Heterogeneity of the labour input: methodological issues in constructing labour quality measures

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Abstract

The importance of labour quality as an input into the production process has long since been recognised. Failure to take proper account of the diversity within the labour force is likely to result in an overestimation of total factor productivity and failure to properly account for differences in labour quality between countries is likely hamper cross-country comparisons of productivity growth. However, effective labour quality measures require significant amounts of data, and at a detailed industry level, such data may be scarce and sample sizes may be small. The purpose in this paper is to present two methodological approaches for dealing with gaps or inconsistencies in the data available. Using UK data by skill group, gender and age band, for 1996-2002, the paper shows that with partial data availability, econometric estimation, following a Mincer-type equation of returns to skill, offers a close approximation to the labour quality measure when the full dataset is used.

1. Introduction

It is generally agreed that labour, as a factor of production, is highly heterogeneous, varying across different dimensions. Failure to adequately account for the different dimensions of labour will result in an overestimation of the contribution of the Solow residual, i.e. total factor productivity (*c.f.* Brondolini and Cipollone, 2001). A complete measure of labour should therefore take into account several characteristics of the labour force, such as working time, experience, education, effort, age and gender, to allow a more comprehensive evaluation of labour services. Different indices of quality adjusted labour can be constructed, depending on the focus of research and data availability. However, to construct a measure that captures all these effects requires considerable quantities of data, particularly when dealing with industry level data.

In this paper, the main focus is on the skill dimension, measured as the number of workers with a certain level of qualification in each industry. In many instances we may find that while wage data for different skill levels is largely available, difficulties arise when we try to refine the construction of the labour index by including other characteristics, such as age and gender. This paper proposes two methodologies that can assist researchers in the derivation of quality adjusted labour indices when either the data are missing or the available information is inconsistent. To address this issue we can either use econometric estimation of the returns to education or more aggregate data. We will check the performance of the two methodologies by presenting an example based on the distributive sector. Our results indicate that both methodologies provide a good approximation of the actual data, with the econometric estimation being characterised by a higher degree of accuracy.

This paper is structured as follows: Section 2 outlines the importance of accurate labour input measurement and discusses some of the implicit assumptions underlying the labour measure. Section 3 outlines the way in which labour quality is calculated. Section 4 provides a detailed description of the data used and limitations of the sources available. Section 5 presents the methodologies proposed to deal with inconsistent or missing data as the result of small samples. Section 6 contains the results of the application of these methodologies, in comparison with the fully adjusted labour quality index. In Section 7 we draw conclusions on the usefulness and possible limitations of this approach.

2. The importance of labour input

Whilst the importance of differences in quality and composition of labour inputs has long since been recognised (Jorgenson and Griliches, 1967), the increase in educational attainment in all OECD countries has increased emphasis on the importance of accounting for the quality of the labour input (Fosgerau *et a*l. 2001). Moreover, the importance of labour quality has been recently stressed in connection with the widespread use of ICT capital and the increased investment in complementary assets (including skills) to aid diffusion. Investment in labour force skills is part of this complementary investment and as such the evaluation of labour quality is necessary to distinguish between returns to ICT capital and returns to labour input (O'Mahony and Vecchi 2005). Together, investments in ICT and education are among the most important sources of growth at both industry and economy wide levels (Jorgenson et al. 2005).

Accounting for the skill dimension is particularly important in productivity studies, as workers with different qualifications will have a different impact on productivity growth. The problems in simply using total number of hours worked in this framework is summarised by the Bureau of Labour Statistics:

> *"Labour productivity measures have traditionally defined labour input as the sum of all hours worked by employees, proprietors and unpaid workers. As a result, an hour worked by a highly experienced surgeon and an hour worked by a newly hired teenager at a fast food restaurant are treated as equal amounts of labour."*

A more comprehensive measure of labour that accounts for the skill level of the workforce normally increases the revenue share of the labour input in a production function framework and decreases the unexplained part of productivity growth, i.e. the Solow residual. This adds to the understanding of the factors determining productivity growth. Moreover, a comparison of an adjusted and unadjusted measure of labour input yields a measure of the corresponding compositional or quality change of labour input. This can usefully be interpreted as one aspect in the formation of human capital.

There is however less consensus about which other factors are the most important in measuring labour quality. In some earlier work, Jorgenson *et al*. (1987) used occupational data to differentiate labour, among other characteristics. Subsequently occupation was deleted since it had little effect on labour quality after gender, age and education were taken into account (Ho and Jorgenson 1999).

The impact of labour quality on productivity growth has been estimated for example to range between 0.54 and 1.13 in France, over the period 1982-2001, and between 0.36 and 0.55 in the US (Melka and Nayman, 2004). Moreover, it can be seen from these examples that there is considerable variation between countries on its estimated impact on productivity. This suggests that failure to incorporate labour quality into a cross country growth accounting framework is likely to result in misleading comparisons between national fortunes.

3. Computing a quality adjusted labour index

Regardless of the number of differentiating traits, hours of highly skilled persons and hours worked of unskilled persons cannot simply be added to obtain an aggregate measure of labour input - they have to be weighted by their respective relative productivity to account for differences in skills. Assuming a perfectly competitive market, a firm will hire an additional hour of labour up to the point where his marginal productivity equals his marginal cost. This implies that for a measure of total labour input, the individual labour inputs of different quality can be weighted with the respective relative wage rate, or more specifically, with the share that each type of labour occupies in total labour compensation. A Törnqvist index of hours worked distinguished by skill type can then be computed, with each type's share of the total wage share bills as weights.

A quality adjusted labour index QL is defined as:

(1) $$QL = \sum_h \bar{v}_h^L \Delta \ln L_h \ ,$$

where Δ is the first difference operator, L is hours worked for each of h labour types, v_h is the share of type h labour in the total wage bill, with the shares averaged across period t and t-1.

In order to examine the importance in using a quality adjusted labour index and a standard measure of labour input, based on total number of hours multiplied by total number of workers, we can simply take the difference between the two, usually defined as labour quality:

(2) $$\Delta \ln q^{L} = \sum_{h} \bar{v}_{h}^{L} \Delta \ln L_{h} - \Delta \ln \sum_{h} L_{h} .$$

Labour quality is in itself an important measure of the contribution of labour input to productivity growth and can be viewed as a proxy for the effort in each industry (Melka and Nayman 2004).

Other characteristics of the labour force can be included to refine the index, such as age and gender. When more than one characteristic is used it is possible to distinguish between the comparative importance of the different components, for example how gender differences are important compared to education differences.

Information requirements are very high as data on the number of hours by skill, age and gender are not always available, particularly at the industry level (see section 4). When data is missing implicit differentiation can be used, i.e. the rate of change in hours worked by industry is aggregated to the economy-wide level and industry's share in total labour compensation is used as the aggregation weight. However, these approximations can at times seem *ad hoc* and makeshift; a more formal approach to dealing with missing data is likely to lead to more transparent and consistent measures of labour quality. These issues are discussed in more detail below.

4. Data availability

Data on employment and wage by type have been derived from the UK Labour Force Survey (LFS), for the period 1996-2002. The LFS is harmonised at the European level, and therefore, much of the information should be available to EUKLEMS partners. However, given that the data are based on the individual, gaining access to the micro data may be problematic, and there will be differences in the nature of the variables available, reflecting the different institutional arrangements (especially in the case of education). However, the overriding issue for many countries will be problems of small sample sizes at the 72 industry breakdown.

In this study five skill types are identified, and described below in Table 1. Initially in the LFS, earnings information was only collected in the final (fifth) wave, to keep attrition rates to a minimum, but was collected from the first and fifth waves from Spring 1997.

As an example to develop the methodology, data used here have been collated at a 47 industry breakdown (see appendix for industry list), and cover the period 1996-2002. Educational attainment is measured using the question 'what is the highest qualification you have attained?'. Typically, there have been around 40 possible answers to this question, and these have been grouped into 5 'skill' categories, listed below. In addition, data on the number of men and women in each of these industries (and in each of these skill categories) has also been obtained from the LFS, along with a further disaggregation into 3 age bands (under 30; between 30 and 45 and over 45), again, for each industry and for both genders. Given this level of disaggregation, and also given that the 'target' industry list for EUKLEMS consists of 72 industries, it is envisaged that it will not always be possible to obtain the full level of disaggregation proposed. The purpose in this paper therefore, is to provide possible ways forward when the full disaggregation is not available, and to demonstrate how alternative approaches to 'filling the gaps' compare.

Table 1

Skill categories, employment and wage bill shares in 2000.

	N shares	W shares
1. First degrees and above	16	24
2. Other National Vocational Qualifications: level 4 (NVQ4)	8	10
3. National Vocational Qualifications: level 3 (NVQ3)	30	31
4. National Vocational Qualifications: levels 2 and 1 (NVQ1_2)	34	26
5. No formal qualifications	13	9

* shares of non-agricultural market economy employment – total economy estimates would show larger share for the highest group in all four countries as non-market services intensively employ graduates.

4. Dealing with small samples

Accounting for the heterogeneity of labour requires cross classification of the workforce along a number of dimensions of which the level of education is among the most important. While a large number of educational categories is always desirable, existing evidence for Denmark shows that the difference in labour quality indices that use four categories and those using more groups is not significant (Fosgerau et al. 2001). Similar results were found for the UK by the ONS, using five skill categories (ONS 2004). This recommends that the attention should be directed towards other issues. Given this, information on wage rates and numbers over the gender split are considered important as well as across different age groups, to account for workplace experience. Therefore, in the best case, data should be collected by age band, gender and skill/educational attainment for each industry.

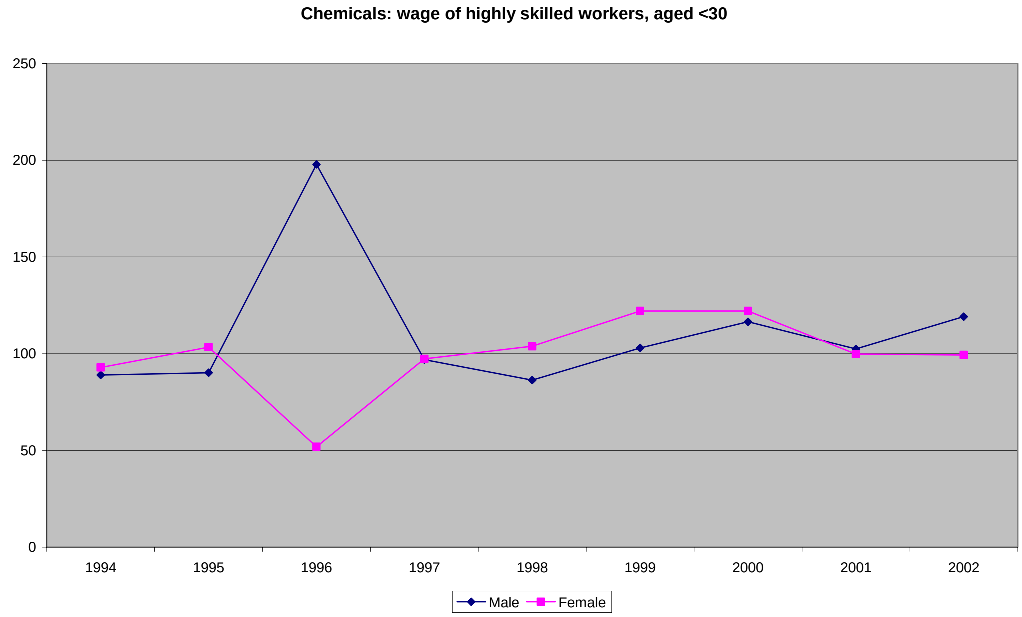
However, it is very likely that in most countries data will be at least partially missing or highly volatile, particularly for wage by skill, gender and age. Wages by gender and age are generally available but further disaggregation into skills may be problematic because of the relatively small sample sizes on which the data are based. For example, consider the chemical sector, presented in Table 2 below:

Table 2
Chemical sector: wages by skill, age and gender

	High qualification	NVQ4	NVQ3	NVQ21	No qualification
			Male aged <30		
1996	198	55	65	59	43
1997	97	70	77	57	41
1998	86	75	76	70	
1999	103	78	63	50	81
2000	117	106	73	104	
2001	102	107	70	59	49
2002	119	126	101	54	83
			Female aged <30		
1996	52	93	51	55	
1997	97	92	67	49	44
1998	104	111	61	55	59
1999	122	80	66	59	54
2000	122	52	84	83	14
2001	100	82	88	58	30
2002	99	87	76	104	

It can be seen that although most of the data is available, there is a high degree of volatility. For example, female average wage for the skill group NVQ21 goes from 58 in 2001 to 104 in 2002 (see figure 2). This volatility is caused by the very low number of survey respondents in particular groups. With further investigation we find that the average wage of 104 is based on 4 observations. In several cases, the average wage data in Table 2 are based on less than 10 observations so they are likely to be less than reliable. Figure 1 summarises the time series patterns of wages of highly skilled male and female workers, less than 30 years old. The presence of outliers in both series can seriously undermine the quality of the data.

Figure 1



On the other hand, when we look at the wage by age and gender, the volatility is considerably reduced, as we can see in Table 3. Moreover, it should be pointed out that the variability in the wage data tends to be greater than that in the employment data. This is due to differences in sample sizes.

Table 3
Chemical industry: wage by age and gender

Year	**Male<30**	**Male 31-45**	**Male>46**	**Female<30**	**Female 31-45**	**Female>46**
1996	361.42	470.60	412.68	241.23	366.89	227.70
1997	293.32	459.50	509.07	297.45	353.63	270.54
1998	306.03	496.22	512.76	303.57	402.42	341.17
1999	303.27	537.44	507.29	340.30	471.47	317.02
2000	396.92	502.65	593.06	373.64	387.21	312.29
2001	321.46	505.01	508.84	328.51	460.06	309.73
2002	350.80	598.37	529.36	368.43	485.77	325.44

Obtaining employment data by skill, age and gender is usually less problematic as employment data are largely available at the industry breakdown used in this paper and with the level of details needed for our analysis. For example, in the chemical industry a large number of observations are available, as shown in table 4 for male and female workers of less than 30 years of age. Similar data are available for the other wage groups.

Table 4

Chemical industry: employment by skill, age and gender.

	High qualification	NVQ4	NVQ3	NVQ21	No qualification
Male aged <30					
	11,813	4,079	13,725	16,049	4,998
1997	16,185	6,868	12,976	18,663	3,056
1998	17,693	5,638	17,402	17,197	2,830
1999	16,888	5,334	15,979	20,657	3,860
2000	21,160	6,882	9,129	12,154	2,656
2001	13,128	7,042	8,799	9,053	2,931
2002	12,714	1,839	5,684	7,656	1,311
Female aged <30					
1996	10,474	2,388	4,869	20,003	1,617
1997	11,100	3,732	9,925	12,361	1,243
1998	10,911	2,908	5,781	9,785	2,599
1999	7,792	2,374	5,708	14,579	3,854
2000	13,656	4,423	3,993	8,657	1,884
2001	11,384	2,279	6,183	8,359	2,229
2002	11,634	2,608	5,171	2,546	442

In this paper, we introduce two alternative methodologies that deal with the presence of gaps in the data, deriving from either missing observations, or highly volatile data deriving from very small samples. Both methodologies rely an the availability of the data in Table 3 and Table 4 and hence they do not require wage classifications by skill, age and gender.

5. Methodological approach

The starting point in our analysis is to obtain the split by skill, age and gender using results from existing information. Specifically, our target is to derive a correction term that, multiplied by the wage data by gender and age, allows to derive a reasonable estimate for the wage by skill, age and gender, to use in the computation of quality adjusted labour indices. We are going to describe two ways of doing this; one derives the correction term from existing (or new) estimates on the returns to education (estimated quality adjusted labour index – QL(t)_e); a second method consists in computing the correction term using broader industry classification (aggregate quality adjusted labour index - QL(t)_a). To check the robustness of the two methods, we will consider few industries where all the data are available and we will compare the performance of the estimated and aggregate indices with the quality adjusted labour index based on actual data (QL(t)).

5.1 The estimated quality adjusted labour index

According to the first method, we can derive a correction term from the estimation of a Mincer returns to education equation, specified as follows (Mincer 1974):

$$\ln(W) = \alpha_0 + \sum_j \alpha_{1i} i + \alpha_{21} e + \alpha_{22} e^2 + \alpha_{23} e^3 + \sum_k \alpha_{3k} C_k + \varepsilon \quad (1)$$

where

W = earnings,
i = levels of education/qualifications achieved,
e = experience (years in employment)[1],
C = a vector of control variables
ε = is an error term $\varepsilon \sim N(0,\sigma)$.

The estimates of α_{1i}, the returns to education, are equal to the ratio of the highest skill group wage divided by the lowest skill group wage (the base category), controlling for age and gender. Suppose, for example, that we only have two skill groups. In this case we only have one estimate of α_{1j}, α_{11}, which is equal to:

$$\hat{\alpha}_{11} = \left(\frac{\hat{W}s_1}{Ws_2} \right) \Big| g, a \quad (2)$$

where s_1 is the highest skill and s_2 is the lowest skill group. Remember also that average wage across all skill groups ($\overline{W}$) is given by:

$$\overline{W} = \frac{Ws_1 Ns_1 + Ws_2 Ns_2}{Ns_1 + Ns_2} \quad (3)$$

Using equation (2) and substituting into (3) we can derive the wage relative to average wage across all skill groups:

[1] Ideally for our specific application we should have the different age groups as an explanatory. However, experience and age are highly correlated.

$$(4) \qquad \left(\frac{\hat{W}s_1}{\overline{\overline{W}}}\right) = \frac{\hat{\alpha}_{11}\ (NS_1 + Ns_2)}{\hat{\alpha}_{11} Ns_1 + Ns_2} \quad \text{and} \quad \left(\frac{\hat{W}s_2}{\overline{\overline{W}}}\right) = \frac{(NS_1 + Ns_2)}{\hat{\alpha}_{11} Ns_1 + Ns_2}$$

Equation (4) describes the derivation of our two corrections term for Industry *i*, in a particular year. An illustration of how to use it is given in the table below :

Table 5

Application of the correction term to the available data

Desirable data	Available data	Corrected data
$Ws_1a_1g_1$	Wa_1g_1	$Wa_1g_1 * \left(\frac{\hat{W}s_1}{\overline{\overline{W}}}\right)$
$Ws_2a_1g_1$		$Wa_1g_1 * \left(\frac{\hat{W}s_2}{W}\right)$
$Ws_1a_2g_1$	Wa_2g_1	$Wa_2g_1 * \left(\frac{\hat{W}s_1}{\overline{\overline{W}}}\right)$
$Ws_2a_2g_1$		$Wa_2g_1 * \left(\frac{\hat{W}s_2}{W}\right)$
$Ws_1a_1g_2$	Wa_1g_2	$Wa_1g_2 * \left(\frac{\hat{W}s_1}{\overline{\overline{W}}}\right)$
$Ws_2a_1g_2$		$Wa_1g_2 * \left(\frac{\hat{W}s_2}{W}\right)$
$Ws_1a_2g_2$	Wa_2g_2	$Wa_2g_2 * \left(\frac{\hat{W}s_1}{\overline{\overline{W}}}\right)$
$Ws_2a_2g_2$		$Wa_2g_2 * \left(\frac{\hat{W}s_2}{W}\right)$

Generalised to N skill groups and imposing $\hat{\alpha}_N = 1$, where N is the lowest skill group:

(5) $$\left(\frac{\hat{W}s_i}{\overline{\overline{Ws}}}\right) = \frac{\hat{\alpha}_{i1}\sum_{i=1}^{N} Ns_i}{\sum_{i=1}^{N}\hat{\alpha}_i Ns_i}$$

The average share can then be multiplied by the average wage by age and gender to obtain average wage by skill, age and gender, $\hat{W}s_i a_j g_k$:

(6) $$\hat{W}s_i a_j g_k = \left(\frac{\hat{W}s_i}{\overline{\overline{Ws}}}\right) * (Wa_j g_k) \quad . \qquad \begin{array}{l} i = 1,\ldots\ldots, N \\ j = 1,\ldots\ldots, J \\ k = 2 \end{array}$$

The average wage by skill, age and gender is then multiplied by total employment by skill, age and gender, and the result is used to calculate the wage bill shares for the Tornqvist index ($\hat{W}Bs_i a_j g_k(t,t-1)$):

(7) $$\hat{W}Bs_i a_j g_k\_s = \frac{\hat{W}s_i a_j g_k * Ns_i a_j g_k}{\hat{W}tot} ,$$

(8) $$\hat{W}Bs_i a_j g_k\_s(t,t-1) = \frac{\hat{W}Bs_i a_j g_k\_s(t) + \hat{W}Bs_i a_j g_k\_s(t-1))}{2} .$$

Note that total wage is computed using the estimated wage and not the actual wage:

(7b) $$\hat{W}tot = \sum \hat{W}s_i a_j g_k * Ns_i a_j g_k \qquad \begin{array}{l} i = 1,\ldots, N \\ j = 1,\ldots., J \\ k = 2 \end{array}$$

Finally, quality adjusted labour is equal to the sum of rates of growth for each employment type multiplied by the wage share:

(9) $$QL(t)\_e = \sum \hat{W}Bs_i a_j g_k(t,t-1) * (\log(ns_i a_j g_k(t) / ns_i a_j g_k(t-1))$$

$$\begin{array}{l} i = 1,\ldots, N \\ j = 1,\ldots., J \\ k = 2 \end{array}$$

This methodology assumes that wages differ across skill levels but not across industries.

An example

To show an application of the methodology we compute quality adjusted labour indices for the retail, wholesale and hotel and catering industries. Data on employment and wage by skill, age and gender are available for there three industries. This allows us to compare the performance of our estimated labour index with the one based on the actual data (see equation 1).

The alphas used in equation (5) are derived from Stevens and O'Mahony (2005). These are based on UK data from 1979-2002, from the LFS and, prior to wage data being collected in the LFS, wage data were derived from the General Household Survey (GHS) [2]. The Mincer equation estimated in this paper is based on slightly different educational categories to the skill breakdown employed here; therefore, the alphas derived from this estimation are not precisely consistent with the estimate of labour quality from the full dataset. This however does illustrate that returns to education are available from a number of academic sources and likely to be available in other countries.

The results are presented in Figures 2-4. For all three industries the estimated quality adjusted labour index provides a good approximation of the index derived from the actual data. This result is particularly encouraging, given that the available estimates of the returns to education were based on a different skill breakdown to our actual data.

[2] For further information on the estimation of returns to education in the UK, see Stevens and O'Mahony (2005) and for further details of the data on which the estimation was based, see Mason and Forth (2003).

Figure 2

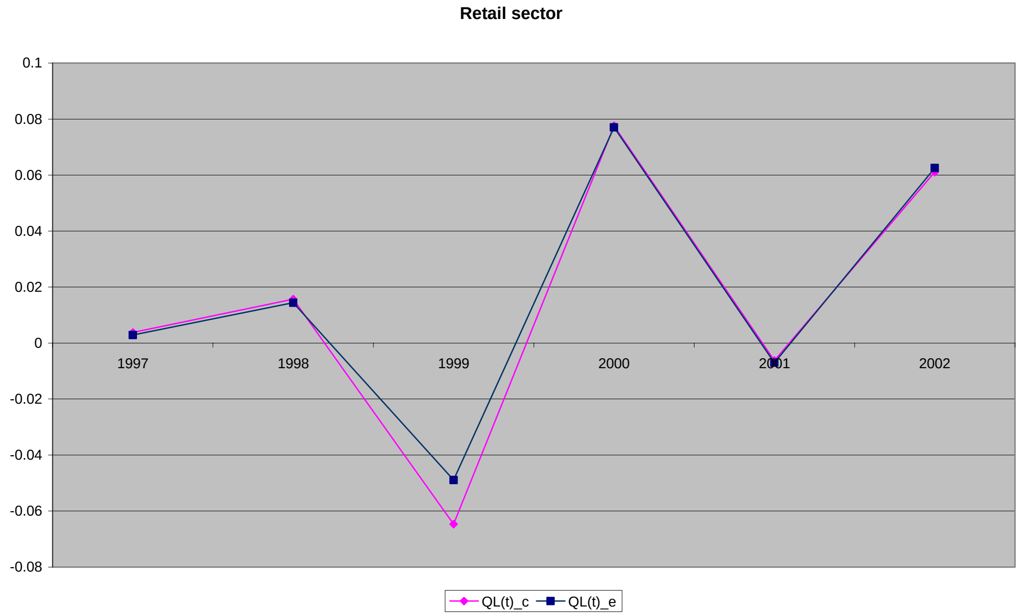


Figure 3

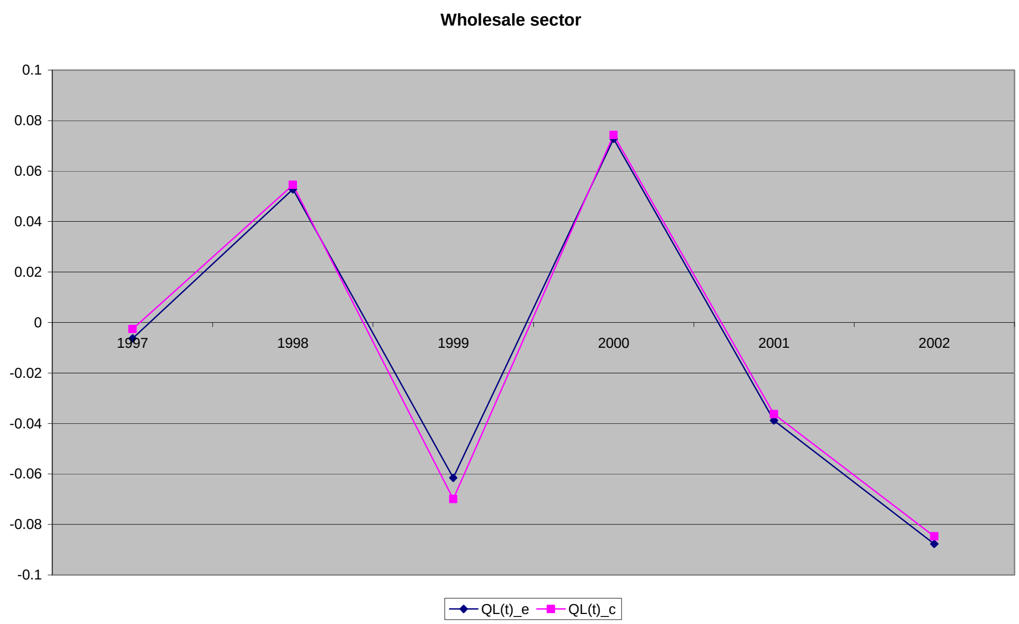


Figure 4

5.2 The aggregate quality adjusted labour index

A second approach to compute a quality adjusted labour index in the presence of missing and/or highly volatile data for a single industry is based on the computation of the correction term using more aggregated data rather than an estimate of the returns to skills. For example, instead of using data for the retail industry, we use data for the distributive sector, including Repair of motor vehicles and maintenance, Wholesale, Retail, Hotel and Catering.

We begin with the computation of ratios of skilled to average wages by age and gender for the aggregate distribution group (d), i.e we compute:

$$\frac{W_s^d}{\bar{W}^d} \text{ for each skill, age and gender group}$$

We can then follow the same steps described above to derive the correction term and the wages by skill age and gender. The aggregate quality adjusted labour index (QL(t)_d) is presented in Figures 5-7, next to the index based on the actual data:

Figure 5

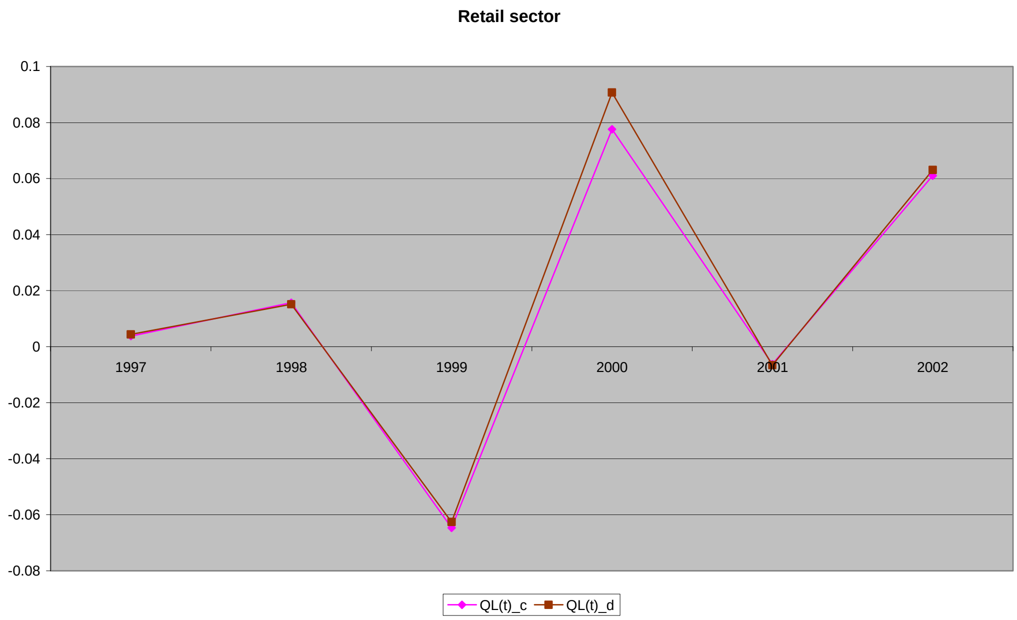


Figure 6

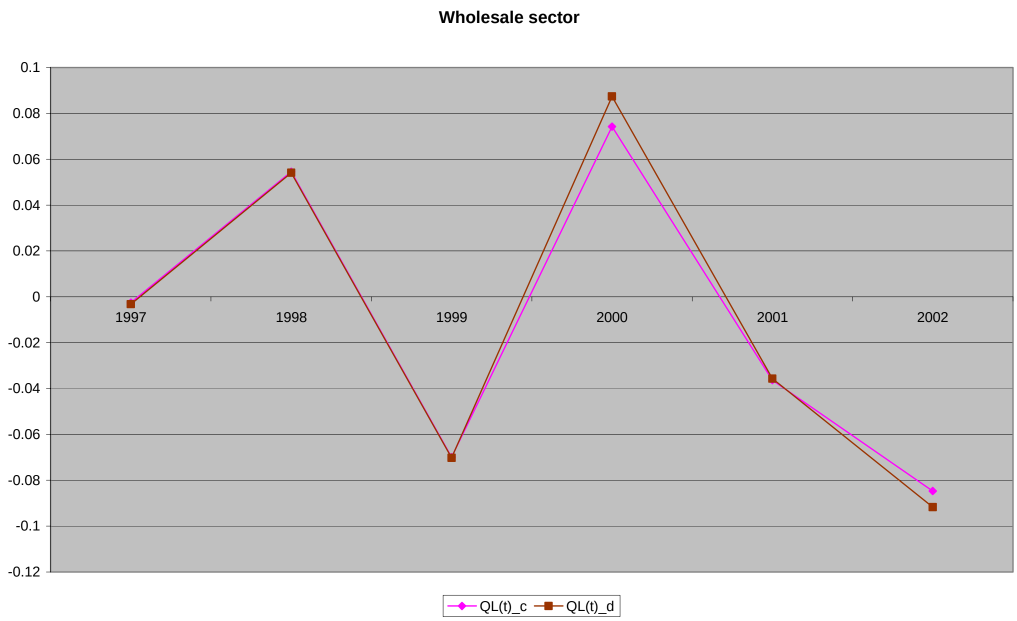
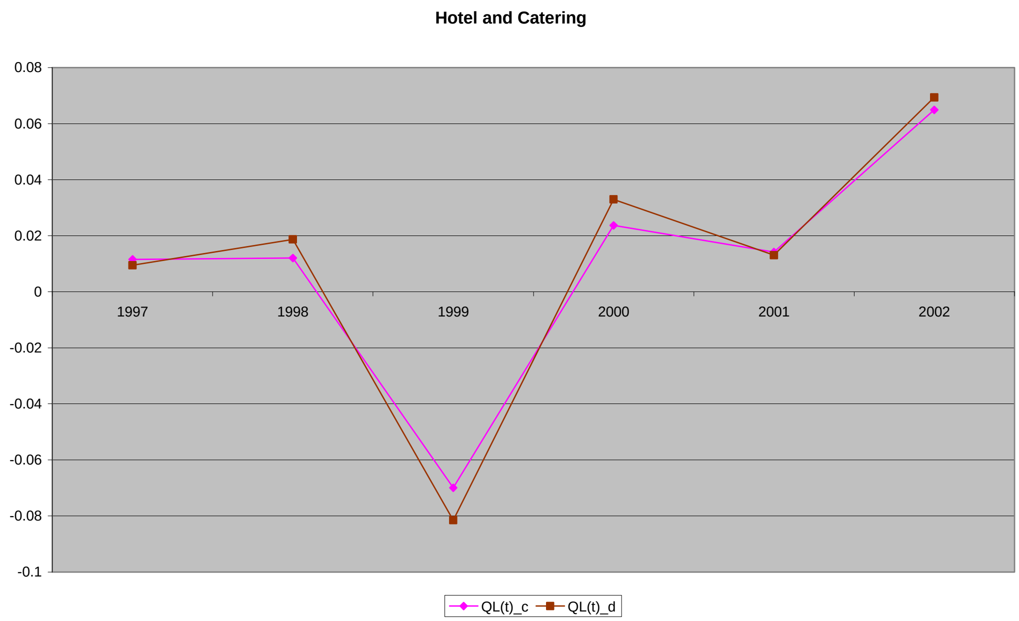


Figure 7



The aggregate quality adjusted labour index provides a close approximation of the index based on the actual data and it does not differ much from the performance of the estimated index. The latter is however slightly more accurate than the former, as show in Figures A.1-A.3 in the appendix. The data underlying all figures are presented in Appendix table 1.

This second procedure might appeal at first because it is not dependent on obtaining estimates of the coefficient of a Mincer equation. However, with the econometric estimation approach it is possible to control for other factors (such as experience and other background information) that can affect the returns to education and hence we can obtain a better evaluation of such returns. Moreover, while several econometric results are already available, getting all the data might be complicated even when concentrating on broader industrial classifications.

7. Conclusions

This paper has highlighted some of the problems associated with constructing quality adjusted labour indices and suggested two ways of dealing with gaps or inconsistencies in the wage data. The focus of this paper has been to account for skill, age and gender in the construction of the index when wage data for the desired characteristics are unreliable. The first proposed method is based on using econometric estimates of the returns to education to derive the appropriate wage data needed for the construction of the quality adjusted labour index. An alternative approach is based on the use of more broadly defined industry classification to compute the returns to education.

Using data for the distributive sector, our results show that the quality adjusted labour indices constructed using the two methodologies are very similar to those based on the actual data, with the estimated index performing slightly better than the one based on more aggregate data. This is an important result as it shed some light in addressing the problem of missing or inconsistent data, problems which are likely to become more cumbersome in pursuing a finer industry classification than the one used in this study.

As to which of these two methods is to be preferred, it is likely to be the case of which is most readily available. The effort involved in the estimation of a Mincer type equation may favour the use of more aggregate data. However, estimates of Mincer type equations are likely to be available for many countries, which may save the estimation of the returns to education. In addition, the estimated returns may well take into account other influences on the returns to education and will thus control for other extraneous effects.

Finally, the methodologies described in this paper have so far been applied to a limited number of industries within the service sector. More work is needed to check their performance in different types of industries, especially in manufacturing where variations in the returns to education might be characterised by higher volatility.

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Table A1: 47 Industry list

1	Agriculture, forestry & fishing
2	Mining & quarrying
3	Food, drink & tobacco
4	Textiles, leather, footwear & clothing
5	Wood products
6	Pulp & paper products, printing & publishing
7	Mineral oil refining, coke & nuclear fuel
8	Chemicals
9	Rubber & plastics
10	Non-metallic mineral products
11	Basic metals
12	Fabricated metal products
13	Mechanical engineering
14	Computers, office machinery
15	Electrical machinery
16	Radio, TV & communications equipment
17	Instrument engineering
18	Motor vehicles
19	Other transport equipment
20	Miscellaneous manufacturing
21	Electricity, gas & water supply
22	Construction
23	Vehicle maintenance & repair
24	Wholesale trade
25	Retailing
26	Hotels & catering
27	Railways
28	Other inland transport
29	Water transport
30	Air transport
31	Supporting transport activities, travel agencies
32	Post & courier services
33	Telecommunications
34	Financial intermediation (excluding insurance & pension funding)
35	Insurance & pension funding
36	Auxiliary activities to financial intermediation
37	Real estate
38	Renting machinery & equipment
39	Computer services
40	Research & development
41	Other business services
42	Other community, social & personal services
43	Private households with employed persons
44	extra territorial ….
45	Public admin & defence; compulsory social security
46	Education
47	Health & social work

Figure A.1

Figure A.2

Figure A.3

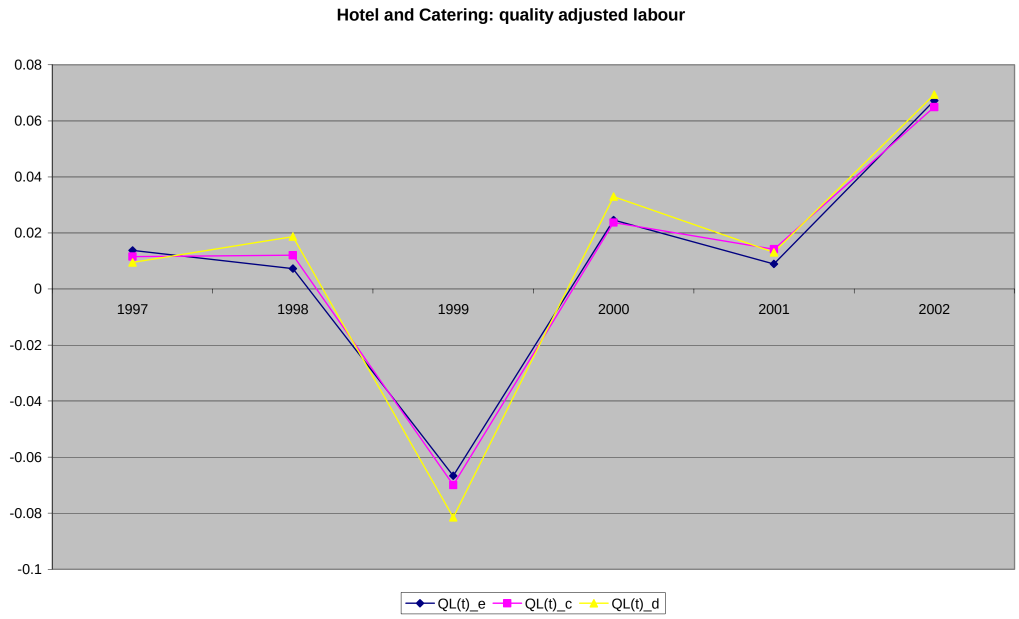

Table A.2

Quality adjusted labour indices: comparison of the two methodologies with the actual data

Hotels & catering				*Wholesale*			*Retail*		
year	**QL(t)_e**	**QL(t)_c**	**QL(t)_d**	**QL(t)_e**	**QL(t)_c**	**QL(t)_d**	**QL(t)_e**	**QL(t)_c**	**QL(t)_d**
1997	0.013778	0.011537	0.009448	-0.00631	-0.00257	-0.00324	0.002883	0.00377	0.004365
1998	0.007252	0.012044	0.018701	0.052783	0.054515	0.054084	0.014423	0.01566	0.015114
1999	-0.06669	-0.06996	-0.08149	-0.06157	-0.06993	-0.07019	-0.04891	-0.06469	-0.06263
2000	0.024651	0.023681	0.033005	0.072778	0.07428	0.087387	0.07706	0.077572	0.090745
2001	0.008944	0.014167	0.013062	-0.03881	-0.03632	-0.03565	-0.00703	-0.00625	-0.00661
2002	0.067223	0.064933	0.069364	-0.08771	-0.08472	-0.09174	0.062483	0.061028	0.063033