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Skill splits of labour input values in GTAP

An approach based on ILO and UBS data

1 Introduction

Researchers working empirically at the intersection of labour market economics and international trade with macroeconomic interest need datasets with regional, sectoral and skill-specific detail. Important strands of the literature where these interlinkages are centre stage are the testing of theories that explain the patterns of trade with factor endowments (Heckscher-Ohlin type), the analysis of the consequences of trade liberalisation for the distribution of income and the relocation of labour as a result of migration. In this paper, we propose an approach to skill split data that can be used in a computable general equilibrium context, in particular when working with the GTAP dataset.

In the testing of theories of trade, it has long been recognised that it is not sufficient to characterise countries as "labour intensive" or "capital intensive". One has to take a step beyond and take account of the level of education and the distribution of skills (Bowen et al., 1987) as well as the complementarity patterns between different skill types and capital (Wood, 1994). The same mechanisms that are at work here also determine the different effects of trade liberalisation across skill groups, which have always been crucial for the assessment of trade policy (Wood and Ridao-Cano, 1999).

If one chooses a computable general equilibrium approach to questions like these, the GTAP dataset (Diamaranan, 2006) is a natural point of departure. The GTAP data need to be handled with care, because they are constructed from heterogeneous sources, which are not easily matched. Nevertheless, GTAP is without question the preferred data source if a consistent and detailed dataset of international trade flows and national input-output interlinkages is required. Since the 1998 release of GTAP (version 4, base year 1995), GTAP takes account of labour market heterogeneity and provides a split of the labour input values into a skilled and an unskilled component.

There are two main problems with this part of the GTAP dataset that motivate us to propose a different approach in this paper. The first is that the original labour market data used for the decomposition are rather old and restricted to a relatively small subset of countries (see the review of the current GTAP approach in Section 3). Second, the split is only provided for input values, and it is hardly possible to recover the underlying quantity and price components. As long as one works only with value shares, this is fine. But questions like international migration (Walmsley et al., 2007) require information not only on values, but also on persons.[1]

In this situation, we can either try to combine the GTAP value shares with independent quantity information, to reconstruct the wages, or we can build a completely new value-spilt.

[1] Our own motivation to engage in a reconstruction of the skill-split in labour input values in GTAP stems from a study where we extend our model "WorldScan" with features needed to evaluate the labour market targets in the "Lisbon strategy" of the European Union (Boeters and van Leeuwen, 2008). Information on the relative wages of high and low skilled workers proved essential to get a coherent picture of wages, unemployment benefit replacement rates and the public budget consequences of unemployment.

Consistency considerations (see Section 4.2) made us favour the latter approach. We construct value splits from independent information on quantities and prices, namely skill-specific employment information from the International Labour Office (ILO, 2008) and information on relative wages provided by the Union Bank of Switzerland (UBS, 2006).

In the remainder of this paper we proceed as follows. In Section 2, we take a step back and ask what options of a skill split there are in principle. In Section 3, we review the current GTAP approach and place it in this context. Sections 4 and 5 then present our own approach. Section 4 is about the basics, while Section 5 describes an extension that allows us to account for additional sectoral detail.

2 Which skill split?

Heterogeneity is the essence of empirical labour market analysis. Labour economists routinely run wage regressions where they take account of several dimensions of heterogeneity: education, experience, age, sex, household composition – and in addition sectoral and firm characteristics (the seminal approach in Mincer (1974), which has been extended in many directions). In such an environment of multiple dimensions of heterogeneity, it is heroic to sort individuals into a finite set of "skill types". However, this is what is suggested by the usual approach to production analysis, which is dominated by production functions with a small number of inputs.

Even more restrictive, if one wants to work with empirically founded elasticities of substitution between skill types and other factors of production, one is bound to a split in only two skill types (e.g. Krusell et al., 2000). Attempts to estimate production functions with more than two types of labour have turned out to produce unstable and volatile results that are difficult to interpret (e.g. Falk and Koebel, 1997). Given that labour is to be split into two skill categories, we are left with three principal options: using an educational, an occupational or a wage level criterion.

The first approach tries to establish an educational split. The level of education is most of the time measured in years of schooling (although, ideally, you would want to correct for quality). If it comes to a single split, most US-focussed studies rely on the college premium, i.e. separating those who have at most high-school education from those who did at least enter college, or try to construct a similar measure for countries where no colleges in a narrow sense exist. Examples of studies that focus on the college premium are Gottschalk and Smeeding (1997) and Acemoglu (2003). However, constructing an internationally comparable measure of education is full of problems (Barro and Lee, 2001).

Therefore, as a second approach, working with an occupational split, is well established. In most of the cases, this means working with the International Standard Classification of Occupations (ISCO), which provides nine occupational types (Bowen et al., 1987, Bowen and

Sveikauskas, 1992) . The most aggregated version of this approach is the split between production and non-production workers (Berman et al., 1998, Machin and Van Reenen, 1998).

Third, one can choose an approach that deliberately remains ignorant about the sources of skill differences (education, occupation) and just interprets the wage received as revealed skills (Juhn et al., 1993). This is closely related to working with indicators like the 9th-to-1st-decile ratio in inequality analysis.

There is clearly no best way of constructing skill categories. Much depends on the question we want to answer. Of the three approaches, education is closest to measuring endowments (although it can also be seen as the product of innate abilities and an educational technology). Occupations include more aspects of vertical specialisation. However, if one is mostly interested in labour mobility and the effects of (trade policy) shocks on specific groups on the labour market, these vertical cleavages might be more important than the pure level of education. (A lawyer might have the same education level as a physician, but they will never replace each other if one group is subject to a shock.) This suggests that an educational split is more suited for a long-term analysis, whereas the occupational split has its advantages in the short and medium term. Finally, the wage-level approach is open about the interference of educational, occupational and other, probably unobservable, effects. It is most suited in the context of distribution analysis, but has its obvious limitations when it comes to describing the effects of shocks on specific groups on the labour market. It is merely a method to attribute changes in quantities, prices and a residual to the wage distribution (e.g., Juhn et al., 1993, for the United States).

The broader the sample of countries we want to cover, the more severe the comparability problems with both the educational and the wage-level approach. Here, data availability considerations make the occupational approach clearly dominating. The wage-level approach can only be used when we go back to micro data. In the most important international labour market macro data set (ILO 2008), sectoral employment is only given in an occupational, not in an educational breakdown. This was decisive for using occupation as split criterion in our approach.

Some comparative studies (although only for manufacturing in high-income countries) show that the correlations between classifications based on the three approaches are high (Berman et al., 1994, Machin et al., 1996). So we can be fairly confident that the focus on occupational criteria will not systematically bias the results.

3 Current labour input value decomposition in GTAP

In the GTAP data, labour was treated as a homogeneous factor until version 3 of the dataset (base year 1992). Since GTAP 4 (base year 1995), the regional and sectoral labour input values are split into an unskilled and a skilled component. The details of the method used are documented in Liu et al. (1998a,b). In the remainder of this chapter, we summarise the procedure of Liu et al., because it forms the background for our own approach. We end with some brief remarks about the expansion of this approach in GTAP 5 (base year 1997) and GTAP 6 (base year 2001).

3.1 Empirical basis of the skill split

The principal decision in making the GTAP skill split was to base it on micro-data information on sectoral employment. As micro data is not available for all countries and requires a considerable amount of preparation work before it can be used in the analysis, the number of countries in the database is restricted. Basically, the GTAP skill split relies on data assembled by Vo and Tyers (1996) from labour force surveys and national censuses in 13 countries[2].

The skill split was based on the ILO one digit occupational split[3]. "Skilled labour" was defined as professional workers, which consists of the categories 1 to 3 (managers and administrators, professionals, and para-professionals). All other categories (4 to 9) are "unskilled workers" (trades-persons, clerks, salespersons and personal service workers, plant and machine operators and drivers, labourers and related workers and farm workers). In addition, the sectors of the original labour market data were mapped to the 50 GTAP sectors of the GTAP 4 database.

3.2 Imputation of values for other regions

The original survey data produced sectoral labour value splits for the 13 countries for which micro data were available, which is considerably less than the 45 regions covered in GTAP 4. Liu et al. imputed the remaining values by results of a linear regression explaining skill value shares by region-specific factors. The independent variables used are real GDP per capita, measured at 1987 prices, and the average number of years of tertiary education. Since the regional survey data were for different base years (between 1985 and 1992), extrapolation of the tertiary education data from time-series data for 1980-1987 was done to the benchmark year of the GTAP 4 database (1992).

The following regression equation was estimated:

[2] The Vo and Tyers dataset was assembled in the context of a World Bank-funded project assessing the impact of trade on relative wages in the OECD. The countries in the sample are United States, Canada, Australia, EU-15 (aggregated), Japan, Taiwan, South Korea, Brazil, Indonesia, Philippines, Thailand, Hong Kong. Shortly after India was added to this sample.

[3] Interestingly, the authors don't give an explicit reason for using an occupational instead of an educational classification. We can guess that occupations were better represented in the micro data.

$$V_{H,j,r} = a_0 + a_1 TER_r + a_2 GDPC_r \quad (3.1)$$

in which:

$V_{H,j,r}$ = Share of skilled labour in the total wage bill in sector *j* of country *r*

TER = average years of tertiary education

GDPC = real GDP per capita, measured at 1987 prices

The predicted values of the regression[4] were used for the aggregated sectors in the 32 GTAP regions for which survey data was not available.

3.3 Results

One important indicator that can be used as a plausibility check for the results are the implied economy-wide wage bill shares of skilled and unskilled labour. Table 3.1 shows these economy-wide shares, which are obtained by combining the sectoral shares with sectoral value-added as represented in GTAP, for the 30 regions of GTAP 3 database. It turns out that developed economies in general have a higher skilled labour share than developing economies.

Table 3.1 Economy-wide skilled labour wage bill share (in %) for 30 GTAP regions

Australia	42.4	United States of America	40.7
New Zealand	36.4	Mexico	30.8
Japan	38.4	Central America and the Caribbean	29.0
Korea	28.9	Argentina	28.4
Indonesia	26.8	Brazil	34.6
Malaysia	26.8	Chile	30.1
Philippines	26.6	Rest of South America	29.3
Singapore	34.8	EU-15	40.1
Thailand	27.3	Rest of European Union	38.5
China	20.4	EFTA	42.4
Hong Kong	42.7	Central European Associates	25.6
Taiwan	39.8	Former Soviet Union	32.2
India	22.2	Middle East and North Africa	34.0
Rest of South Asia	23.6	Sub-Saharan Africa	27.0
Canada	28.7	Rest of World	30.5

source: Liu et al. (1998a) table 19

As a second plausibility check, Liu et al. combined these economy-wide skilled labour shares with body count data from the ILO. This gives economy-wide wage ratios, which are reported for 16 GTAP regions in Table 3.2.

[4] The regression results are reported in Table 18.4 of Liu et. al (1998b).

Table 3.2	Implied wage ratio of skilled to unskilled for some GTAP 3 regions				
	skilled body count share	payment share (predicted)	skilled / unskilled wage ratio (predicted)	payment share (actual)	skilled / unskilled wage ratio (actual)
United States of America	29.73	40.9	1.64	40.7	1.62
Canada	29.57	34.8	1.27	28.7	0.96
Mexico	11.53	30.7	3.4		
Japan	15.76	40.6	3.65	38.4	3.33
Hong Kong	14.01	33.7	3.12	42.7	4.57
Korea	10.03	32.5	4.32	28.9	3.65
Singapore	29.17	34.5	1.28		
Australia	24.37	38.1	1.91	42.4	2.28
New Zealand	25.37	36.6	1.7		
Philippines	7.01	26.7	4.83		
Malaysia	9.45	26.8	3.51		
Thailand	4.79	27.3	7.47		
Indonesia	3.6	26.7	9.75		
China	6.63	20.5	3.63		
Brazil	8.17	34.6	5.95		
Chile	11.66	30.1	3.26		

source: Lie et al (1998a), Table 20

In general, the developed regions show lower skilled to unskilled wage ratios than the low income regions. In addition, for the countries with data, the estimated ratios were close to actual ones (see the two rightmost columns of Table 3.2). The authors concluded from these result that the methodology proposed can be used as a reasonable starting point.

3.4 Extensions in GTAP 5 and 6

The basic set-up of the GTAP 4 methodology was retained in the subsequent GTAP versions. The predicted values of skilled labour were used, except for the survey regions, where the actual values were available. The data set was expanded to 226 standard countries using a mapping between the GTAP 4 regions and the respective standard countries. The sector dimension was also expanded. The data was then aggregated to the GTAP 5 and 6 regions using country-level GDP as share weights. The data file containing the value shares of skilled and unskilled labour, by sector, for each region was used to disaggregate the total wage bill for each GTAP region in the global data base assembly procedure.

3.5 Problems

There are two main problems with the current set-up that motivate the alternative approach presented below. First, we still in essence rely on a relatively old and small dataset. Second, the skill-specific input values cannot be decomposed into a volume and a price component. This could in principle (yet not in practice) be done for the 13 countries in the original dataset. However, the regression results refer genuinely to value share information and lack any handle for decomposition.

4 A decomposition approach based on ILO and UBS data

The problems with the current labour input value split in GTAP led us to a complete revision. Basically, the procedure is as follows: (1) We derive sectoral skilled and unskilled shares for persons employed from ILO (2008) statistics. (2) We take a skilled-to-unskilled wage ratio from UBS (2006) statistics and assume that it is uniform across sectors. (3) From this we calculate sectoral skilled to unskilled value ratios, which are used to split the value share of labour in GTAP. This procedure is carried out at the level of the International Standard Industrial Classification of all Economic Activities (ISIC-Rev. 3)[5], which is relatively coarse. In Section 5 we describe a more ambitious disaggregation.

4.1 Sectoral workforce data from ILO

The International Labour Office (ILO, 2006) provides information on the “Economically active population” for a large number of countries, which is based on country-level labour force surveys. In general, the data is given both in an educational and an occupational breakdown. However, the educational classification is only available for the economy as a whole, whereas employment by occupation is reported on a sectoral (ISIC) basis[6]. This is our reason to use the occupational split, although education might be closer to the endowment approach (see the discussion in Section 2).

In Appendix B we reproduce the International Standard Classification of Occupations (ISCO-88)[7] that we use. We follow Liu et al. (1998a, b) in classifying major groups 1, 2 and 3 as “skilled”, whereas all the other occupations are “unskilled”. This decision can have a large impact on the resulting head-count shares, not so much on the country-wide levels, but on the values for specific sectors in specific countries. For example, as a consequence of our considering major group 6 (skilled agricultural and fishery workers) to be unskilled, the agricultural sectors in most countries have a very low skill level.

The one-digit ISIC sectoral classification has the disadvantage that it is much coarser than the sectoral disaggregation in GTAP. As a consequence, we have 23 GTAP sectors within

[5] See Appendix C for a list and a concordance with the GTAP sectors. In the following, we simply speak of “ISIC” for brevity when we refer to Rev. 3.

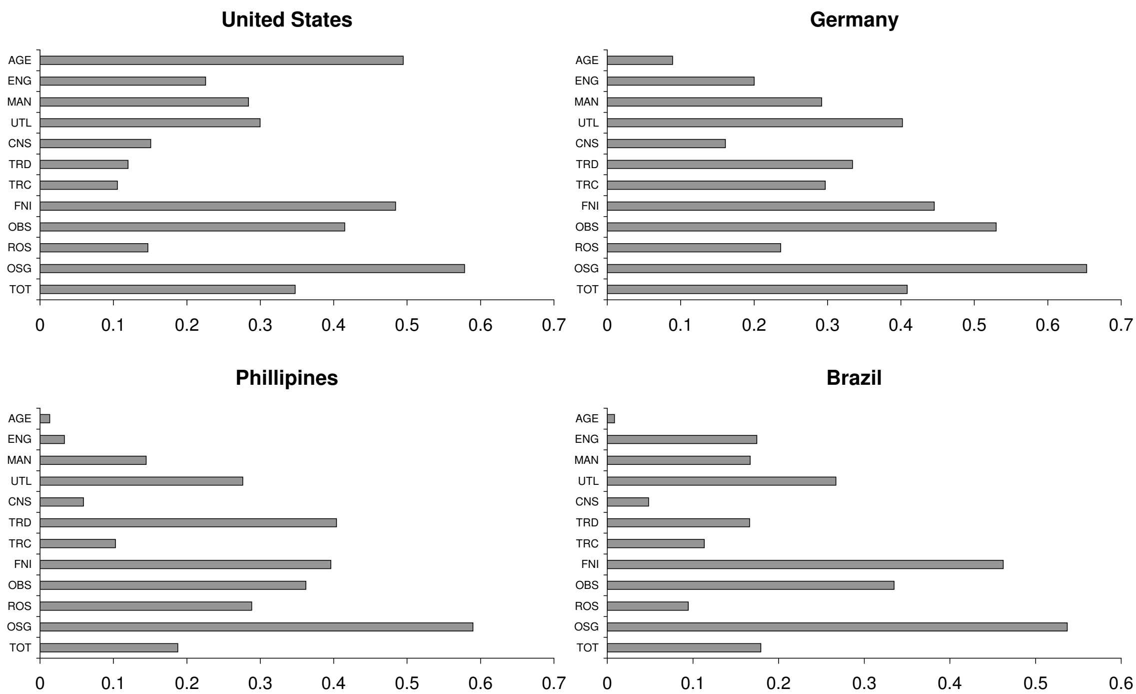
[6] Data sources that may be used for a labour skill split on educational basis are EU KLEMS (2007) and EUROSTAT (2005). We remained with the occupational split, because in EU KLEMS, the split is presented in three levels, with a high skilled share of less than 0.1, and in EUROSTAT, only a limited number of EU countries is covered.

[7] For some developing countries the ISCO-88 classification is not available, and we are bound to use the less detailed ISCO-68 classification. In the following, we simply speak of “ISCO” for brevity when we refer to ISCO-88.

the ISIC sector "Manufacturing" (D), which, without additional information, will end up with a uniform skill share. Similarly, more disaggregation is desirable for the ISIC sectors "Transport, Storage and Communications" (I) and "Financial Intermediation" (J). We deal with this issue in section 5.

We have ILO labour force data available for the 17 ISIC sectors (see Appendix C) and for 46 individual countries. The benchmark years vary from 1997 to 2006. For most countries this leads to 11 broad sectors[8]. Figure 4.1 shows the skilled to unskilled body count shares for these 11 sectors in four selected countries, two with high income, and two with low income: United States, Germany, Philippines and Brazil. In general, the share of skilled workers is higher in high-income countries, which is reflected in our sample. In all countries the variation between sectors is substantial, with a general tendency for a larger skilled share in services sectors than in agricultural and manufacturing sectors. In all four countries displayed in Figure 4.1, the share of skilled workers is highest in the sector "Public Administration, Defence, Education, Health" (OSG). The high skilled share in Agriculture (AGE) in the United States is striking. The discrepancy with the other countries suggests that classification is not uniformly applied.

Figure 4.1 Skilled body count shares for four selected countries (ILO)



[8] Although category B (Fishing) is both an ISIC as well as a GTAP sector we have included this ISIC sector In agriculture since the numbers were either close to zero or not available in many countries. Furthermore, category P (Private Households with Employed Persons) and category Q (Extra-Territorial Organizations and Bodies) are not considered to be GTAP sectors. Finally some ISIC sectors are aggregated to a GTAP sector.

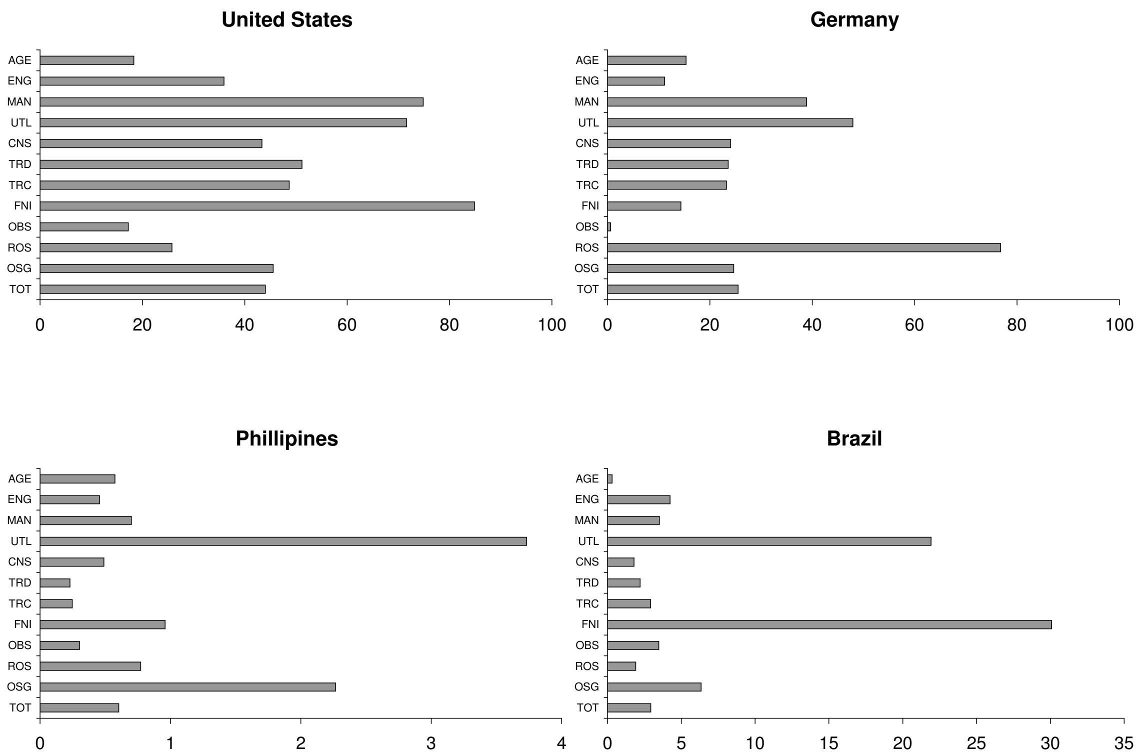
4.2 Combining ILO volumes with GTAP values

One option that we have at this point would be to combine the ILO labour volume data with the existing GTAP skill-specific value shares to recover the volume-price split. In this section, we report the consequences of this approach and argue that results are not plausible along three dimensions: sectoral wage differentials within countries, skilled-to-unskilled wage ratios across sectors and skilled-to-unskilled wage ratios across countries.

4.2.1 Sectoral wage differentials within countries

If we divide the GTAP sectoral values for labour by the number of workers from the ILO statistics, we get average wages per country and sector. Figure 4.2 shows these wages for the 11 GTAP broad sectors in the four-country sample of Figure 4.1. The picture of sectoral implicit wage levels that we get is not convincing. It is well known that there are wage differences between sectors, and that, in particular wages in industry and services are generally higher than in agriculture (see, e.g. Genre et al., 2009, for the Euro area). However, the implicit wage differentials we get are much larger than what could be expected from this literature. Magda et al. (2009) report a maximum wage ratio between the highest and lowest paying sector of 6.6 (Latvia, Tobacco products versus Hotels and restaurants). In contrast to this, we get a difference in ratio more than 100 (Germany, Recreational services versus Business services nec)

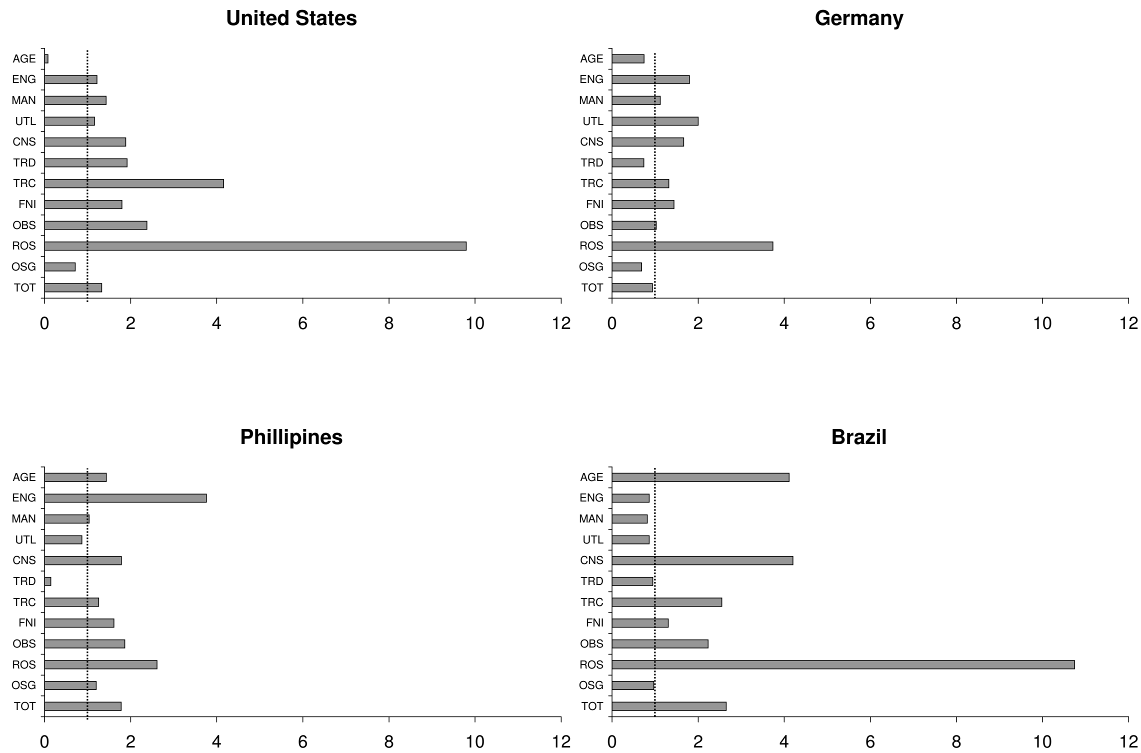
Figure 4.2 Wage levels per sector for four selected countries (in thousand dollars per year)



4.2.2 Skilled to unskilled wage ratios across sectors

If we divide sector-specific skilled to unskilled value ratio from GTAP by skilled to unskilled volume ratio from ILO, we get the implicit skilled to unskilled wage ratios. These are displayed in Figure 4.3 for the four countries we focus on. It turns out that the variation between the sectors is implausibly high. In particular, the value in Services (OSG) is way off the values in the other sectors in three of the four countries. Moreover, for some sectors the skilled-to-unskilled wage ratio is less than one (the dotted bar in all figures), which is not plausible. This problem is particularly severe in Germany, which is also reflected in the country-wide average ratio of this country (see next paragraph). We come back to the skill wage ratio in Section 4.3.

Figure 4.3 Skilled to unskilled wage ratio for four selected countries and per sector



4.2.3 Skilled to unskilled wage ratios across countries

If we look at the economy-wide implicit skilled to unskilled wage ratios (bars labelled "TOT" in Figure 4.3), we recognise the general pattern that these are higher in low-income countries than in high-income countries. The values for the United States (1.3), the Philippines (1.8) and Brazil (2.7) are in a plausible range, whereas a value for Germany (below one) is implausible.

4.2.4 Conclusions

The combination of ILO volumes and GTAP values does not produce plausible results. It turns out that neither the sectoral nor the skill match is sufficiently good to produce results that can be used as a basis for policy analysis.[9] In the next subsection we therefore rely on country-specific skilled to unskilled wage ratios derived from UBS data. These will replace the varying implicit wage ratios per country and sector in this section.

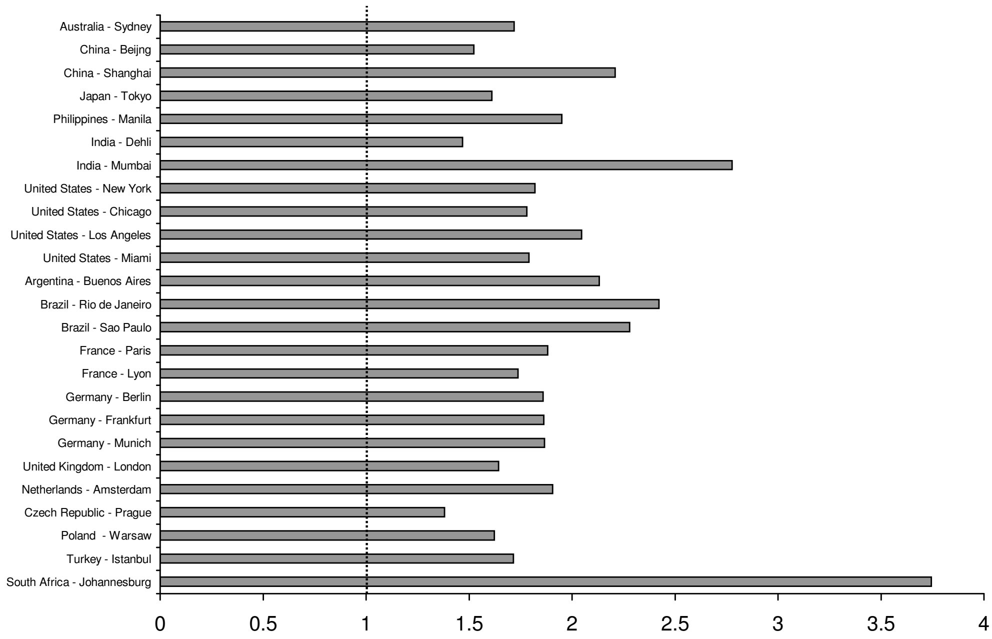
4.3 Wage ratio data from UBS

The Union Bank of Switzerland (UBS) provides tables of "Earnings and working hours of certain professions in major towns all over the World" (UBS 2006). These tables assemble yearly gross and net income as well as weekly working hours by profession and location. In Appendix A the professions are listed. As with the ISCO classification, a line must be drawn between "skilled" and "unskilled" professions. We have tried to remain as close to the ISCO classification of Liu et al. (1998a, b) as possible. The following professions are classified as "skilled": engineers, department heads, product managers and primary school teachers. All other professions are considered to be "unskilled". A natural weight for averaging profession-specific wages would be the number of persons in each profession. However, these are not given in the UBS data, so that we cannot do better than taking the unweighted average of all wages. Figure 4.4 presents a selection of the result in skilled-to-unskilled wage ratios by city.

The skilled-to-unskilled wage ratios for developed economies are in the range of 2, while considerably higher values prevail in some developing countries. In countries with only one observation (town) and in countries where the ratios are almost identical, the town-to-country matching is straightforward. In China and India, however, we have two widely diverging observations. Here we use an unweighted average of the two.

[9] Similar problems were encountered in Walsmley et al. (2007), in which a database (GMig2) has been created that was set up as an extension to GTAP for studying internationally migration issues. GMig2 misses the sectoral dimension, however, because only country averages are considered. Skilled-to-unskilled wage ratios of below one were dealt with by ad-hoc adjustments.

Figure 4.4 Skilled to unskilled wage ratios in selected cities in 2006 (UBS)



4.4 Value split

Combining ILO headcount ratios and UBS wage ratios, we arrive at a value split per sector and region. We assume that the UBS wage ratio uniformly applies to all sectors. This is a simplification, but we do not know of any source that would give a systematic overview of international and sectoral differences in the skilled-to-unskilled relative wages. Such an overview would be a difficult econometric task anyway, because, just as with simple sectoral wage differences (see the discussion in Section 4.6), it must be decided for which individual characteristics to correct before calculating the respective differences.

With the assumption of a uniform skilled-to-unskilled wage ratio, the value split is obtained by a simple combination of the headcount and wage ratios. This is done for the eleven broad GTAP sectors, *i*, mapped to the ISIC scheme:

$$V_i^{HTL} = N_i^{HTL} * W^{HTL} \tag{4.1}$$

$$V_i^{L} = V_i^{T} / (V_i^{HTL} + 1) \tag{4.2}$$

$$V_i^{H} = V_i^{T} - V_i^{L} \tag{4.3}$$

in which:

V_i^{HTL} Skilled-to-unskilled value ratio

N_i^{HTL} Skilled-to-unskilled headcount ratio

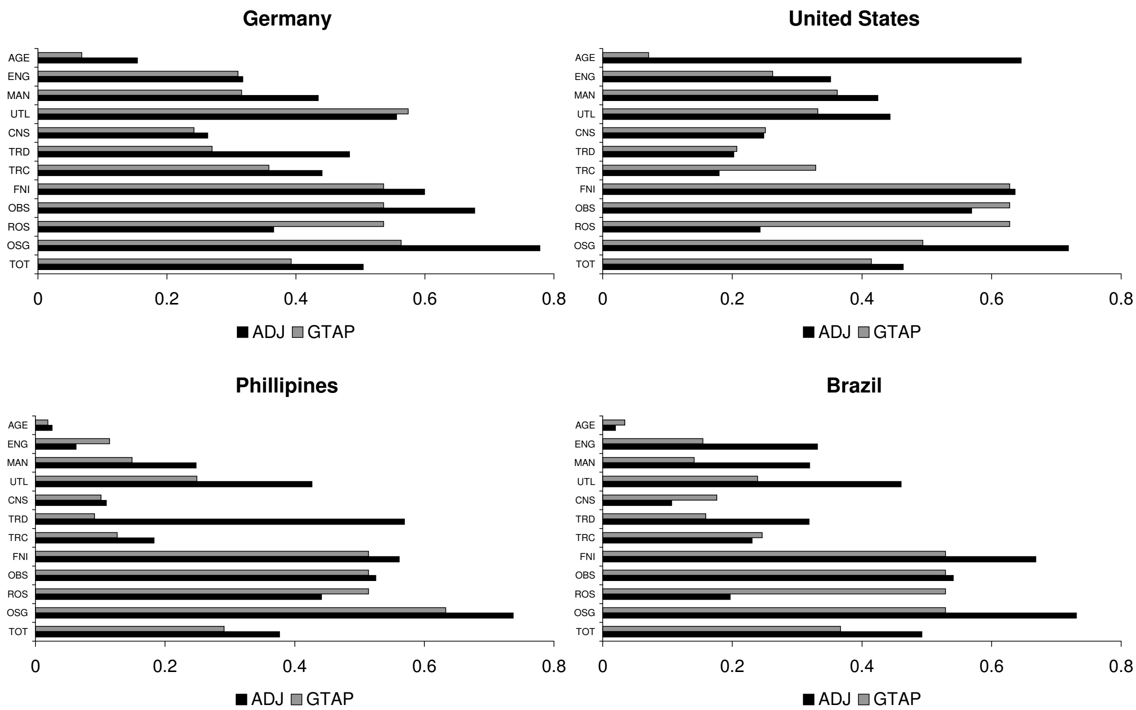
W^{HTL} Skilled-to-unskilled wage ratio

V_j^T Total labour input value

V_j^s Labour input value of skill type *s*

In the next figure we show the skilled value shares in the same countries and sectors as in the other figures. On average (“TOT”), in all four countries share of the skilled is higher than in GTAP.[10] The most striking difference for an individual sector is the enormous increase in the skilled value share in agriculture in the United States, which is mainly caused by the extraordinary high share of skilled workers in US agriculture compared to other countries (see Figure 4.1).

Figure 4.5 Skilled value shares: our approach and GTAP 6



[10] It is not possible to determine whether this difference is mainly due to a price or a volume effect, because this split is not available for the GTAP data.

4.5 Sectoral volume data

As a last step, there remains the calculation of sectoral number of workers by skill group. We start from the total workforce by country, which is calculated by multiplying the total population (United Nations, 2005) by calculated total participation rate per country (ILO, 2006).

The missing link for calculating the number of workers by sector and skill group is inter-sectoral wage differences. It is well known that there are large differences between wages in different sectors, even if one controls for individual characteristics. Wages in the financial sector are particularly high, while agriculture normally is among the least-paying sectors (see, e.g. van der Wiel, 1999, or Magda et al., 2009). There are two problems, however, with using information on sectoral wage differentials. First, these are not available in an internationally comparable format, so that data from individual studies must be gathered. (Even Magda et al., 2009, which has a considerable scope, only covers eleven countries). Second, the decisions which wage measure to use (hourly, monthly or yearly wages) and for which individual characteristics to control leaves a considerable degree of arbitrariness. Magda et al. (2009) report gross inter-industry wage differentials (without any correction for individual characteristics) in the range of between -83% and +446% of the respective country average. Once one controls for individual characteristics, this range shrinks considerably to between -59% and +358%.

Because of these aspects of arbitrariness in the data, we do not opt for a particular set of intersectoral wage differentials, but instead provide formulas for calculating the sector and skill-specific wages, $W_{i,s}$, and number of workers, $N_{i,s}$, for an arbitrary set of these differentials, δ_i. We assume that we have $I-1$ differentials (where I is the number of sectors), and all differentials are expressed relative to one arbitrarily chosen sector, indexed "1". In addition, intersectoral wage differentials apply equally to both skill types, i.e. if the skilled wage in sector *i* is 10% higher than in sector 1, then this is also the case for the unskilled wage.

Under these assumptions we have the following set of $4\times I$ equations in the $4\times I$ unknowns $W_{i,s}$ and $N_{i,s}$:

$$W_{i,s}\times N_{i,s}=\bar{V}_{i,s} \qquad (2\times I \text{ equations}) \qquad (4.4)$$

$$W_{i,s}\times\delta_i=W_{1,s} \qquad (i\neq 1,\ 2\times(I-1) \text{ equations}) \qquad (4.5\ )$$

$$\sum_{i,s}N_{i,s}=\bar{N} \qquad (1 \text{ equation}) \qquad (4.6)$$

$$\frac{W_{1,H}}{W_{1,L}}=\bar{W}^{HTL} \qquad (1 \text{ equation}) \qquad (4.7)$$

which can be solved as a simultaneous equation system. Observe the following implications:

(a) $\frac{W_{i,H}}{W_{i,L}} = \overline{W}^{HTL}$ for all *i* (from (4.5) and (4.7).

(b) $\frac{\sum_i N_{i,H}}{\sum_i N_{i,L}}$ is endogenous and will in general not precisely equal statistical data

(c) $\frac{W_H}{W_L} = \frac{\sum_i W_{i,H} N_{i,H}}{\sum_i N_{i,H}} \frac{\sum_i N_{i,L}}{\sum_i W_{i,L} N_{i,L}}$ will in general not equal $\overline{W}^{HTL}$

(d) The $N_{i,s}$ deviate from the original numbers in the ILO database, because (1) we rely on the UN totals for $\overline{N}$ and (2) because we rely on the sectoral headcount shares that are implicit in the sectoral value added shares of GTAP in combination with the intersectoral wage differentials δ_i.

In the particular case of the model WorldScan, we have the additional restriction of a labour market mechanism that assumes mobility of workers (of a given skill type) between sectors. This is only possible if there are no wage differentials, because otherwise all workers would go to the sector with the highest wages. In WorldScan, we therefore work with the assumption of $\delta_i = 1$ for all sectors.

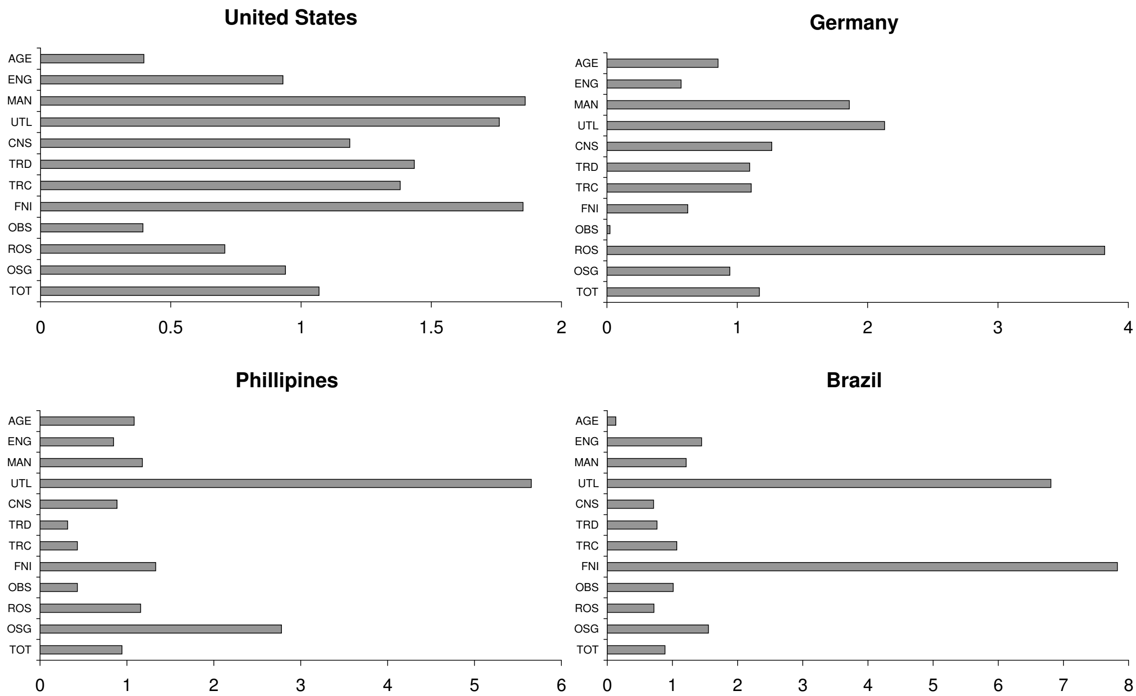
4.6 Points for attention

Our procedure starts from heterogeneous, non-harmonised datasets and imposes a number of consistency requirements. This has as a consequence that not all original data are reproduced. In this section, we describe two resulting deviations from the original data, which can be used as a basis for a further plausibility check.

(1) The average skill-specific wages per country that result from our procedure do not coincide with the absolute values in the UBS dataset. E.g., for the United States the average wage level per year reduces from 46,900 to 40,200 US dollar. For Brazil we find 12,500 and 2,900 US dollar respectively. This produces a US/Brazil wage ratio of 13.9, compared to 3.8 in the UBS data. The reason is that the UBS values refer to wages in major cities and do not reflect the general wage level of the country. In contrast, the wages that we generate are directly linked to income per head calculated from country averages. When we look at country averages, incomes vary a lot more internationally than the UBS data from large cities suggest. These cities are much closer to the picture of a “Flat World” than are countries as a whole.

(2) Our reliance on GTAP value shares and intersectoral wage differentials (in the particular case of WorldScan: *no* differentials) leads to re-allocation of workers across sectors, compared to the original ILO data (see the discussion at the end of Section 4.5). This is shown in Figure 4.6 for the subset of four countries that we have repeatedly used.[11] The sectoral results vary a lot. The range of adjustment is considerable, between -98% in Business services nec, (OBS) in Germany and +680% in Financial Intermediation (FNI) in Brazil. This is partly a consequence of our assumption of no sectoral wage differentials. We over-allocate workers to sectors with particular high wages, e.g. Financial Intermediation. A second, intertwined effect is the implicit correction of differences in sector borders between the ILO and GTAP dataset. Very large deviations like in Utilities (UTL) in the Philippines and Brazil certainly cannot only be explained by sectoral wage differentials. If, say, ILO defines a sector more narrowly than GTAP (more precisely: our ILO-GTAP mapping), then this would result in artificially low wages in this sector when we combine the relatively high body count numbers from ILO with the relatively low value added numbers from GTAP. As GTAP is our most important reference point, we opted for giving priority to the value information and adjusting the body count numbers.

Figure 4.6 Relative adjustment of total body count



[11] The effect is the same for skilled and unskilled workers, so we only report sectoral numbers here.

The two effects could only be disentangled if we took – at least for some test countries – the sectoral wage differentials that can be obtained from micro studies and combined them with the macro data.

The last rows in the panels of Figure 4.5 (“TOT”) shows the economy-wide adjustment of the number of workers. This reproduces the difference between the ILO and the UN statistics and is moderate for the countries displayed.

5 Skill-split at the sub-ISIC-Rev.3-sector level

In the previous section we have presented a labour skill split at the relatively coarse ISIC level, which, after matching with the GTAP data, left us with 11 broad sectors. This means that at the level of the 57 GTAP sectors, many are assigned precisely the same skill structure (see Appendix E). The broad sector “Manufacturing” (MAN), which contains 23 GTAP sectors, is the extreme case, but also for “Transport, Storage and Communications” (TRC, 4 GTAP sectors) and “Financial Intermediation” (FNI, 2 GTAP6 sectors) more disaggregation is desirable.

We use a detailed sectoral database from a single country, the Netherlands (Statistics Netherlands, 2007), to come to a further breakdown. From this database, we can see which sub-sectors[12] are relatively skill intensive. We then assume that the ranking of skill intensity within sectors is the same in all countries.[13] The level, however, is adjusted to the country and sector specific information we have as a result of the procedure described in Section 4.

5.1 Data from Statistics Netherlands

The data at the basis of the sub-sector disaggregation step is “Economically active population by detailed industrial sectors, by educational and occupational levels for the Netherlands for the period 1996-2006” (Statistics Netherland, 2007). The dataset gives employment in three educational and five occupational levels for 38 sectors and each of the years covered. Unfortunately, the occupational split consist of the groups elementary, low, middle, high and scientific occupational levels and this does not correspond at all to the International Standard Classification of Occupations (ISCO) classification in the ILO data. We decided to use the educational split (low, middle and high educational level), which corresponds better with the International Standard Classification of Education (ISCED) classification.

[12] In the following, “sector” refers to the one-letter ISIC sectors and “sub-sector” to the GTAP sectors.

[13] This, of course, is a strong assumption, which should be cross-checked with data from other countries. However, no comparable dataset for another country was easily available to us.

We use this information to disaggregate the ISIC sectors "Manufacturing", "Transport, Storage and Communications" and "Financial Intermediation". A concordance between these three ISIC-Rev3 sectors, the underlying GTAP sectors and the sectors in Statistics Netherlands can be found in Appendix F.

5.2 Re-grouping of skill levels

In a first step, we must regroup the three skill levels at the sub-sector level to get a two-skill classification compatible with the information at the sectoral level. We determine the share of the medium-skilled that needs to be added to skilled to match the shares at the ILO sector level. Then we assume that the percentage split of the medium skilled into an unskilled and a skilled component is uniform over sub-sectors. This gives the following reallocation of workers into skill groups:

$$s_{i,m\to h} = \frac{s_{i,H} - s_{i,h}}{s_{i,m}} \tag{5.1}$$

$$s_{j,H} = s_{j,h} + s_{i,j\to h} s_{j,m} \tag{5.2}$$

$$s_{j,L} = s_{j,l} + (1 - s_{i,j\to h}) s_{j,m} \tag{5.3}$$

where:

$s_{i,H}$ and $s_{i,L}$ are the shares for two skill groups at sector level *i* from the ILO data.
$s_{j,h}$, $s_{j,m}$ and $s_{j,l}$ are the shares for three skill groups at sub-sector level *j* from CBS.
$s_{i,h}$, $s_{i,m}$ and $s_{i,l}$ the same aggregated to sectoral level.
$s_{i,m\to h}$ the share of medium-skilled workers re-allocated to the skilled group.

5.3 Calibration of skill shares at sub-sector level

The next step is to determine the number of workers and corresponding value shares at the sub-sector level. For *n* sub-sectors *j = 1,..n,* of sector *I,* skill levels *s = L, H* and region *r*, we start from the following information:

- Skill-specific labour input values per sector, from Section 4: $VA_{i,s,r}$
- Number of skilled and unskilled workers per sector, from Section 4: $N_{i,s,r}$
- Number of workers per sub-sector and skill type in the Netherlands, from Section 5.2: $N_{j,s,NLD}$

From this we can calculate the skill-specific sectoral wages:[14]

$$w_{i,s,r} = \frac{VA_{i,s,r}}{N_{i,s,r}} \tag{5.4}$$

We translate the sub-sector data for the Netherlands into relative share information with respect to an arbitrary sub-sector, indexed “1”:

$$\alpha_{j,i} = \frac{N_{j,L,NLD}}{N_{j,H,NLD}} \Bigg/ \frac{N_{1,L,NLD}}{N_{1,H,NLD}} \tag{5.5}$$

Then we set up the following simultaneous equation system:

$$\frac{N_{j,L,r}}{N_{j,H,r}} = \alpha_{j,i} \frac{N_{1,L,r}}{N_{1,H,r}} \qquad (j \neq 1) \qquad \text{(n-1 equations)} \tag{5.6}$$

$$\sum_j \left(N_{j,L,r} + N_{j,H,r} \right) = N_{i,r} \qquad \text{(1 equation)} \tag{5.7}$$

$$\sum_s \left(N_{j,s,r} \times w_{i,s,r} \right) = VA_{i,s,r} \qquad \text{(n equations)} \tag{5.8}$$

These are 2n equations in the 2n unknowns $N_{j,s,r}$, which, in general, gives a unique solution. Sub-sector value added then follow as:

$$VA_{j,s,r} = N_{j,s,r} \times w_{j,s,r} \tag{5.9}$$

which, given the procedure chosen, precisely adds up to sectoral value added, $VA_{i,s,r}$.

In Table 5.1 we show the resulting sub-sector skilled shares (and the average before disaggregation) for the three ISIC sectors and for two countries (one with high income, USA, and one with low income, Philippines).

The adjusted shares for GTAP sectors within the ISIC sector manufacturing for both the United States and Philippines are generally higher than the GTAP 6 shares. The adjusted share for sector Transport nec (OTP) in the United States is very low and needs a further check[15].

[14] We do not consider the case of wage differentials between sub-sectors.

[15] The reason is seems to be in a implausibly low body count share for the corresponding sector in Statistics Netherlands (2007).

Table 5.1 **Skilled value shares: GTAP 6 and our approach for the three ISIC sector and their underlying GTAP sectors in a high- and low income country**

	United States		Philippines	
	GTAP-6	adjusted	GTAP-6	adjusted
cmt	0.141	0.368	0.073	0.235
omt	0.141	0.368	0.073	0.235
vol	0.271	0.368	0.167	0.235
mil	0.141	0.368	0.061	0.235
pcr	0.239	0.368	0.124	0.235
sgr	0.271	0.368	0.167	0.235
ofd	0.271	0.368	0.167	0.235
b_t	0.324	0.368	0.110	0.235
tex	0.178	0.208	0.099	0.122
wap	0.216	0.208	0.130	0.122
lea	0.200	0.208	0.105	0.122
lum	0.226	0.285	0.085	0.174
ppp	0.355	0.486	0.150	0.332
p_c	0.356	0.381	0.090	0.245
crp	0.439	0.562	0.209	0.403
nmm	0.252	0.391	0.113	0.253
i_s	0.206	0.391	0.085	0.253
nfm	0.244	0.391	0.123	0.253
fmp	0.278	0.320	0.137	0.199
mvh	0.387	0.317	0.178	0.197
otn	0.387	0.360	0.178	0.228
ele	0.478	0.509	0.229	0.353
ome	0.478	0.509	0.229	0.353
omf	0.285	0.310	0.091	0.192
MAN	0.362	0.425	0.149	0.248
otp	0.207	0.087	0.091	0.107
wtp	0.207	0.391	0.091	0.447
atp	0.207	0.256	0.091	0.302
cmn	0.628	0.267	0.514	0.315
TRC	0.329	0.180	0.126	0.183
ofi	0.628	0.634	0.514	0.557
isr	0.628	0.643	0.514	0.566
FNI	0.628	0.636	0.514	0.561

6 Summary and conclusions

In this paper, we have described a method for splitting GTAP labour input values into components for skilled and unskilled workers. For the purposes of the study that formed the background for this disaggregation procedure (an assessment of the labour market targets of the EU "Lisbon" strategy in Boeters and van Leeuwen, 2008), we found the resulting split preferable to the one previously existing in GTAP. The aim of the detailed documentation in this paper is to allow other modelling groups an assessment of whether they want to follow this approach, extend it, or remain with the original GTAP data.

The basic situation is that we face a number of inconsistent data sets from which a selection must be made:

- The original GTAP value data by region, sector and skill type, which result from micro data (where available) or from a regression based on these micro data.
- Headcount data by region, sector and skill type from ILO (2008) statistics.
- Wage data from the UBS (2006) dataset.

Our basic decision was to reconstruct the skill value split altogether. In our view, this is the only way to arrive at consistent quantity and price information, without treating one of these components arbitrarily as a residual (which, in extreme cases, can lead to inacceptable outcomes, e.g. skilled-to-unskilled wage ratios of below one). In particular, our procedure is based on the following choices:

- We do not change total value added from labour by sector and region, but we alter the split between the skilled and unskilled components (Section 4.5).
- We use the sectoral skilled to unskilled headcount ratio from the ILO (2008 statistics, but allow the absolute number of workers to deviate from the original data (Section 4.1).
- We use the skilled to unskilled wage ratio from the UBS (2006) statistics, but allow the absolute level of the wages to deviate from the original data (Section 4.3).
- We construct the size of the absolute workforce from UN population data and ILO participation rates (Section 4.5).

In addition, two assumptions play a role in our final dataset that must be thought as default assumptions due to lack of more detailed data rather then economic plausibility choices:

- There are no sectoral wage differentials. (We provide formulas, though, for adjustments if information on sectoral wage differentials is available, Section 4.5.)
- The skill-intensity ranking of sub-sectors in the Netherlands is representative for all countries (Section 5).

Given the purposes that we had with the construction of the dataset and the model based on it, we found these defensible choices. In other context and for other purposes one might want to invest more in cross-country intersectoral and sub-sectoral data.

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Appendices

Appendix A: Professions used by Union Bank of Switzerland in "Prices and Earnings 2006"

Car mechanic
Building labourer
Skilled industrial worker
Female Factory worker
Engineer
Department head
Product managers
Primary school teacher
Bus driver
Cook
Personal assistant
Female sales assistants
Call center agent
Bank credit officer

Appendix B: Professions according to the International Standard Classification of occupations (ISCO-88)

Major Group 1	Legislators, senior officials and managers
Major Group 2	Professionals
Major Group 3	Technicians and associate professionals
Major Group 4	Clerks
Major Group 5	Service workers and shop and market sales workers
Major Group 6	Skilled agricultural and fishery workers
Major Group 7	Craft and related trade workers
Major Group 8	Plant and machine operators and assemblers
Major Group 9	Elementary occupations
Major Group 0	Armed forces

Appendix C: Sectors according to International Standard Industrial Classification of all Economic Activities (ISIC-Rev. 3)

Tabulation category A	Agriculture, Hunting and Forestry
Tabulation category B	Fishing
Tabulation category C	Mining and Quarrying
Tabulation category D	Manufacturing
Tabulation category E	Electricity, Gas and Water Supply
Tabulation category F	Construction
Tabulation category G	Wholesale and Retail Trade; Repair of Motor Vehicles, Motorcycles and Personal and Household Goods
Tabulation category H	Hotels and Restaurants
Tabulation category I	Transport, Storage and Communications
Tabulation category J	Financial Intermediation
Tabulation category K	Real Estate, Renting and Business Activities
Tabulation category L	Public Administration and Defence; Compulsory Social Security
Tabulation category M	Education
Tabulation category N	Health and Social Work
Tabulation category O	Other Community, Social and Personal Service Activities
Tabulation category P	Private Households with Employed Persons
Tabulation category Q	Extra-Territorial Organizations and Bodies
Additional category X	Not classifiable by economic activity

Appendix D: Concordance between 11 broad GTAP sectors and 14 ISIC-REV3 sectors

Code	description	ISIC Rev3 Tabulation category
AGE	Agriculture incl. fishing	A
ENG	Mining and Quarrying	C
MAN	Manufacturing	D
UTL	Electricity, Gas and Water Supply	E
CNS	Construction	F
TRD	Trade	G
TRC	Transport, Storage and Communications	I
FNI	Financial Intermediation	J
OBS	Business services nec	K + O
ROS	Recreational and other services	H
OSG	Public admin. and defence, education, health	L + M + N

Appendix E: Concordance between all GTAP sectors and 14 ISIC-REV3 sectors

GTAP		ISIC-REV3	
Code	Description	letter	Description
PDR	Paddy rice	A	Agriculture, Hunting and Forestry
WHT	Wheat	A	Agriculture, Hunting and Forestry
GRO	Cereal grains nec	A	Agriculture, Hunting and Forestry
V_F	Vegetables, fruit, nuts	A	Agriculture, Hunting and Forestry
OSD	Oil seeds	A	Agriculture, Hunting and Forestry
C_B	Sugar cane, sugar beet	A	Agriculture, Hunting and Forestry
PFB	Plant-based fibres	A	Agriculture, Hunting and Forestry
OCR	Crops nec	A	Agriculture, Hunting and Forestry
CTL	Bovine cattle, sheep and goats, horses	A	Agriculture, Hunting and Forestry
OAP	Animal products nec	A	Agriculture, Hunting and Forestry
RMK	Raw milk	A	Agriculture, Hunting and Forestry
WOL	Wool, silk-worm cocoons	A	Agriculture, Hunting and Forestry
FRS	Forestry	A	Agriculture, Hunting and Forestry
FSH	Fishing	A	Agriculture, Hunting and Forestry
COA	Coal	C	Mining and Quarrying
OIL	Oil	C	Mining and Quarrying
GAS	Gas	C	Mining and Quarrying
OMN	Minerals nec	C	Mining and Quarrying
CMT	Bovine meat products	D	Manufacturing
OMT	Meat products nec	D	Manufacturing
VOL	Vegetable oils and fats	D	Manufacturing
MIL	Dairy products	D	Manufacturing
PCR	Processed rice	D	Manufacturing
SGR	Sugar	D	Manufacturing
OFD	Food products nec	D	Manufacturing
B_T	Beverages and tobacco products	D	Manufacturing
TEX	Textiles	D	Manufacturing
WAP	Wearing apparel	D	Manufacturing
LEA	Leather products	D	Manufacturing
LUM	Wood products	D	Manufacturing
PPP	Paper products, publishing	D	Manufacturing
P_C	Petroleum, coal products	D	Manufacturing
CRP	Chemical, rubber, plastic products	D	Manufacturing
NMM	Mineral products nec	D	Manufacturing
I_S	Ferrous metals	D	Manufacturing
NFM	Metals nec	D	Manufacturing
FMP	Metal products	D	Manufacturing
MVH	Motor vehicles and parts	D	Manufacturing
OTN	Transport equipment nec	D	Manufacturing
ELE	Electronic equipment	D	Manufacturing
OME	Machinery and equipment nec	D	Manufacturing
OMF	Manufactures nec	D	Manufacturing

Appendix E: Concordance between GTAP sectors and ISIC-REV3 (continued)

GTAP code	description	ISIC-REV3 letter	Description
ELY	Electricity	E	Electricity, Gas and Water Supply
GDT	Gas manufacture, distribution	E	Electricity, Gas and Water Supply
WTR	Water	E	Electricity, Gas and Water Supply
CNS	Construction	F	Construction
TRD	Trade	G	Wholesale and Retail Trade. Repair of Motor Vehicles, Motorcycles and Personal and Household Goods
OTP	Transport nec	I	Transport, Storage and Communications
WTP	Water transport	I	Transport, Storage and Communications
ATP	Air transport	I	Transport, Storage and Communications
CMN	Communication	I	Transport, Storage and Communications
OFI	Financial services nec	J	Financial Intermediation
ISR	Insurance	J	Financial Intermediation
OBS	Business services nec	K+O	Real Estate, Renting and Business Activities + Other Community, Social and Personal Service Activities
ROS	Recreational and other services	H	Hotels and Restaurants
OSG	Public Administration, Defence, Education, Health	L+M+N	Public Administration and Defence. Compulsory Social Security + Education + Health and Social Work
DWE	Dwellings	H	Real Estate, Renting and Business Activities + Other Community, Social and Personal Service Activities

Appendix E: Concordance between sectors of ISIC REV3, GTAP and Statistics Netherlands

GTAP code	Description	Statistics Netherlands number	Description
ISIC-Rev 3 - Manufacturing			
CMT	Bovine meat products	1500	Food, drink & tobacco
OMT	Meat products nec	1500	Food, drink & tobacco
VOL	Vegetable oils and fats	1500	Food, drink & tobacco
MIL	Dairy products	1500	Food, drink & tobacco
PCR	Processed rice	1500	Food, drink & tobacco
SGR	Sugar	1500	Food, drink & tobacco
OFD	Food products nec	1500	Food, drink & tobacco
B_T	Beverages and tobacco	1500	Food, drink & tobacco
TEX	Textiles	1700	Textiles
WAP	Wearing apparel	1700	Textiles
LEA	Leather products	1700	Textiles
LUM	Wood products	2000	Wood & products of wood and cork
PPP	Paper products, publishing	2100	Pulp, paper & paper products
P_C	Petroleum, coal products	2300	Mineral oil refining, coke & nuclear fuel
CRP	Chemical, rubber, plastic	24	Chemicals
NMM	Mineral products nec	27	Basic metals
I_S	Ferrous metals	27	Basic metals
NFM	Metals nec	27	Basic metals
FMP	Metal products	28	Fabricated metal products
MVH	Motor vehicles and parts	34	Motor vehicles
OTN	Transport equipment nec	35	Other Transport Equipment
ELE	Electronic equipment	29+3000	Mechanical engineering, Office machinery
OME	Machinery and equipment	29+3000	Mechanical engineering, Office machinery
OMF	Manufactures nec	3600	Furniture, miscellaneous manufacturing; recycling
ISIC-Rev 3 - Transport, Storage and Communications			
OTP	Transport nec	60	Inland transport
WTP	Water transport	6100	Water transport
ATP	Air transport	63	Supporting and auxiliary transport activities; activities of travel agencies
CMN	Communication	64	Communications
ISIC-Rev 3 - Financial Intermediation.			
OFI	Financial services nec	65+67	Financial intermediation, except insurance and pension funding, Activities auxiliary to financial intermediation
INS	Insurance	66	Insurance and pension funding, except compulsory social security