LABOR STATISTICS FOR THE GTAP DATABASE

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1. INTRODUCTION

Wages and employment are an integral part of the general equilibrium effects of trade. Previous research has used labor data to measure factor allocation and labor productivity, within-country inequality, purchasing power parity, and migration.[1] This research often relies on labor payments that are split by industry and by workers' skill level.[2] The GTAP database is one of the best resources for applied general equilibrium (AGE) modeling.[3] However, its statistics only split labor employment within industries to skilled and unskilled worker categories.[4] The purpose of this paper is to propose a new source of data and methodology for splitting labor payments in the GTAP database to more types of workers than in the previous version.

The GTAP database currently splits each country's labor payments based on a 1998 study by Liu, *et al*. that standardized employment and wage data for 13 countries.[5] The underlying data was taken from mostly national data sources for years ranging from 1970 to 1992. Skilled workers were defined in terms of occupation or education, depending on the categories in the original sources. Liu, *et al*. combined wage and employment measures to calculate the percentage of payments to skilled workers by industry in each of these 13 countries. However, compiling this data was labor-intensive and required many subjective comparisons, aggregations, and cross-country assumptions. These problems limited the sample size to 13 countries. Labor splits for the remaining countries and regions in GTAP v4 were derived using regression techniques, as detailed in Liu, *et al*. (1998).[6] Following up on their work, Dimaranan and Narayanan (2008) expanded the labor splits to 226 countries for GTAP v7 using Liu, *et al*'s data. Thus, the labor splits in the GTAP database are still based on wage and employment data from 1970–92.

More comprehensive and recent labor data is an important input to further research. As Krugman (2008) recently highlighted,

> Until recently, however, surprisingly little attention was given to the increasingly out-of-date nature of the data behind the reassuring consensus that trade has only modest effects on income distribution. Yet the problem is obvious, and was in fact noted by Ben Bernanke [e.d.] last year: "Unfortunately, much of the available empirical research on the influence of trade on earnings inequality dates from the 1980s and 1990s and thus does

[1] See, for example Tokarick (2002), Suryahadi, Chen, and Tyers (2001), Chor (2001), and Tyers, Bain, and Vedi (2006).

[2] See, for example Harris, Robertson, and Wong (2007).

[3] The GTAP database v7 is described in Narayanan and Walmsley (2008).

[4] The current GTAP splits are described in Dimaranan and Narayanan (2008).

[5] The countries in the initial sample were the United States, Canada, Australia, EU, Japan, Taiwan, South Korea, Brazil, Indonesia, Philippines, Thailand, Hong Kong, and India.

[6] The GTAP v4 contained 45 regions and 50 industries. Its reference year was 1995. Global Trade Analysis Project (2009).

> not address later developments". And there have been a lot of later developments.

In this paper we propose an update of the GTAP labor splits using several sources of data from the International Labour Organization (ILO). We are motivated to find a new set of labor splits that are based on more recent data and a larger set of countries. We also intend to expand the GTAP labor data by providing separate price (wages) and quantity (employment) information and changing the skill definition from skilled/unskilled to a split across five occupational categories.

We devised a method for imputing missing wages by occupation and industry and applied this procedure to 48 countries. This updates the employment and wage data to average years of 2004 and 2005, respectively and does not impose any assumptions from one country to another. For each country we obtain employment data from the *ILO Yearbook of Labour Statistics*, which typically allows us to split labor into five occupational categories across fifteen industries.[7] However, wage data are not reported for the same occupation and industry dimensions. Industry average wages are available from the *ILO Yearbook of Labour Statistics* and wages by job are available from the Occupational Wages around the World database, based on the *ILO October Inquiry*.[8] To estimate wages by occupation and industry, we start with wages by job and use a minimization of squared errors approach to adjust the observations and fill in missing values. The equations are designed to minimize wage variations within occupations and to give results that satisfy the observed average wages by industry.

The remainder of this paper is organized as follows. Section 2 summarizes previous work on GTAP labor splits. Section 3 sets out the framework of our proposed methodology for obtaining wages by occupation and industry. Section 4 describes the ILO employment and wage data and lists the countries in our proposed sample. Section 5 shows the observed and final matrices for Germany and Section 6 discusses the results for all countries. Section 7 concludes.

2. PREVIOUS WORK

The original labor splits for GTAP v4 were based on 13 countries, as described in Liu, *et al*. (1998). Data from national labor force surveys, censuses, and CGE models were used to find measures of wages and employment by workers' skill level. Where occupation was given, workers were apportioned to the "skilled" category if they were in ILO occupation 1–3 (managers, professionals, and para-professionals); "unskilled" workers

[7] The number of industries vary depending on data availability. See Section 4.
[8] The Occupational Wages around the World database was prepared by Freeman and Oostendorp (2000) and Oostendorp (2005).

were those in ILO occupations 4–9 (tradespersons, clerks, salespersons, machine operators, laborers, and farm workers). The wage and employment data was used to calculation the proportion of labor payments to skilled workers for each industry sector.

However, many of the sources used by Liu, *et al*. did not classify workers by occupation or skill level. Where occupation was not available, educational attainment or manual/non-manual descriptions were used to apportion labor into skilled and unskilled categories. In some cases, data from other countries were used to fill in the gaps for unknown distributions as noted in Table 1.

Table 1 Sources of Wage and Employment Data in GTAP v4

Region	Year	Source	Data limitations and adjustments
U.S.	1992	1992 U.S. CPS	
Canada	1986	1986 Census	US distribution by industry used to find splits from Canadian employment and earnings by occupation
Australia	1991	ORANI CGE model	
E.U.	1988	Eurostat	Australian data used to find splits from manual/non-manual labor definitions
Japan	1970 & 1992	Japan Wage Survey	Income levels used to infer presence of skilled labor
Taiwan	1979 & 1990	Directorate-General of Budget and Dept. of Agriculture	Uses Korea's education data for later regression.
South Korea	1991	Korea National Statistical	Taiwanese data used to find splits from operative/office-worker labor definitions
Brazil	1992	ILO	
Indonesia	1992	Sakarnas Survey	Skilled workers defined by high upper-secondary education.
Philippines([a])	1986	APEX model	Skilled workers defined by high school completion.
Thailand([a])	1985	PARA CGE model	Skilled workers defined by long-term (at least monthly) employment arrangement.
Hong Kong	1991	1991 Census	Uses Singapore's education data for later regression.
India	1981	1981 Census	

Source: Liu, *et al*. (1998).

Notes:
([a]) The Philippines and Thailand were later dropped from sample because both showed "serious overestimation of skilled labor payment share." Liu, *et. al,* (1998).

The authors designated the labor splits from Table 1 as the observed set. A regression model was designed to find coefficients for the other GTAP countries using two independent variables: per capita GDP and average level of tertiary education.[9] Problems with the definitions of skilled labor in the Philippines and Thailand led the authors to omit these countries from the sample.[10] Using the revised regression coefficients, predicted labor splits by industry were estimated for all countries. For nine of the countries with detailed sample data the observed splits were used instead of the predicted ones.

In 2008 Dimaranan and Narayanan extended the splits to match the countries and sectors in the GTAP v7 database, base year 2004, using the same underlying data (see Dimaranan and Narayanan, 2008). Therefore, the current GTAP labor splits are based on a sample of 11 countries, extrapolated to the rest of the GTAP countries. The labor payments are split between skilled and unskilled workers and most of the data is indexed to 1992.

3. OBSERVED DATA AND PROPOSED METHOD OF IMPUTATION

Our study utilizes several sources of global, recent, and publicly available statistics from the ILO.[11] We need data on employment and wages to derive the labor splits. Since wage data are not available with the desired dimensions, we use a constrained optimization model to impute them from the ILO data. This methodology produces country-specific measures that can be used to split labor payments by industry into occupational shares [$S_{Occ,\ Ind}$] using the formula below.

$$S_{ij} = \frac{W_{ij} \cdot N_{ij}}{\sum_{i \in Occ} W_{ij} \cdot N_{ij}}, \qquad i \in Occ, \quad j \in Ind \tag{1}$$

To find these shares, we generate matrices of employment and wages for each country with the dimensions of occupation by industry. The matrices of employment data are readily obtained from the *ILO Yearbook of Labour Statistics*, which reports the number of workers by occupation and industry [$N_{Occ,\ Ind}$]. The matrices of wage data can be estimated from the *ILO Yearbook*, which reports the average wage by industry [$w._{Ind}$] and the Occupational Wages around the World database (based on *ILO October Inquiry* data), which gives more detailed wages by job [w_{Job}].[12]

[9] Per capita GDP was measured in constant 1987 U.S. dollars. Average education level was based on World Bank data for 1980–87 and extrapolated for years 1970–92.
[10] According to Liu, *et al*. (1998), removing these countries increased the average R-squared value from the range of 0.20–0.30 to roughly 0.50, depending on the functional form of the equations.
[11] A detailed description of this data can be found in Section 4.
[12] See Appendix A for the corresponding lists of occupations, industries, and jobs.

The w_{Job} statistics can be used to estimate wages by occupation and industry, $w_{Occ,\ Ind}$ but they are not available for all occupation/industry combinations. From the 161 w_{Job} observations we can estimate about 35 $w_{Occ,\ Ind}$ per country. For the 23 cases in which multiple wages by job [w_{Job}] map to the same $w_{Occ,\ Ind}$ category, we calculate the arithmetic average to find an estimate of $w_{Occ,\ Ind}$ because there are no weights to aggregate them precisely. In this manner we build matrices of wages with dimensions occupation by industry. However, this leaves many elements of the roughly 5 by 15 $w_{Occ,\ Ind}$ matrices blank, which we fill in with the occupational median wages derived from w_{Job}.[13] We treat these wage matrices as Bayesian priors that can be adjusted to reflect the observed $w_{.\ Ind}$ average wages by industry.

Next we apply a method which minimizes the distance between the initial wage matrix [$w_{i\ j}$] and the final wage matrix [$W_{i\ j}$], attaching a degree of belief [$B_{i\ j}$] to each $w_{i\ j}$ that is inversely related to the standard deviation of the underlying w_{Job} observations.[14] An additional term in the objective function minimizes the distance between each wage observation and its average wage [$w_{i\ j}$] by occupation:[15]

$$\text{minimize} \sum_{i \in Occ} \sum_{j \in Ind} \beta_{ij} [w_{ij} - W_{ij}]^2 + \sum_{i \in Occ} \sum_{j \in Ind} [w_{i.} - W_{ij}]^2$$

$$\text{subject to} \quad \sum_{i \in Occ} W_{ij} \cdot N_{ij} = \sum_{i \in Occ} w_{.j} \cdot N_{ij}, \quad i \in Occ, \quad j \in Ind \tag{2}$$

The constraint ensures that the final weighted average wage over all occupations in a given industry equals the industry average wage [$w_{.\ j}$] that comes from the *ILO Yearbook*. Thus, the initial wage matrix [$w_{i\ j}$] mostly affects the distribution of the estimates across occupations.

The method we employ has been used to balance national account matrices, as originally documented in Stone, Champernowne, and Meade (1942). According to them, a minimization of squared errors approach like ours gives maximum likelihood estimates

[13] ISCO one-digit codes consist of roughly nine occupations. Unfortunately, occupations 7 though 9 were grouped together in the ILO employment data and occupation 6 was specific to the agriculture industry so it did not have enough $w_{Occ,\ Ind}$ to be imputed separately. Similarly, occupation 1 (senior officials and managers) had a maximum of one w_{Job} so its wage and employment numbers were combined with occupation 2 (professionals). Wages tend to be under-reported for occupation 1 in all countries and in the United States in particular the w_{Ind} data is only given for non-supervisory workers.

[14] Elements of $w_{i\ j}$ that were blank or had only one w_{Job} observation were given a degree of belief of one. For all other elements, the degree of belief for each $w_{i\ j}$ was calculated as 0.25 divided by the standard deviation of w_{Job} observations (in percentage terms). The intuition is that any element of $w_{i\ j}$ derived from w_{Job} with less than 25% standard deviation is more informative, and thus given a degree of belief greater than one.

[15] This, in effect, minimizes the dispersion of wages across industries for each occupation.

when the errors distributions are normal. In their paper an external margin of error parameter is incorporated into the objective function; this is analogous to the parameter we call "degree of belief". The intuition is that the minimization of squared errors approach minimizes overall variance with more weight given to observations that are thought to be more accurate.[16]

4. DETAILED DESCRIPTION OF SOURCE DATA

The ILO has been compiling and disseminating data on employment by occupation and industry, wages by industry, and wages by job for more than 30 years. The ILO data is publicly available though the LABORSTA web interface.[17] It is based on annual surveys of more than 150 countries, which makes its data fairly consistent across countries.

The *ILO Yearbook* reports employment data by industry and occupation for 138 countries. The survey is sent out annually but many countries respond only every four years or so. The countries base their reporting on domestic sources of data, with 95% reporting from labor force surveys and the rest reporting from Census, household surveys, and official estimates. The data are divided into seven occupations and 10–18 industries, depending on the ISIC classification scheme. The occupational categories are consistent across industries, with categories such as "Professionals", "Associate professionals", "Clerks", and "Machine operators".[18] For each country this data could be standardized to give a matrix of employment by industry and occupation, $N_{Occ,\, Ind}$.

The *ILO Yearbook* also asks each country to provide data on average wages by industry, w_{Ind}. The classification scheme for industries is similar to that of the employment data, with some reporting at the ISIC2 scheme and others reporting at the ISIC3 scheme.[19] Overall, data is available for 151 countries. Of these countries, 83% report for more than 5 industries and 57% report for more than 10 industries.

The final piece of our wages data, w_{Job}, is based on the *ILO October Inquiry*. It is completely separate from the *ILO Yearbook* and asks countries to give average wages for a list of 161 jobs. The *October Inquiry* data has been processed extensively by Freeman

[16] Appendix B provides an illustration of the impact of the degree of belief parameter. We refer to Lenzen, Gallego, and Wood (2009) for the relative merits of different matrix balancing approaches.
[17] Available at http://laborsta.ilo.org/
[18] For example, a job such as "Mathematics teacher" is equivalent to the occupation of "Professional" in the industry of "Education". The concordance between jobs in the October Inquiry database with ISCO codes (for occupation) and ISIC codes (for industry) is available here: http://laborsta.ilo.org/applv8/data/to1ae.html. Our study maps these classifications to their one-digit codes.
[19] For a reference on the ISIC classification schemes, see http://unstats.un.org/unsd/cr/registry/regct.asp

and Oostendorp (2000) and Oostendorp (2005), who corrected for differences in reporting by country.[20] Rather than reproducing their work, we have used their data as a starting point. Their data is available through 2003 and includes imputed values for missing data across 163 countries.[21]

The 46 countries listed in Table 2 have all the necessary pieces of data for our wage imputation method. These countries cover a variety of regions and stages of development. To determine whether countries had sufficient data, the most recent year was chosen for each piece of data (employment, average wages, and wages by job), excluding years before 1990 and those with very incomplete data.[22] Since countries reported the various pieces of ILO data separately, in most cases it would not have been possible to match the years of data exactly.[23] Those countries with sufficient data on employment, average wages, and wages by job are listed below.

Table 2 Most Recent and Complete Year of ILO Data for Countries with Wage and Employment Data

Country	$N_{Occ, Ind}$	$w_{. Ind}$ [(a)]	Industries	Country	$N_{Occ, Ind}$	$w_{. Ind}$ [(a)]	Industries
	Best year		Number		Best year		Number
Australia	2006	2000	14	Mauritius	2006	2007	15
Austria	2006	2004	15	Mexico	2006	2007	18
Barbados	2003	1991	9	Moldova	2006	2007	15
Bolivia	2000	2007	8	Netherlands	2005	2005	14
Brazil	2004	2002	16	New Zealand	2006	2006	13
Bulgaria	2006	2007	14	Nicaragua	2006	2004	6
Canada	2006	2007	14	Peru	2006	2007	13
Costa Rica	2006	2007	16	Philippines	2006	2007	17
Croatia	1991	2006	7	Poland	2006	2007	15
Cyprus	2006	2006	15	Portugal	2006	2007	12
Czech Republic	2006	2006	15	Romania	2006	2006	14
Estonia	2006	2007	15	Russia	2006	2007	15
Finland	2006	2001	14	San Marino	1999	2004	10
Germany	2006	2007	13	Singapore	2006	2007	7
Hungary	2006	2007	15	Slovakia	2006	2007	14
Iceland	2000	2007	5	Slovenia	2006	2006	15
Japan	2006	2006	11	Sri Lanka	1998	2007	5
Korea	2006	2007	14	Sweden	2006	2007	12

[20] For example, some countries report earnings while others report wages and some report only for men or women rather than a composite measure.
[21] Freeman and Oostendorp have not updated their work beyond 2003 and have no plans to do so. Remco Oostendorp, email communication, July 22, 2009.
[22] Very incomplete data was defined as fewer than three industries for employment data, fewer than three industries for average wage data, and fewer than ten jobs for wages by job data. The data for wages by job is not listed in Table 2.
[23] In some cases, other choices were made to select the best year of ILO statistics. The Australian data only reported average wages for the agriculture industry through 2000, so that year was selected even though average wage data for its other industries was available for 2002, 2004, and 2006. For the U.S., years after 2002 did not have average wages for the finance/real estate sector, so 2002 was selected as the best year.

Table 2 Most Recent and Complete Year of ILO Data for Countries with Wage and Employment Data

Country	$N_{Occ, Ind}$	$w._{Ind}$ [a]	Industries	Country	$N_{Occ, Ind}$	$w._{Ind}$ [a]	Industries
Kyrgyzstan	2006	2007	15	Thailand	1998	2007	9
Latvia	2006	2007	15	Turkey	2006	1992	6
Lithuania	2006	2007	15	U.K.	2006	2007	16
Luxembourg	1991	2007	6	United States	2005	2002	8
Malawi	1998	1994	7	Venezuela	1997	1997	9

Source: Authors' calculations

Notes:
[a] The best year of wages refers to the *ILO Yearbook*. For some countries the best year of wages in the Freeman and Oostendorp *October Inquiry* data does not match the best year of wages in the *ILO Yearbook*.

In addition to the countries with complete ILO data, a further 47 countries have employment data without sufficient wage information. We intend to use this data in full but match it to appropriate estimates of wage distributions. The countries with employment data are given in Table 3.

Table 3 Most Recent and Complete Year of ILO Data for Countries with Employment Data Only

Country	$N_{Occ, Ind}$	Industries	Country	$N_{Occ, Ind}$	Industries
	Best year	Number		Best year	Number
Algeria	2004	18	Ireland	2006	18
Anguilla	2001	17	Israel	2006	15
Argentina	2006	18	Italy	2006	18
Bahrain	1991	10	Macau, China	2003	18
Bangladesh	2005	16	Malaysia	1995	10
Belgium	2006	18	Maldives	2006	18
Belize	2005	18	Malta	2006	18
Bermuda	2006	18	Namibia	1991	10
Botswana	2001	18	Nepal	1991	10
Cape Verde	1990	10	Norway	2006	17
Chile	1996	10	Oman	2000	18
Colombia	1994	10	Pakistan	2006	10
Denmark	2002	18	Panama	2006	18
Ecuador	2006	18	Paraguay	1993	10
Egypt	2003	17	Qatar	2006	18
El Salvador	2006	13	Réunion	1999	18
Ethiopia	2005	16	Serbia	2006	18
France	2005	18	South Africa	2003	12
Greece	2006	18	Spain	2006	17
Guatemala	1991	10	Suriname	1996	10
Honduras	1992	10	Trinidad and Tobago	2002	10
Hong Kong	2004	10	Uruguay	1998	10
Indonesia	1997	10	West Bank and Gaza Strip	2006	18
Iran	2005	18	Ireland	2006	18

Source: Authors' calculations

For the 46 countries in Table 2, we can apply our method of imputing wages to find matrices of wages and employment by occupation and industry. This ensures that each country's data remains self-contained, which makes our data suitable for comparative research.

4.2 CHINA AND INDIA

For China and India we utilized national data since much of their ILO data were incomplete or dated.[24] Adding China and India to the countries listed in Table 2 resulted in 48 countries for which we could find wage and employment matrices.

Table 4 Summary of Data Years for India and China: ILO and National Sources

	ILO Sources		National Sources		Overall
	Employment ($N_{Occ, Ind}$)	Avg Wages ($w._{Ind}$)	Employment ($N_{Occ, Ind}$)	Avg Wages ($w._{Ind}$)	Industries
Country	Best year	Best year	Best year	Best year	Number
China	1982[(a)]	2007	2002[(b)]	-	7
India	-	-	1991	2006[(c)]	5

Sources: Authors' calculations based on data from China Labor Statistical Yearbook, IndiaStat, Census of India, and ILO.

Notes:
[(a)] ILO employment data from 1982 was outdated and therefore replaced with data from a national source.
[(b)] Chinese National employment data is reported by sector; we disaggregated it using 2006 patterns of education by sector and occupation by education.
[(c)] Indian average wage data is reported separately by urban/rural and male/female workers; we aggregated it using 2001 population weights.

Chinese employment data are available from the 2007 *Labor Statistical Yearbook* but are not reported jointly by industry and occupation.[25] Instead, we approximated the distribution of workers in a given occupation with 2006 statistics on the distribution of education by sector and occupation by education.[26] We applied these distributions to raw employment figures by industry, which allowed us to derive the number of workers by occupation for seven industries with a base year of 2002.[27] The Chinese employment data differed from the ILO in its classification of occupational categories. Whereas the first three categories of ILO data are (1) "Senior officials and managers", (2) "Professionals", and (3) "Technicians and associate professionals", comparable Chinese data were classified into the categories of "Unit head" and "Professional and technical workers." To divide employees into ILO occupations 2 and 3, we referred to China's ILO employment data from 1982. Since the 1982 data show a fairly even split between occupations 2 and 3,

[24] ILO employment data was last available for China in 1982 and missing for India. ILO average wage data was missing for India.
[25] Lett and Banister (2006), 40.
[26] China Labor Statistical Yearbook (2007b) and China Labor Statistical Yearbook (2007c).
[27] China Labor Statistical Yearbook (2007a).

we divided the "Professional and Technical" category in half, apportioning these workers to the categories of (2) "Professionals" and (3) "Technicians and associate professionals".

Average wages by industry data for China are available from the *ILO Yearbook* for 2007 and wages by job for 2006 are available directly from the *ILO October Inquiry*.[28] China's w_{Job} data show that occupation four was highly paid, especially in industries D, G, and I. With the addition of the employment data described above, we were able to construct matrices for China that were equivalent to those for other countries with complete wage and employment observations.

India's ILO data is lacking both employment and average wages. In IndiaStat we found employment data by industry and occupation for 1991,[29] which had dimensions similar to the raw employment data from ILO. Unfortunately, these data were not available for any later year.[30] The employment data reported by IndiaStat are organized into eight industries and we were able to map six of these industries to the ILO classifications. Like the Chinese occupational data, the Indian data have only one occupational category of "Professional, technical and related workers". We divided this evenly to create separate categories for (2) "Professionals" and (3) "Technicians and associate professionals", making it consistent with the ILO format.

For wages we used IndiaStat's data on average daily wages by industry for 2006.[31] However, these wages are only reported for four disaggregated categories: male/female and rural/urban workers. To find overall average hourly wages by industry we applied population weights from the 2001 Census of India and assumed an eight hour workday.[32] We matched this average wage data to wages by job from the ILO October Inquiry (for 2000) and these estimates, along with the employment numbers, were used as the inputs to our wage imputation procedure. The table below summarizes the best years of Chinese and India data available from the ILO and national sources.

[28] No comparable data on average wage by industry was available from the Chinese Labor Statistical Yearbook.

[29] IndiaStat.com, 2009, *Distribution of Main Workers by Industry/Occupation*. IndiaStat is a compilation of national industry and government sources, cited in Kucera and Chataignier, "Labour Developments in Dynamic Asia: What do the Data Show?" 2006, 41.

[30] We checked the India Census of 2001 and contacted IndiaStat.

[31] Indiastat.com, 2009, *Industry Division-wise Average Wage/Salary Received Per Day*.

[32] Census of India (2001). *Table B-4: Main Workers Classified by Age, Industrial Category and Sex*. We had initially communicated with data specialists at IndiaStat but they were unable to give us an aggregated form of the wage data by industry.

5. RESULTS

For Germany, initial wage estimates and final results are shown in Tables 5–7. The *Occupational Wages around the World database* reported monthly earnings but the average wages by industry were typically reported by week. We converted all wages to hourly assuming 40 hours per week and 4.3 weeks per month. The purple cells in Table 5 are estimates from w_{job} observations and the grey cells are those without any corresponding w_{job} measures. The yellow cells are the average wage by industry, $w_{.Ind}$, which are satisfied by the final matrix.

Table 5 Germany's Initial Wage Matrices and Degree of Belief Parameters

Input matrix: Observed wages by job and industry averages

	Agri	Mining	Manu	Util	Constr	Trade	Hotel	Transp	Finance	Proper	Public	Educat	Health
w(occ, ind)	A	C	D	E	F	G	H	I	J	K	M	N	O
onetwo		€ 25	€ 20	€ 29					€ 21		€ 26	€ 25	
three		€ 24	€ 19			€ 16		€ 41	€ 12	€ 20		€ 16	
four			€ 16	€ 21		€ 13	€ 15	€ 19	€ 15				
five						€ 14	€ 10	€ 16					
sixtonine	€ 13	€ 16	€ 13	€ 16	€ 15	€ 13	€ 8	€ 15				€ 16	€ 12
w(. ind)	€ 7	€ 16	€ 16	€ 20	€ 13	€ 15	€ 10	€ 14	€ 20	€ 16	€ 16	€ 15	€ 15

Notes: w(. ind) data is for 2007.
Missing cells represent industry/occupation combinations with no observed wages by job. In our model, these missing values are filled in with the median w_{Job} for the occupational category.

Degree of Belief

	Agri	Mining	Manu	Util	Constr	Trade	Hotel	Transp	Finance	Proper	Public	Educat	Health
B(occ, ind)	A	C	D	E	F	G	H	I	J	K	M	N	O
onetwo	1.0	1.7	1.2	1.0	1.0	1.0	1.0	1.0	1.8	1.0	2.7	1.2	1.0
three	1.0	1.0	1.6	1.0	1.0	1.0	1.0	0.5	1.0	1.0	1.0	5.1	1.0
four	1.0	1.0	2.7	1.0	1.0	8.1	1.0	2.0	3.0	1.0	1.0	1.0	1.0
five	1.0	1.0	1.0	1.0	1.0	3.1	3.0	1.8	1.0	1.0	1.0	1.0	1.0
sixtonine	2.4	2.7	8.4	2.2	6.9	1.0	1.0	4.2	1.0	1.0	1.0	1.0	1.0

Table 6 Germany's Final Wage and Employment Matrices

Number of workers(thousands)

N(occ, ind)	Agri	Mining	Manu	Util	Constr	Trade	Hotel	Transp	Finance	Property	Public	Educat	Health
	A	C	D	E	F	G	H	I	J	K	M	N	O
onetwo	46	16	1349	74	251	1154	253	419	181	1271	1282	743	552
three	39	14	1174	65	175	875	49	223	452	1040	550	1912	414
four	28	9	887	54	234	912	46	500	688	675	103	220	258
five	16	0	350	0	6	1463	1080	63	5	83	125	1129	478
sixtonine	850	95	5099	137	2262	1397	181	1045	25	981	178	509	595

Notes: N(occ, ind) data is for 2006.

Table 7 Germany's Payment Shares by Industry

Payment shares

	Agri	Mining	Manu	Util	Constr	Trade	Hotel	Transp	Finance	Property	Public	Educat	Health
	A	C	D	E	F	G	H	I	J	K	M	N	O
12	18%	19%	21%	32%	16%	33%	40%	16%	15%	42%	69%	25%	37%
3	10%	15%	17%	18%	8%	14%	6%	18%	34%	25%	16%	41%	19%
4	6%	6%	11%	17%	7%	14%	4%	16%	49%	12%	4%	5%	10%
5	3%	0%	4%	0%	0%	22%	41%	3%	0%	2%	4%	18%	14%
6789	62%	60%	48%	33%	69%	18%	9%	47%	1%	19%	6%	11%	20%

6. DISCUSSION

Imputing the missing wage data required a flexible non-parametric approach that put more weight on the observed $w_{Occ, Ind}$ elements of the matrix but allowed final estimates to deviate from their initial values. In the final matrix some of the $w_{Occ, Ind}$ elements were actually more than 50% lower than their initial estimates. In these cases a matrix balancing method would have produced negative results for the unobserved $w_{Occ,Ind}$ elements.

We were concerned that these large differences between the known $w_{Occ, Ind}$ data and the $w_{.\ Ind}$ averages reflected a problem in data quality, but in comparing the most questionable pieces of the U.S. ILO data to national sources we found that the both w_{job} *and* the w_{Ind} observations were accurate. The difference occurred because the $w_{Occ, Ind}$ category only had a few w_{job} observations out of many jobs but these w_{job} observations were skewed relative to the full $w_{Occ, Ind}$ group.[33]

Although the w_{job} observations also did not cover all of the $w_{Occ, Ind}$ groups, we needed to assign values to them for the the initial wage matrix. Our best guess was the median of wage for the occupation group, so we assigned these naive values to unknown $w_{Occ, Ind}$ elements but let them vary more than observed $w_{Occ, Ind}$ by giving them a lower degree of belief. To ensure that the $w_{Occ, Ind}$ of a certain occupation remained similar to the $w_{Occ, Ind}$ of the same occupation in a different industry, the objective function minimized the distance of each $w_{Occ, Ind}$ from the initial average wage by occupation. In most industries this preserved an approximate hierarchy of wages by skill level, while our other constraint ensured that the wages in each industry matched the observed $w_{.\ Ind}$ averages.

For Portugal, we were able to directly compare our model results to Portugal's national statistics, which use the same ISIC (industry) and ISCO (occupational) definitions. We found that our weighted average wages by occupation (final results) were accurate within 15%, or less than €0.80 differences.[34]

Table 8 compares measures of fit for all 48 countries in our sample. This is the sum of the squared distance between each observed wage and its final estimated value.[35] In general,

[33] The United States had two w_{job} observations for laborers in agriculture: loggers and tree fellers/buckers, which are both paid more than $16/hour. However, the average wage of all agriculture workers is only $8.50. Since more than 86% of the workers in U.S. agriculture are laborers, the final imputed wage for laborers in agriculture had to fall significantly to fit the industry average.

[34] Statistics Portugal (2006a) and Statistics Portugal (2006b).

[35] It could be described as the first term of the objective function, which is $\sum_{i \in Occ} \sum_{j \in Ind} \beta_{ij} [w_{ij} - W_{ij}]^2$, without the degree of belief parameter.

we found that countries with the highest squared deviations were those with more wage inequality or very high inflation.[36]

Table 8 Sum of squared deviations

Country	Value	Country	Value
Australia	2.02	Malawi	162.69
Austria	5.20	Mauritius	3.49
Barbados	4.24	Mexico	4.04
Bolivia	3.00	Moldova	23.24
Brazil	7.77	Netherlands	35.77
Bulgaria	5.65	New Zealand	5.71
Canada	1.62	Nicaragua	1.91
China	1.76	Peru	445.09
Costa Rica	5.77	Philippines	51.63
Croatia	9.69	Poland	4.14
Cyprus	15.20	Portugal	4.81
Czech Republic	4.57	Romania	27.92
Estonia	15.39	Russia	55.12
Finland	0.20	San Marino	2.71
Germany	4.44	Singapore	4.01
Hungary	4.90	Slovakia	3.35
Iceland	6.02	Slovenia	9.33
India	3.01	Sri Lanka	0.09
Japan	8.33	Sweden	0.80
Korea	18.09	Thailand	2.69
Kyrgyzstan	13.56	Turkey	7.79
Latvia	23.00	United Kingdom	1.53
Lithuania	7.82	United States	7.17
Luxembourg	0.72	Venezuela	8.43

Source: Authors' calculations

[36] For example, the highest squared deviation is for Peru, where the real estate sector has average wages that are more than 5 times the wages of most other sectors. Malawi also has some large differences in wages by occupation and industry and extremely high and volatile inflation.

7. CONCLUSIONS

Our methodology that finds wage and employment matrices across many countries has the potential to improve the labor payment splits in the GTAP database. Two clear advantages are that we use much more current data as a starting point and that the ILO data allows us to apply a consistent methodology to a large sample of countries. Furthermore, we are able to separate labor payments into the employment and wages components and expand the skilled/unskilled worker splits to five occupational categories.

We applied our method to find wages for 48 countries. Like previous versions of the GTAP labor splits, a regression could be used to find estimates of missing splits for other countries. Alternatively, hot-deck imputation or national sources could be used to estimate unknown values using some of the countries' observed (but incomplete) ILO data. One of these methods should be chosen, but at least our 48 countries gives a more complete sample of labor splits when compared to the set of 13 countries used in previous GTAP versions. Our split across five occupational categories matches up to the previous split by skilled/unskilled workers, with ILO occupations 1–3 corresponding to skilled and 4–9 corresponding to unskilled workers. Therefore, it should be possible to use our data in conjunction with previous work on this topic.

The most significant drawback of our method is the limited number of industries per country. This is a problem mainly for agriculture and manufacturing, for which the GTAP database uses more detailed industries than the one-digit ISIC level.[37] Although national-level statistics could be applied to revise our splits, we prefer to limit the data sources to those from the ILO wherever possible and we have chosen to not impute missing data using distributions from other countries. Another possible extension would be to harmonize the 2003–07 *ILO October Inquiry* surveys across countries (using the Freeman and Oostendorp methodology) and add this newer data to our wages by job.

The merits of our procedure are a large sample of countries, a consistent methodology, disaggregation across five occupations, and the separation of the price and quantity components of labor payments. Our proposed GTAP contribution should be a valuable resource to researchers looking for globally comparable data on wages and employment.

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[37] In the study by Liu, *et al.* (1998) some ILO sources were used to find wages and employment numbers for Brazil but the authors noted that the data suffered from overly aggregated industries, especially in agriculture and manufacturing.

APPENDIX A: LIST OF OCCUPATIONS, INDUSTRIES, AND JOBS

Table A.1 List of Occupations by ISCO-88 One-Digit Classification

1: Senior officials and managers	5: Service and shop workers
2: Professionals	6: Skilled agricultural workers
3: Technicians and associate professionals	7, 8, 9: Machine operators, assemblers, craft workers, etc.
4: Clerks	

Table A.2 List of Industries by ISIC Rev 3 One-Digit Classification

A: Agriculture, hunting and forestry	J: Financial intermediation
B: Fishing	K: Real estate, renting and business activities
C: Mining and quarrying	L: Public administration and defense; soc.security
D: Manufacturing	M: Education
E: Electricity, gas and water supply	N: Health and social work
F: Construction	O: Other community, social and personal services
G: Wholesale and retail trade; repair of motor vehicles, personal and household goods	P: Private households with employed persons
H: Hotels and restaurants	Q: Extra-territorial organizations and bodies
I: Transport, storage and communications	X: Not classifiable by economic activity

Table A.3 List of Jobs in the *ILO October Inquiry* (with ISIC industry letter and ISCO occupation number)

1. Farm supervisor (A6)	82. Plumber (F7)
2. Field crop farm worker (A6)	83. Constructional steel erector (F7)
3. Plantation supervisor (A6)	84. Building painter (F7)
4. Plantation worker (A6)	85. Bricklayer (construction) (F7)
5. Forest supervisor (A6)	86. Reinforced concreter (F7)
6. Forestry worker (A6)	87. Cement finisher (F7)
7. Logger (A6)	88. Construction carpenter (F7)
8. Tree feller and bucker (A6)	89. Plasterer (F7)
9. Deep-sea fisherman (B6)	90. Labourer (F9)
10. Inshore (coastal) maritime fisherman (B6)	91. Stenographer-typist (G4)
11. Coalmining engineer (C2)	92. Stock records clerk (G4)
12. Miner (C7)	93. Salesperson (G5)
13. Underground helper, loader (C9)	94. Book-keeper (G3)
14. Petroleum and natural gas engineer (C2)	95. Cash desk cashier (G4)
15. Petroleum and natural gas extraction technician (C3)	96. Salesperson (G5)
16. Supervisor or general foreman (C8)	97. Hotel receptionist (H4)
17. Derrickman (C8)	98. Cook (H5)
18. Miner (C7)	99. Waiter (H5)
19. Quarryman (C7)	100. Room attendant or chambermaid (H9)
20. Butcher (D7)	101. Ticket seller (cash desk cashier) (I4)
21. Packer (D0)	102. Railway services supervisor (I4)
22. Dairy product processor (D8)	103. Railway passenger train guard (I5)
23. Grain miller (D8)	104. Railway vehicle loader (I9)
24. Baker (ovenman) (D7)	105. Railway engine-driver (I8)
25. Thread and yarn spinner (D8)	106. Railway steam-engine fireman (I8)
26. Loom fixer, tuner (D7)	107. Railway signalman (I8)
27. Cloth weaver (machine) (D8)	108. Road transport services supervisor (I4)
28. Labourer (D9)	109. Bus conductor (I5)
29. Garment cutter (D7)	110. Automobile mechanic (I7)

Table A.3 List of Jobs in the *ILO October Inquiry* (with ISIC industry letter and ISCO occupation number)

30. Sewing-machine operator (D8)
31. Tanner (D8)
32. Leather goods maker (D7)
33. Clicker cutter (machine) (D7)
34. Laster (D7)
35. Shoe sewer (machine) (D7)
36. Sawmill sawyer (D8)
37. Veneer cutter (D8)
38. Plywood press operator (D8)
39. Furniture upholsterer (D7)
40. Cabinetmaker (D7)
41. Wooden furniture finisher (D7)
42. Wood grinder (D8)
43. Paper-making-machine operator (D8)
44. Journalist (D2)
45. Stenographer-typist (D4)
46. Office clerk (D4)
47. Hand compositor (D7)
48. Machine compositor (D7)
49. Printing pressman (D8)
50. Bookbinder (machine) (D8)
51. Labourer (D9)
52. Chemical engineer (D2)
53. Chemistry technician (D3)
54. Supervisor or general foreman (D8)
55. Mixing- and blending-machine operator (D8)
56. Labourer (D9)
57. Mixing- and blending-machine operator (D8)
58. Packer (D0)
59. Labourer (D9)
60. Controlman (D8)
61. Occupational health nurse (D2)
62. Blast furnaceman (ore smelting) (D8)
63. Hot-roller (steel) (D8)
64. Metal melter (D8)
65. Labourer (D8)
66. Metalworking machine setter (D7)
67. Welder (D7)
68. Bench moulder (metal) (D7)
69. Machinery fitter-assembler (D8)
70. Labourer (D9)
71. Electronics draughtsman (D3)
72. Electronics engineering technician (D3)
73. Electronics fitter (D7)
74. Electronic equipment assembler (D8)
75. Ship plater (D7)
76. Power distribution/transmission engineer (E2)
77. Office clerk (E4)
78. Electric power lineman (E7)
79. Power- generating machinery operator (E8)
80. Labourer (E9)
81. Building electrician (F7)

111.Motor bus driver (I8)
112. Urban motor truck driver (I8)
113. Long-distance motor truck driver (I8)
114. Ship's chief engineer (I3)
115. Ship's steward (passenger) (I5)
116. Able seaman (I8)
117. Dockworker (I9)
118. Air transport pilot (I3)
119. Flight operations officer (I4)
120. Airline ground receptionist (I4)
121. Aircraft cabin attendant (I5)
122. Aircraft engine mechanic (I7)
123. Aircraft loader (I9)
124. Air traffic controller (I3)
125. Aircraft accident fire-fighter (I5)
126. Post office counter clerk (I4)
127. Postman (I4)
128. Telephone switchboard operator (I4)
129. Accountant (J2)
130. Stenographer-typist (J4)
131. Bank teller (J4)
132. Book-keeping machine operator (J4)
133. Computer programmer (J2)
134. Stenographer-typist (J4)
135. Card- or tape-punching machine operator (J4)
136. Insurance agent (J3)
137. Clerk of works (K3)
138. Computer programmer (L2)
139(a). Government executive official: central (L0)
139(b). Government executive official: regional (L0)
139(c). Government executive official: local (L0)
140. Stenographer-typist (L4)
141. Card- or tape-punching machine operator (L4)
142. Office clerk (L4)
143. Fire-fighter (L5)
144. Refuse collector (O9)
145. Third-level mathematics teacher (M2)
146. Third-level languages/literature teacher (M2)
147. Second-level languages/literature teacher (M2)
148. Second-level mathematics teacher (M2)
149. Second-level technical education teacher (M2)
150. First-level education teacher (M2)
151. Kindergarten teacher (M2)
152. General physician (N2)
153. Dentist (general) (N2)
154. Professional nurse (general) (N2)
155. Auxiliary nurse (N3)
156. Physiotherapist (N3)
157. Medical X-ray technician (N3)
158. Ambulance driver (N8)
159. Automobile mechanic (G7)

APPENDIX B: DEGREE OF BELIEF PARAMETER

This section shows the sensitivity of Germany's wage matrix to the degree of belief parameters. It compares the results using the full model we described in Chapter 3 to those with all degree of belief entries set to one.

In most industries except transportation, the degree of belief parameter has only a minor impact on the results. Wages in the transportation industry are a problem for many countries because dissimilar workers like bus drivers and airline pilots are grouped together in occupation 3. The high wages of airline pilots leads to a high average wage which is not entirely representative of occupation 3 category of workers. With the inclusion of a degree of belief parameter, the (less believable) average wage in industry I occupation 3 is allowed to adjust more than other wages to satisfy the objective function. Without the degree of belief parameter, the average wage in transportation occupation 3 is remains much higher and closer to its initial value. This also depresses the other final wages in the transportation industry (industry I).

Input matrix: Observed wages by job and industry averages

	Agri	Mining	Manu	Util	Constr	Trade	Hotel	Transp	Finance	Proper	Public	Educat	Health
w(occ, ind)	A	C	D	E	F	G	H	I	J	K	M	N	O
onetwo		€ 25	€ 20	€ 29					€ 21		€ 26	€ 25	
three		€ 24	€ 19			€ 16		€ 41	€ 12	€ 20		€ 16	
four			€ 16	€ 21		€ 13	€ 15	€ 19	€ 15				
five						€ 14	€ 10	€ 16					
sixtonine	€ 13	€ 16	€ 13	€ 16	€ 15	€ 13	€ 8	€ 15				€ 16	€ 12
w(. ind)	€ 7	€ 16	€ 16	€ 20	€ 13	€ 15	€ 10	€ 14	€ 20	€ 16	€ 16	€ 15	€ 15

Degree of Belief

	Agri	Mining	Manu	Util	Constr	Trade	Hotel	Transp	Finance	Proper	Public	Educat	Health
B(occ, ind)	A	C	D	E	F	G	H	I	J	K	M	N	O
onetwo	1.0	1.7	1.2	1.0	1.0	1.0	1.0	1.0	1.8	1.0	2.7	1.2	1.0
three	1.0	1.0	1.6	1.0	1.0	1.0	1.0	0.5	1.0	1.0	1.0	5.1	1.0
four	1.0	1.0	2.7	1.0	1.0	8.1	1.0	2.0	3.0	1.0	1.0	1.0	1.0
five	1.0	1.0	1.0	1.0	1.0	3.1	3.0	1.8	1.0	1.0	1.0	1.0	1.0
sixtonine	2.4	2.7	8.4	2.2	6.9	1.0	1.0	4.2	1.0	1.0	1.0	1.0	1.0

Results using degree of belief parameter

	Agri	Mining	Manu	Util	Constr	Trade	Hotel	Transp	Finance	Propert	Public	Educat	Health
wage_NBER	A	C	D	E	F	G	H	I	J	K	M	N	O
12	€ 26	€ 23	€ 21	€ 27	€ 24	€ 24	€ 24	€ 12	€ 23	€ 20	€ 19	€ 24	€ 22
3	€ 17	€ 21	€ 19	€ 17	€ 16	€ 13	€ 18	€ 25	€ 20	€ 15	€ 11	€ 15	€ 15
4	€ 14	€ 14	€ 17	€ 20	€ 12	€ 13	€ 14	€ 10	€ 20	€ 11	€ 13	€ 14	€ 13
5	€ 13	€ 14	€ 14	€ 14	€ 14	€ 13	€ 6	€ 14	€ 14	€ 13	€ 12	€ 11	€ 10
6789	€ 5	€ 13	€ 13	€ 15	€ 11	€ 10	€ 7	€ 14	€ 13	€ 12	€ 13	€ 16	€ 11

Results without degree of belief parameter

	Agri	Mining	Manu	Util	Constr	Trade	Hotel	Transp	Finance	Propert	Public	Educat	Health
wage_NBER	A	C	D	E	F	G	H	I	J	K	M	N	O
12	€ 27	€ 24	€ 21	€ 27	€ 27	€ 25	€ 26	€ 15	€ 23	€ 20	€ 17	€ 24	€ 22
3	€ 18	€ 23	€ 19	€ 18	€ 18	€ 14	€ 18	€ 34	€ 16	€ 15	€ 15	€ 14	€ 15
4	€ 15	€ 14	€ 17	€ 20	€ 14	€ 11	€ 15	€ 4	€ 22	€ 11	€ 14	€ 15	€ 13
5	€ 13	€ 14	€ 14	€ 14	€ 14	€ 11	€ 5	€ 14	€ 14	€ 13	€ 13	€ 12	€ 10
6789	€ 5	€ 12	€ 13	€ 14	€ 11	€ 11	€ 8	€ 12	€ 13	€ 12	€ 13	€ 16	€ 11

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