.899 and the UK at 1.621) will see the conditional growth rate rise by 0.0045 (using Table 4, column 1, OLS) compared to a sample mean growth rate of 0.029, a rise of some 15.5%. This is not a trivial amount[18], and indeed using the IV estimates would almost double it. It compares for example, to a sample mean change of 0.070 in 'Higher Education', which combined with the Table 4 column 1 coefficient estimate gives a difference in growth rate of 0.0046 – almost exactly the same.

7. Conclusion

In this paper we consider the potential importance of labour market efficiency for aggregate growth. The idea is that efficient labour markets move workers more quickly from low to high productivity sites, thereby raising aggregate productivity growth. We adopt a matching function approach and define a measure of efficiency as a structural parameter from the matching function. Using labour market data on 15 OECD countries, we estimate this and show that this has a significant effect on growth. The results are robust to a number of different estimation techniques. Microeconomic evidence on the importance of labour market frictions for aggregate growth would be very useful. Nevertheless, these results are suggestive, and provide a new set of factors to think about in contemplating policy to raise growth.

[18] Recall our earlier caveat that this refers to conditional growth rates, and therefore to the long-run level of income.

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Figure 1: Efficiency Measure and EPL Strictness

*Regression is: Efficiency = 0.0745*epl (t = 2.41), N = 14;* $R^2 = 0.33$

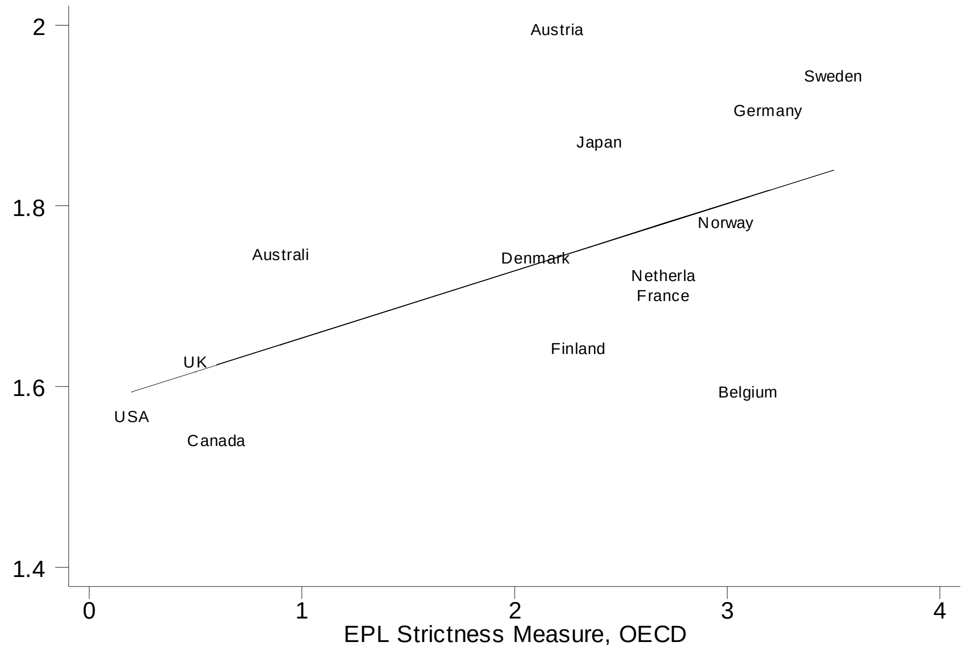

Figure 2: Mean Growth Rate and Labour Market Efficiency: Raw Data

Note: "Labour market frictions" is our measure of (the inverse of) labour market efficiency

Figure 3: Mean Growth Rate and Labour Market Efficiency: Adjusted Variable Plot

Note: "Labour market frictions" is our measure of (the inverse of) labour market efficiency

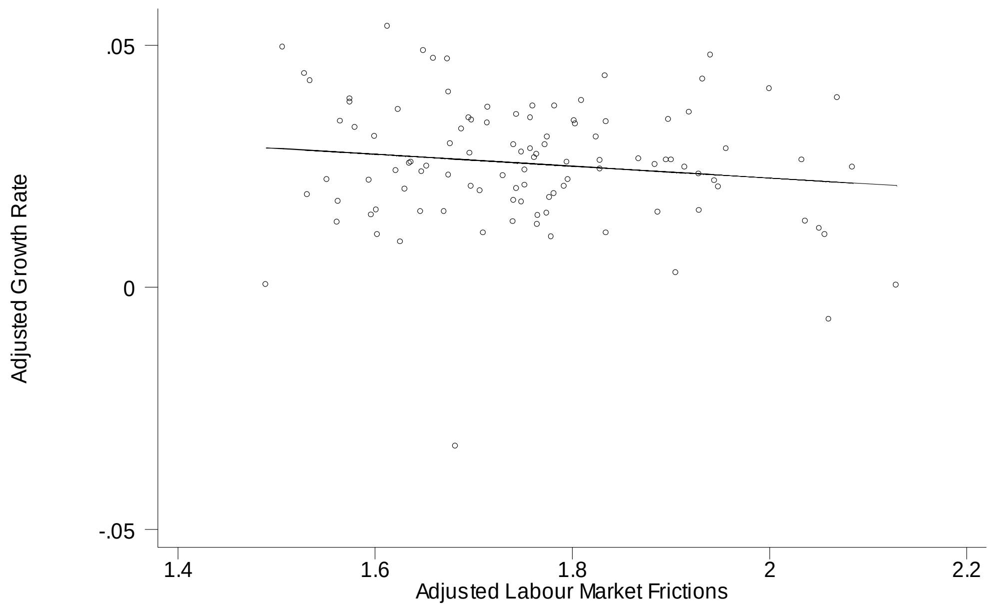

Figure 4: Mean Growth Rate and Labour Market Efficiency: Fixed Effects

Note: "Labour market frictions" is our measure of (the inverse of) labour market efficiency

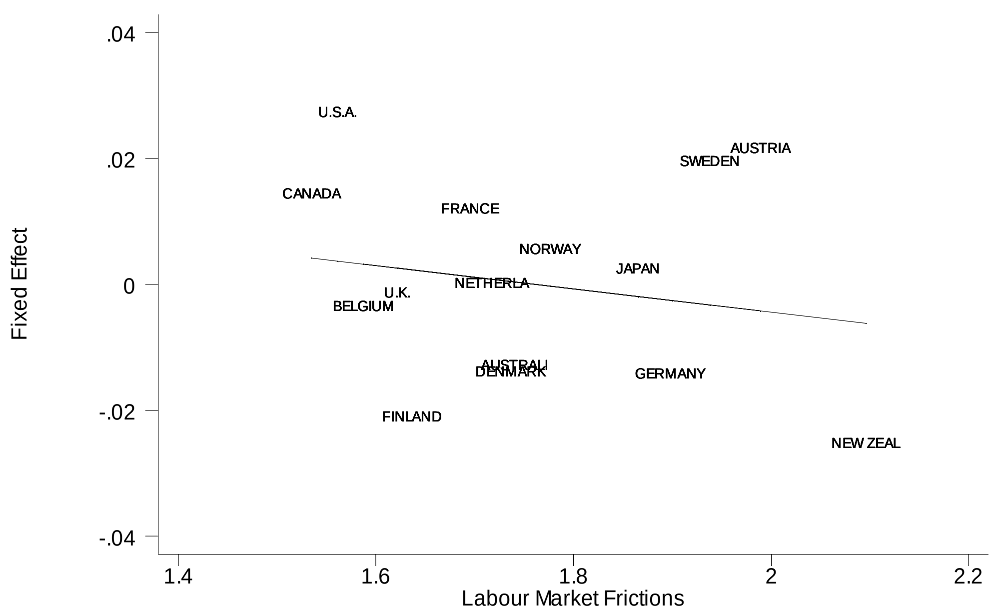

Table 1: Labour Market Efficiency Regressions

Dependent variable: log duration
Max sample is 1967 – 1997, but there are fewer than 31 observations per country mostly due to missing duration data

	Coefficient	s.e.	
log (unemployment rate)	0.2051	(0.0717)	Obs per
log (vacancy rate)	-0.0085	(0.0397)	country
Country effects:			
Australia	1.7404	(0.1778)	18
Austria	1.9888	(0.1689)	19
Belgium	1.5873	(0.1744)	18
Canada	1.5345	(0.1910)	19
Denmark	1.7364	(0.1352)	18
Finland	1.6364	(0.1699)	20
France	1.6948	(0.1668)	19
Germany	1.8993	(0.1861)	19
Japan	1.8650	(0.1488)	21
Netherlands	1.7171	(0.1493)	21
New Zealand	2.0959	(0.1882)	20
Norway	1.7760	(0.1126)	19
Sweden	1.9376	(0.1147)	19
UK	1.6212	(0.1271)	19
USA	1.5610	(0.2190)	18
Obs	287		
R^2	0.9563		

Also included: country*time
Standard errors in parentheses

Table 2: 5 Year Growth Regressions

	OLS		RE		IV	
Constant	0.3179	0.3943	0.3135	0.4119	0.3107	0.3883
	(0.0551)	(0.0616)	(0.0562)	(0.0593)	(0.0909)	(0.1062)
y_{it-1}	-0.0334	-0.0418	-0.0330	-0.0437	-0.0311	-0.0396
	(0.0061)	(0.0069)	(0.0063)	(0.0066)	(0.0099)	(0.0115)
Invsh	0.0006	0.0008	0.0006	0.0008	0.0001	0.0004
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
Gpop	0.3790	0.1353	0.4416	0.0285	0.3819	0.0654
	(0.2959)	(0.3119)	(0.3238)	(0.2752)	(0.4390)	(0.4982)
dev_{yit-1}xSchool	-0.0012	-0.0007	-0.0016	-0.0003	-0.0015	-0.0008
	(0.0012)	(0.0012)	(0.0013)	(0.0011)	(0.0018)	(0.0018)
School	-0.0002		-0.0001		-0.0005	
	(0.0008)		(0.0009)		(0.0909)	
Primary		-0.0017		-0.0019		-0.0019
		(0.0010)		(0.0009)		(0.0013)
Secondary		0.0004		0.00009		-0.0006
		(0.0022)		(0.0020)		(0.0027)
Higher		0.0135		0.0168		0.0136
		(0.0090)		(0.0087)		(0.0114)
Obs	90	90	90	90	90	90

Standard errors in parentheses

Table 3: 10 Year Growth Regressions

	OLS		RE		IV	
Constant	0.3147	0.3967	0.3206	0.4206	0.5819	0.5274
	(0.0490)	(0.0501)	(0.0487)	(0.0495)	(0.1673)	(0.2056)
y_{it-1}	-0.0328	-0.0416	-0.0334	-0.0423	-0.0629	-0.0581
	(0.0054)	(0.0056)	(0.0054)	(0.0055)	(0.0179)	(0.0218)
Invsh	0.0004	0.0005	0.0002	0.0006	0.0006	0.0007
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0004)	(0.0004)
Gpop	0.2760	-0.0331	0.3209	-0.0788	0.3302	0.3647
	(0.2969)	(0.2918)	(0.3504)	(0.2655)	(0.4791)	(0.5567)
dev_{yit-1}xSchool	-0.0014	-0.0015	-0.0020	-0.0005	0.0023	0.0018
	(0.0011)	(0.0012)	(0.0012)	(0.0010)	(0.0026)	(0.0026)
School	0.00007		0.0003		0.0005	
	(0.0007)		(0.0008)		(0.0013)	
Primary		-0.0017		-0.0018		0.0015
		(0.0008)		(0.0008)		(0.0017)
Secondary		0.0002		-0.0001		0.0036
		(0.0018)		(0.0017)		(0.0034)
Higher		0.0171		0.0195		-0.0127
		(0.0074)		(0.0073)		(0.0170)
Obs	45	45	45	45	45	45

Standard errors in parentheses

Table 4: Augmented 5-year growth regressions

	OLS			RE			IV		
Constant	0.4167	0.4280	0.3895	0.4424	0.4567	0.4226	0.4051	0.4268	0.4161
	(0.0708)	(0.0734)	(0.0664)	(0.0790)	(0.0809)	(0.0711)	(0.1239)	(0.1310)	(0.1228)
y_{it-1}	-0.0420	-0.0431	-0.0402	-0.0451	-0.0464	-0.0436	-0.0380	-0.0403	-0.0389
	(0.0079)	(0.0080)	(0.0076)	(0.0088)	(0.0089)	(0.0076)	(0.0131)	(0.0136)	(0.0129)
Invsh	0.0009	0.0009	0.0005	0.0010	0.0010	0.0005	0.0005	0.0006	-0.0005
	(0.0003)	(0.0003)	(0.0003)	(0.0001)	(0.0001)	(0.0001)	(0.0004)	(0.0004)	(0.0006)
Gpop	0.0945	0.0606	0.0277	-0.0946	-0.1324	-0.1613	0.0484	-0.0466	-0.2922
	(0.3086)	(0.3142)	(0.3939)	(0.2113)	(0.2113)	(0.2351)	(0.4499)	(0.4966)	(0.7481)
dev_{yit-1}xSchool	-0.0011	-0.0009	-0.0015	-0.0004	-0.0003	-0.0010	-0.0015	-0.0012	-0.0036
	(0.0013)	(0.0013)	(0.0014)	(0.0010)	(0.0011)	(0.0012)	(0.0017)	(0.0018)	(0.0019)
Primary	-0.0013	-0.0015	-0.0013	-0.0014	-0.0016	-0.0016	-0.0010	-0.0013	-0.0008
	(0.0010)	(0.0010)	(0.0010)	(0.0005)	(0.0005)	(0.0006)	(0.0012)	(0.0012)	(0.0014)
Secondary	0.0021	0.0021	-0.0003	0.0021	0.0021	-0.0009	0.0024	0.0022	-0.0025
	(0.0021)	(0.0022)	(0.0022)	(0.0020)	(0.0021)	(0.0012)	(0.0026)	(0.0029)	(0.0027)
Higher	0.0066	0.0088	0.0082	0.0096	0.0122	0.0138	0.0007	0.0052	-0.0016
	(0.0095)	(0.0094)	(0.0095)	(0.0113)	(0.0109)	(0.0100)	(0.0109)	(0.0114)	(0.0119)
α_{0I}	-0.0149			-0.0141			-0.0245		
	(0.0100)			(0.0070)			(0.0107)		
$\sum(\alpha_{0i}+\alpha_{1i}t)/n$		-0.0191			-0.0189			-0.0300	
		(0.0152)			(0.0107)			(0.0172)	
High Flow			0.0037			0.0042			0.0125
			(0.0060)			(0.0044)			(0.0082)
Low Flow			-0.0040			-0.0038			-0.0125
			(0.0032)			(0.0021)			(0.0044)
Obs	90	90	90	90	90	90	90	90	90

Table 5: Augmented 10 year growth regressions

	OLS			RE			IV		
Constant	0.4125	0.4217	0.3967	0.4186	0.4308	0.4048	0.2446	0.2721	0.3125
	(0.0634)	(0.0678)	(0.0575)	(0.0647)	(0.0678)	(0.0564)	(0.0993)	(0.1015)	(0.0857)
y_{it-1}	-0.0414	-0.0423	-0.0404	-0.0424	-0.0435	-0.0414	-0.0216	-0.0239	-0.0299
	(0.0068)	(0.0070)	(0.0062)	(0.0069)	(0.0072)	(0.0060)	(0.0111)	(0.0114)	(0.0084)
invsh	0.0006	0.0007	0.0003	0.0007	0.0008	0.0003	0.0008	0.0010	0.0002
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0003)
gpop	-0.0667	-0.0970	-0.2235	-0.1396	-0.1797	-0.2816	-0.1140	-0.2379	-0.8285
	(0.2624)	(0.2717)	(0.3491)	(0.1663)	(0.1824)	(0.2283)	(0.4081)	(0.4202)	(0.3835)
dev_{yit-1}xSchool	-0.0010	-0.0009	-0.0015	-0.0007	-0.0006	-0.0013	-0.0012	-0.0010	-0.0032
	(0.0013)	(0.0013)	(0.0013)	(0.0011)	(0.0012)	(0.0011)	(0.0014)	(0.0015)	(0.0013)
Primary	-0.0014	-0.0015	-0.0012	-0.0015	-0.0016	-0.0015	-0.0004	-0.0007	-0.0013
	(0.0006)	(0.0007)	(0.0007)	(0.0003)	(0.0004)	(0.0005)	(0.0010)	(0.0011)	(0.0008)
Secondary	0.0015	0.0016	-0.0006	0.0014	0.0015	-0.0010	0.0026	0.0029	-0.0021
	(0.0016)	(0.0017)	(0.0014)	(0.0014)	(0.0014)	(0.0008)	(0.0020)	(0.0024)	(0.0017)
Higher	0.0012	0.0128	0.0113	0.0130	0.0150	0.0145	-0.0056	-0.0024	0.0031
	(0.0074)	(0.0074)	(0.0075)	(0.0064)	(0.0063)	(0.0055)	(0.0106)	(0.0116)	(0.0075)
α_{0i}	-0.0121			-0.0116			-0.0252		
	(0.0078)			(0.0058)			(0.0071)		
$\sum(\alpha_{0i}+\alpha_{1i}t)/n$		-0.0158			-0.0158			-0.0361	
		(0.0120)			(0.0086)			(0.0120)	
High Flow			0.0051			0.0053			0.0163
			(0.0049)			(0.0030)			(0.0052)
Low Flow			-0.0040			-0.0035			-0.0071
			(0.0029)			(0.0019)			(0.0029)
Obs	45	45	45	45	45	45	45	45	45