2025 UPDATE FOR FEMALE LABOR INCOME SHARE

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Female Labor Income Share

Methodological Note

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0 Overview

The female labor income share update is based on the methodology by Neef and Robilliard (2022). This update provides estimates of the female labor income share for 1990 –2024. This methodological note explains the data sources and methodology in detail, highlighting data availability and new data that was incorporated.

We provide estimates for 216 countries and jurisdictions. 144 jurisdictions have at least one data point throughout the period 1990–2024 for which we can estimate the female labor income share from original data, i.e. information on female and male wage and self-employment incomes. We predict the female labor income share for 44 additional jurisdictions using an OLS regression with female shares of wage and self-employment as the primary predictors. Employment data for this prediction comes from ILO modelled estimates which cover 188 jurisdictions. Finally, for 28 jurisdictions, we lack information on both income and employment. We impute the female labor income share as the regional average for these jurisdictions.

1 Data availability and quality

Micro data

We draw on four key micro survey data sets:

1. The EU-SILC (European Union Statistics on Income and Living Conditions) release of 2025, which covers 32 European countries for the period 2003–2023. For coverage see Figure A.1.
2. LIS (Luxembourg Income Study) providing individualized wage and self-employment income data for 52 countries for varying time spans. For coverage see Figure A.2.
3. The ILO Harmonized Microdata Repository[4] includes survey information on monthly pay from wage employment and self-employment separately for at least one year since 1990 to 2024

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[4] We thank the ILO's Data Production and Analysis Unit for kindly providing this data. Information on the dataset can be found in the following: D. Bescond, S. Kapsos, V. Karkee, D. Limani, Q. Mathys, Y. Perardel and M. Sodergren (2023). Unlocking the Power of Microdata: Enhancing International Comparability and Data Availability in ILOSTAT, and ILO Department of Statistics: Data Production and Analysis Unit (2024): ILOSTAT Microdata processing quick guide. Principles and methods underlying the ILO's processing of anonymized household survey microdata.

for 144 jurisdictions. Original incomes are in current local currency. For coverage see figure A.3.

4. National surveys for China, India and eight Western African countries. For China, we use the Chinese Household Income Project (CHIP). We discuss methodological procedures for China in section 4. For India, we use the data from the national survey available for 1993, 1999, 2004, and 2009. For eight Western African countries - Burkina Faso, Benin, Cote d'Ivoire, Guinea Bissau, Mali, Niger, Senegal, and Togo - we can draw on harmonized national surveys for 2018 (see https://phmecv.uemoa.int/ for more information).

Aggregate data

For the regression imputations, we additionally draw on two aggregate data sources:

1. ILO modelled estimates of employment by sex, age and status in employment (obtained by the code EMP_2EMP_SEX_STE_NB_A), comprising 188 countries for our time period 1990–2024 (see https://ilostat.ilo.org/data/bulk/)
2. National accounts aggregates for net national income (B5n, S1), employees compensation (D1, S1), and net mixed income (B3n, S14) as well as population statistics from the World Inequality database. See Moshrif et al. (2024) for documentation.

2 Main concept

Our main concept is the female labor income share at the country level defined as:

$$Female\ Labor\ Income\ Share = \frac{Labor\ income\ received\ by\ women}{Total\ labor\ income}$$

In line with the Distributional National Accounts method, labor income includes wage and salary income as well as the labor share of self-employed income:

$$Labor\ income = Wage\ income\ + 0.7\ \cdot\ self\ employment\ income$$

To compute the female labor income share for each country, we first aggregate labor income by gender within each country. Our inequality indicator thus comprises gender differentials in earnings as well as labor force participation. This value is therefore lower than the gender pay ratio, as it accounts for differences in earnings and labor force participation.

3 Imputation Methodology

The female labor income share is computed based on country-year aggregates of the female (male) wage (self-employment) income. We build this database in several steps.

1. Combining edited microdata sources EU-SILC, LIS, and ILO by country and year.
2. Selection of data sources in case multiple are available. We set a benchmark series for each country based on the following prioritization:
    a. First, we give priority to EU-SILC data, if available. Exceptions are Germany, Italy, Denmark, France, Great Britain, and Norway, for which we assume LIS to be of higher precision. For Serbia, we rely on ILO data instead of EU-SILC.

b. For India, China, and eight Western African countries we use national survey data.
c. If EU-SILC is not available, we draw on LIS data.
d. If neither EU-SILC nor LIS are available, we use ILO micro data.

From these data sources, we obtain data for 144 countries (jurisdictions) and 1,500 country year observations.

3. We augment the benchmark data sources with secondary choices when they offer a broader year range. For example, we supplement EU-SILC data with LIS or ILO data for years prior to 2003, and supplement LIS data with ILO data where applicable. Adding to 1655 original data points.
4. We interpolate the FLIS and aggregate female (male) wage (self-employment) income linearly between original data points.

This procedure gives us times series of varying data ranges for 144 jurisdictions.

5. To extend the time series for these 144 jurisdictions to cover 1990–2024 and to include countries missing from the earnings database, we use a two-step imputation approach. First, we estimate the female labor income share as a simple linear function of the female shares in wage- and self-employment and world region indicators using the combined LIS-EU-SILC-ILO database. Second, combining the estimated coefficients with ILO's modelled estimate employment series [1990-2024], we predict the female labor income share for all countries and years for which ILO modelled estimates exist (188 countries).
   More precisely, in step 1, we estimate the following regression model:

$$
\begin{aligned}
&\mathit{Female\ Labor\ Income\ Share}_{ct} \\
&\qquad = \alpha + \beta\ \mathit{Female\ Share\ of\ Wage\ Employment}_{ct} \\
&\qquad + \gamma\ \mathit{Female\ Share\ of\ Self\ Employment}_{ct} \\
&\qquad + \delta\ \mathit{World\ Regions}_{c} + \varepsilon_{ct}
\end{aligned}
$$

where *c* indicates countries and *t* years. The variable $\mathit{Female\ Labor\ Income\ Share}_{ct}$ is the female labor income share for country *c* and year *t*, the variables $\mathit{Female\ Share\ of\ Wage\ Employment}_{ct}$ and $\mathit{Female\ Share\ of\ Self\ Employment}_{ct}$ are the female shares of wage- or self-employed among all wage- or self-employed respectively. $\mathit{World\ Regions}_{c}$ corresponds to fixed effects for institutional and cultural differences of nine world regions. We classify countries into nine world regions: Asia (excl. China) comprising 32 jurisdictions, China, the Former Eastern Bloc (24 jurisdictions), Latin America and the Caribbean (43 countries & jurisdictions), Middle East and Northern Africa (20 countries), Northern America (4 countries), Oceania (16 jurisdictions), Sub Saharan Africa (48 countries), and Western Europe (28 countries). Observations are weighted according to population size.

The model fit is high (see Table 1). Employment variables contribute positively to the female labor income share, with wage employment having a significantly higher coefficient. This could be related to the fact that wage employment is associated with a more skilled labor force and higher earnings on average. Compared to Asia (excluding China) most regions exhibit a positive and significant fixed effect.

Next, we impute the Female Labor income Share for the country years with observed Female Share of Wage Employment and Female Share of Self Employment coming from ILO Modelled Estimates (188 countries). To extrapolate the female labor income share beyond the original available data, we retain the original data points and adjust the predicted trend to their level, extending the series using the trend from the imputation. This imputation also provides estimates for 44 additional jurisdictions with previously no earnings data, bringing our final dataset to include female labor income share estimates for 188 jurisdictions covering the period 1990–2024. For 28 jurisdictions without any labor market related information due to a lack of consistent data sources, we provide the regional average.

Table 1. Female labor income share prediction (2025 version)

	flis_bm		
fe_wage_emp_share_bm	0.633	**	(0.016)
fe_self_emp_share_bm	0.264	**	(0.014)
region_num			
China	0.059	**	(0.004)
FormerEasternBloc	0.078	**	(0.004)
LAC	0.052	**	(0.003)
MENA	0.073	**	(0.007)
NorthernAmerica	0.040	**	(0.003)
Oceania	0.054	**	(0.011)
SubSaharanAfrica	0.052	**	(0.005)
WesternEurope	0.048	**	(0.003)
Intercept	-0.075	**	(0.006)
Number of observations	1343		
R-squared	0.875		

*** p<.01, ** p<.05, * p<.10.

4 Methodological discussion on China

Data: The purpose of the Chinese Household Income Project (CHIP) is to measure and estimate the distribution of personal income in both rural and urban areas of the People's Republic of China. The principal investigators based their definition of income on cash payments and on a broad range of additional components: in-kind payments valued at market prices, agricultural output produced for self-consumption valued at market prices, the value of ration coupons and other direct subsidies, and the imputed value of housing. The labor and income related variables available in each wave of the CHIP are listed in Appendix B.1 (note that they also vary by area of residence). Data were collected through a series of questionnaire-based interviews conducted in rural and urban areas in 1988, 1995, 2002, 2007, and 2013. Individual respondents reported on their economic status, employment, level of education, sources of income, household composition, and household expenditures. Table 2 provides sample sizes for each wave of the survey.

Table 2: Sample Size, CHIP survey data.

	Samples sizes		Weighted	
	Households	**Individuals**	**Population**	**% urban**
CHIP 1988	19,267	83,019	1,110,235,947	25.0
CHIP 1995	14,929	56,416	1,211,231,006	31.0
CHIP 2002	16,035	58,513	1,284,520,139	38.0
CHIP 2007	13,002	46,459	1,328,009,554	45.9
CHIP 2013	17,163	58,943	1,360,703,080	54.5
CHIP 2018	20,745	71,259	1,397,648,451	61.5

Methodology: Computing employment and labor income for China by sex using CHIP data presents a challenge: the questionnaire design varies significantly across years and between urban/rural areas. This requires a careful analysis of the questionnaires to identify and harmonize the variables needed for labor income aggregates.

To disaggregate the FLIS and understand its evolution better, we make a distinction between three types of employment and labor income: wage employment, farm and non-farm self-employment. While wage employment largely dominates in OECD countries, the distinction between farm and non-farm self-employment appears relevant to account for the structural transformation experienced by China over the last 30 years. Most household surveys collect income on these three types of employment in different sections and through different questions. In future updates, we aim to apply this distinction to all countries of our sample when possible.

We define six harmonized variables:

wage	Takes the value one if the individual is a wage worker
self	Takes the value one if the individual is self-employed outside of agriculture
farm	Takes the value one if the individual is self-employed in agriculture
pwage	Value of yearly income from wage at the individual level (in yuan)
pself	Value of yearly income from self-employment outside of agriculture (in yuan)
pfarm	Value of yearly income from self-employment in agriculture (in yuan)

Appendix B.2 details how each of these variables is constructed from raw data for every survey and area.

A second challenge arises because some income types are available only at the household level, not individually. This is typical for income generated from family farms or businesses, which is difficult to disaggregate. To distribute this income, we assume that all individuals who declare themselves as farmers or self-employed receive an equal share of their respective household's farm or self-employment income (see Appendix B.2 for survey-specific formulas). We acknowledge that this assumption likely overestimates the self-employment income share for women.

Caveats

The following limitations should be noted regarding the data and methodology:

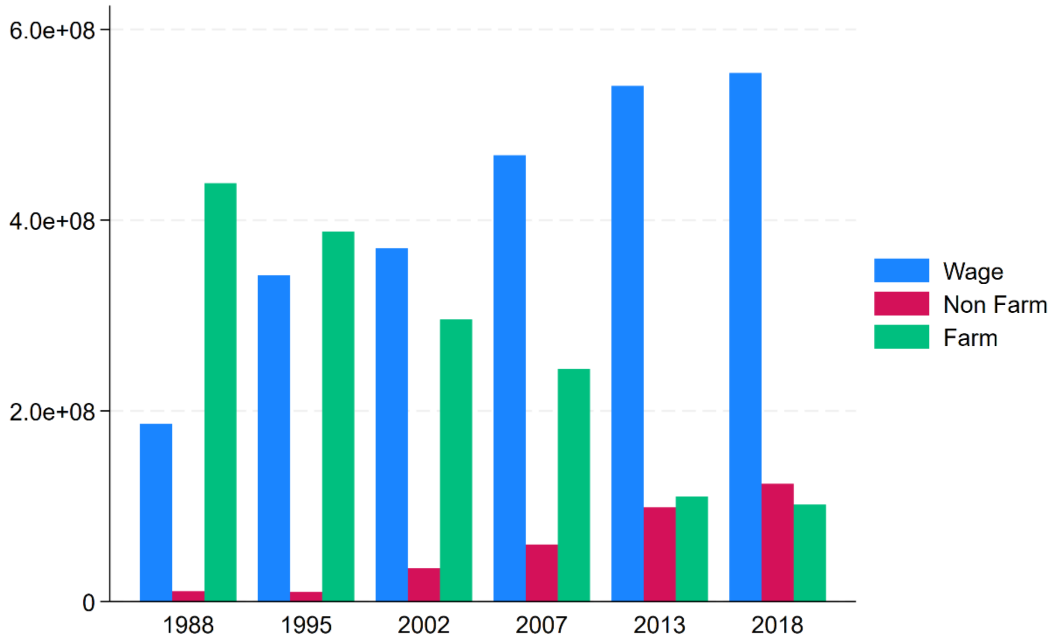
- Valuation of Agricultural Self-Consumption: It is unclear from the questionnaires whether income derived from agricultural output produced for self-consumption is accurately captured by the available income variables in the questionnaires and documentation.
- Missing Farm Income for Specific Years: For three waves (2007, 2013, 2018), only non-agricultural incomes are available. To estimate aggregate farm incomes for these years, we

applied gender-specific ratios of income per worker between farm and wage employment from 2002 (0.49 for males and 0.63 for females). These ratios were then used to project gender-specific aggregate farm incomes for 2007, 2013, and 2018.

- Challenges with Migrant Household Data (Post-2007): Starting in 2007, the surveys include a sample of migrant households in addition to the urban and rural samples. The integration of this data presents challenges due to two main issues: (1) Some critical income variables are missing from the available data files for this sample. (2) The necessary population weights for the migrant household sample are not provided.

Selected Results: Figure 2 depicts the evolution of total employment between 1988 and 2018, underscoring a profound structural transformation over the three-decade period. This transition is characterized by a sustained increase in wage employment, a parallel decline in agricultural employment, and a notable rise in non-farm self-employment.

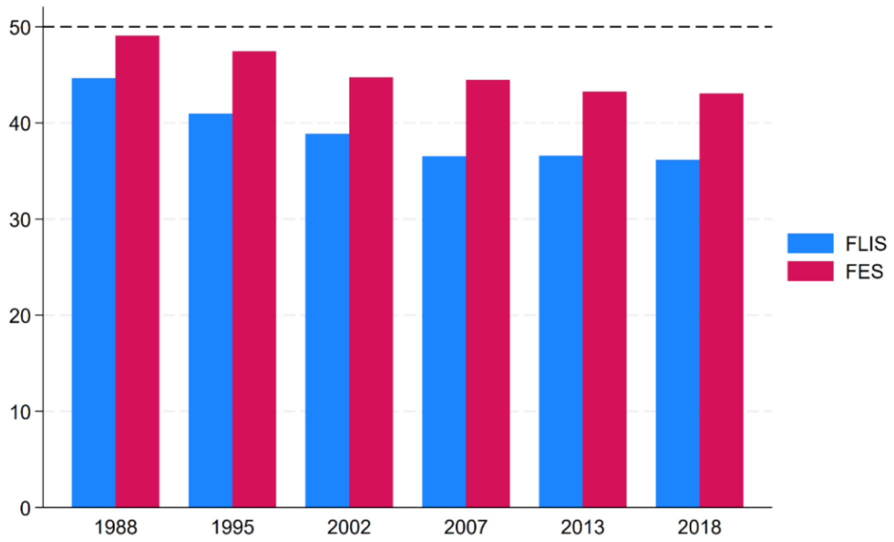
Figure 2: Aggregate employment by type



Source: CHIP data and authors' computation.

Figure 3 presents the evolution of the Female Labor Income Share (FLIS) and the Female Employment Share (FES) over time. In 1988, the FLIS stood at a relatively high 44.7%, a level notable by international standards. However, it exhibited a steady decline over the subsequent three decades, falling to 36.2% by 2018. This downward trend appears to be largely attributable to a concomitant reduction in the FES, which decreased from 49% in 1988 to 43.1% in 2018.

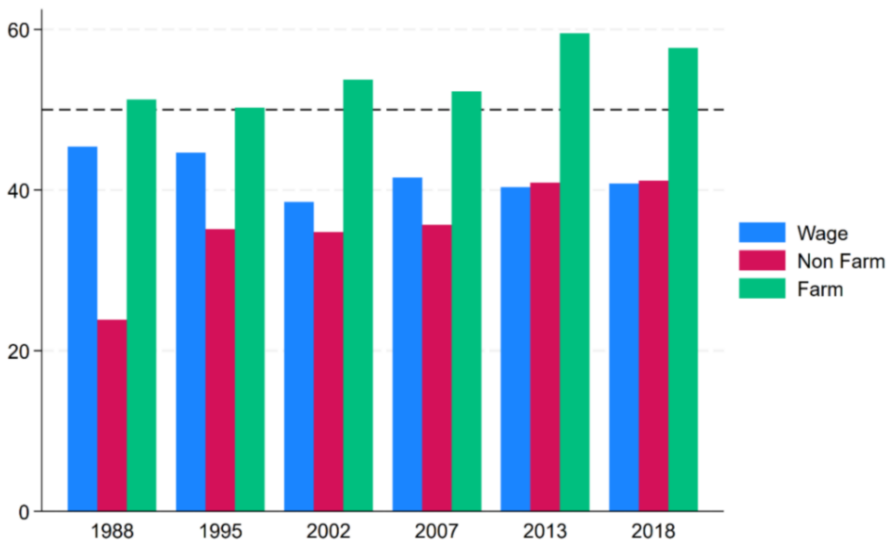
Figure 3: Female Labor Income Share (FLIS) and Female Employment Share (FES)



Source: CHIP data and authors' computation.

The decomposition by employment type—wage, non farm, and farm—suggests that the decline in the female employment share (Figure 3) can be attributed to two interrelated dynamics: the expansion of wage employment overall (Figure 2) and the simultaneous decrease in women's representation within total wage employment, as shown in Figure 4. This concurrent decline in the female share of wage employment likely reflects the gendered nature of structural transformation, wherein men appear to have transitioned more rapidly than women from agricultural self-employment to formal wage employment.

Figure 4: Female Employment Share (FES) by employment type



Source : CHIP data and authors' computation.

6 Specific considerations of this update (December 2025)

This year we are using an updated version of ILO Harmonized Microdata Repository. This new version includes both household income and expenditure surveys (HIES) and labor force surveys (LFS). For a subset of country–year observations, approximately 20 percent of the sample, it was necessary to select one survey as the primary source. We stablish a selection rule that prioritizes the survey with broader coverage and more detailed income information, while the secondary survey is used only to complement missing years or to extend the time series where possible. In addition, some country cases were handled with specific rules. For example, for Liberia the HIES does not report self-employment income, so the LFS is chosen as the primary source for the benchmark labor income series. It should be noted that for Argentina, all estimates are based on data that are representative of urban areas only.

A small number of country–year observations were treated as outliers and excluded from the benchmark series. Outliers were identified based on extreme year-on-year changes in the Female Labor Income Share (FLIS). Specifically, observations with an annual FLIS change exceeding three standard deviations from the country-specific distribution were classified as extreme and removed. This filtering was applied to the ILO series prior to merging with other data sources. 16 country-year where identified as outliers:

- North America & Oceania: Tonga 2021 is excluded due to an implausibly low FLIS (≈0.01) and an extreme jump in male wage income between 2018 and 2021, which might be signaling a measurement error.
- South & South-East Asia: Timor-Leste 2016 is excluded.
- Sub-Saharan Africa: Mali 2014, Mauritius 2023, Niger 2012, Nigeria 2016 and 2019, and South Africa 2001 are excluded based on the same FLIS-change rule.
- MENA: Egypt 2010 and 2019 are flagged as problematic and set aside for more detailed case-by-case analysis.
- Europe: Outliers are not removed in this step because, for this region, ILO data are not the primary source; EU-SILC and LIS are prioritized instead (notably for Switzerland and Lithuania).

Second stage of outliers identification:

- Congo 2009: only one point in the series and flis is larger than 0.5. Due to the high uncertanty for this country, the data point is excluded.
- Ghana 2015: original values for 1991, 2006, 2013, 2015, 2017, 2022. All values come from HIES (ILO) except for 2015, which comes from LFS. Lower than 2013 and 2017. Then, 2015 is excluded.
- Myanmar 2015: slightly higher flis, does not account for self-employment while the other years in the series do. Self-employment correction did not work. The male wage income in 2015 is the largest in the series, there might be a measurement error.
- Tanzania 2008: only year in the series with self-emp gives larger flis that seems inconsistent with the other values in the series. Correcting other years for self-employment ratio does not contribute to have more homogenous trends.

- Cambodia 1996, 1997: flis values are lower than for the rest of the series.
- Egypt 2008, 2009: flis values are much lower than those after 2010.

Self-employment income correction when missing.

To address missing self-employment income in the ILO series, we implement a country–year correction based on the relationship between wage and self-employment income. For each gender, we compute the wage-to-self-employment income ratio by country and year using observations where both components are observed. Extreme ratios above 20 are replaced by the country median, and when a country has more than one observed ratio over time, the ratio is linearly interpolated to fill gaps. For country–years where wage income is observed but self-employment income is missing, we impute self-employment income as wage income divided by the (observed or interpolated) ratio, provided the ratio is available for at least one year in that country. In the squared panel, there are 1,014 country–year observations with wage and self-employment income observed for both genders, 484 observations requiring imputation across 77 countries, and 3,752 observations where both components are missing due to panel completion. Of the 484 cases requiring imputation, self-employment income is successfully imputed for at least one gender in 218 country–years (46 countries), while 266 country–years (34 countries) cannot be corrected because the ratio cannot be constructed or propagated. We assess the magnitude of the correction by comparing the corrected and original FLIS values for the affected observations. The average difference with the original flis is 0.007, the largest difference is 0.15.

Some countries where the correction was implemented are: Benin, Ghana, Myanmar, Gambia, Thailand, among others.

Improvements of this update:

- There are 324 new original observations for 107 countries. Most of the update is for 2021, 2022, 2023.
- Countries with original data for at least 1 year, that di not have any original data in the previous version: Bahamas, Democratic Republic of the Congo, Moldova, Mauritania, New Caledonia, Solomon Islands, Sao tome and Principe, and Tunisia.

Table 2: Number of new original observations in the 2025 update that were not present in the previous version by region and data source

Region	Method	Source	Number of new observations in '25	Number of countries
East Asia	Original	ilo	9	1
East Asia	Original	lis	10	1
Europe	Original	eusilc	63	24
Europe	Augmented	eusilc-ilo	9	2
Europe	Augmented	eusilc-lis	3	1
Europe	Original	ilo	21	3
Europe	Original	lis	5	3
Europe	Augmented	lis-ilo	10	3
Latin America	Original	ilo	30	9
Latin America	Original	lis	8	3
Latin America	Augmented	lis-ilo	26	8
MENA	Original	ilo	15	5
North America & Oceania	Original	ilo	3	3
North America & Oceania	Original	lis	1	1
North America & Oceania	Augmented	lis-ilo	3	2
Russia & Central Asia	Original	ilo	2	1
Russia & Central Asia	Original	lis	2	2
South & South-East Asia	Original	ilo	34	12
Sub-Saharan Africa	Original	ilo	58	25
Sub-Saharan Africa	Original	lis	3	1
Sub-Saharan Africa	Augmented	lis-ilo	9	2
Total			324	

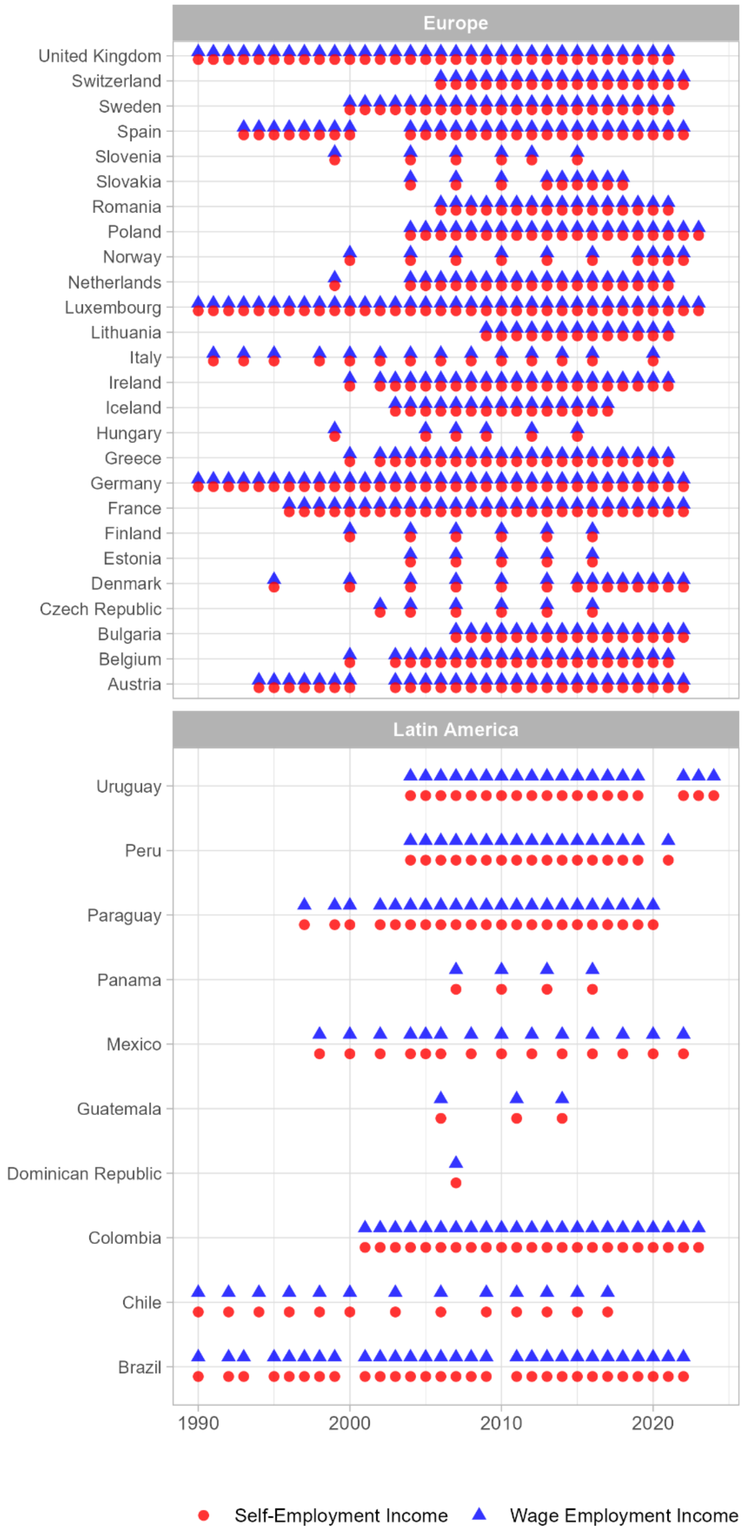
Appendix A: Coverage

Figure A.1: EU-SILC: Coverage individualized wage and self-employment income data.

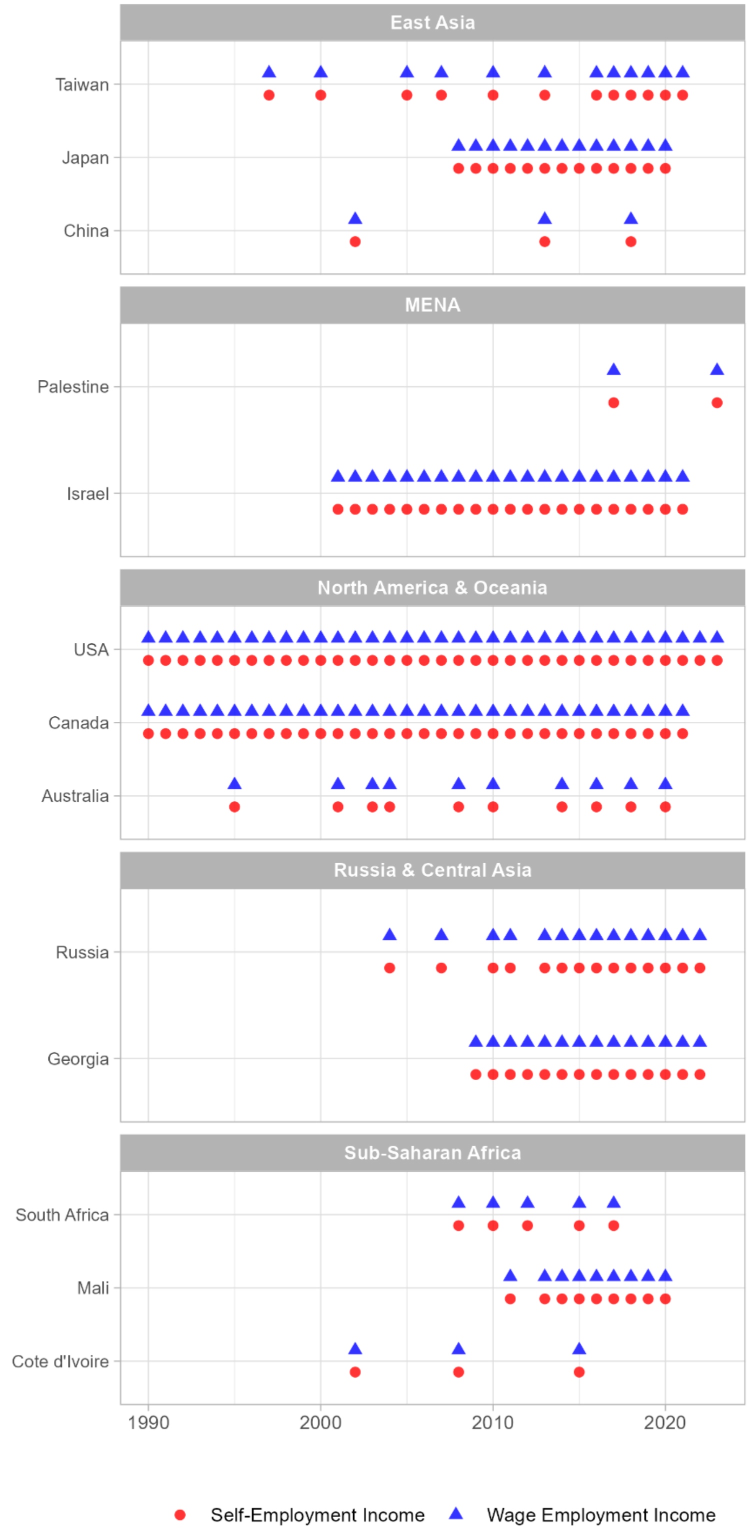
Notes: This figure shows country-year observations with information on wage income (red) and self-employed income (blue) available in the European Union Statistics on Income and Living Conditions (EU-SILC) dataset. Income data spans 2003–2023 for 32 countries.

Figure A.2: Luxembourg Income study: Coverage individualized wage and self-employment income data

Panel A



Panel B

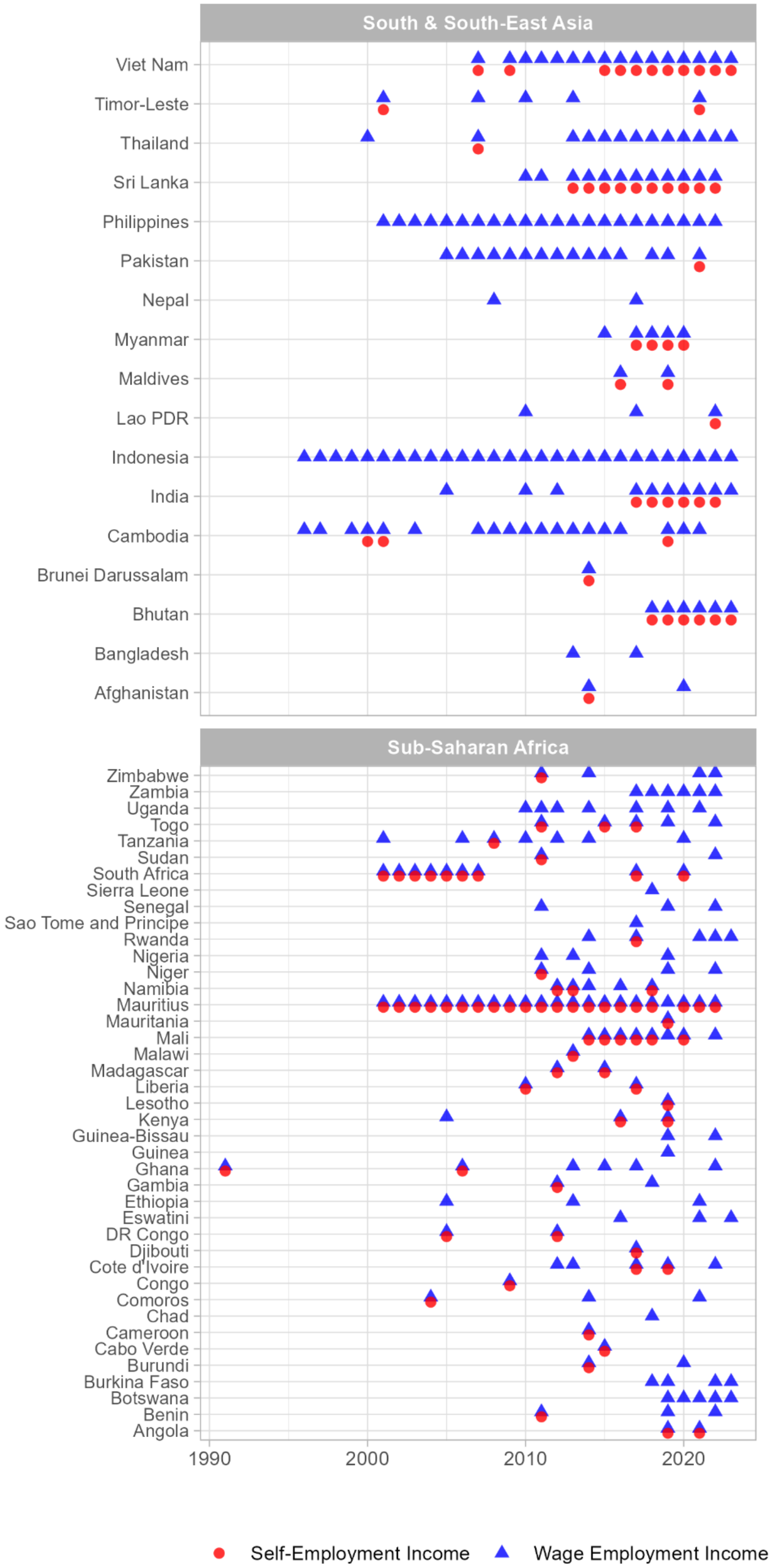


Notes: This figure shows country-year observations with information on wage income (red) and self-employed income (blue) available in the Luxembourg Income Study (LIS). Individualized income data is available for 52 countries, covering various years between 1990 and 2022.

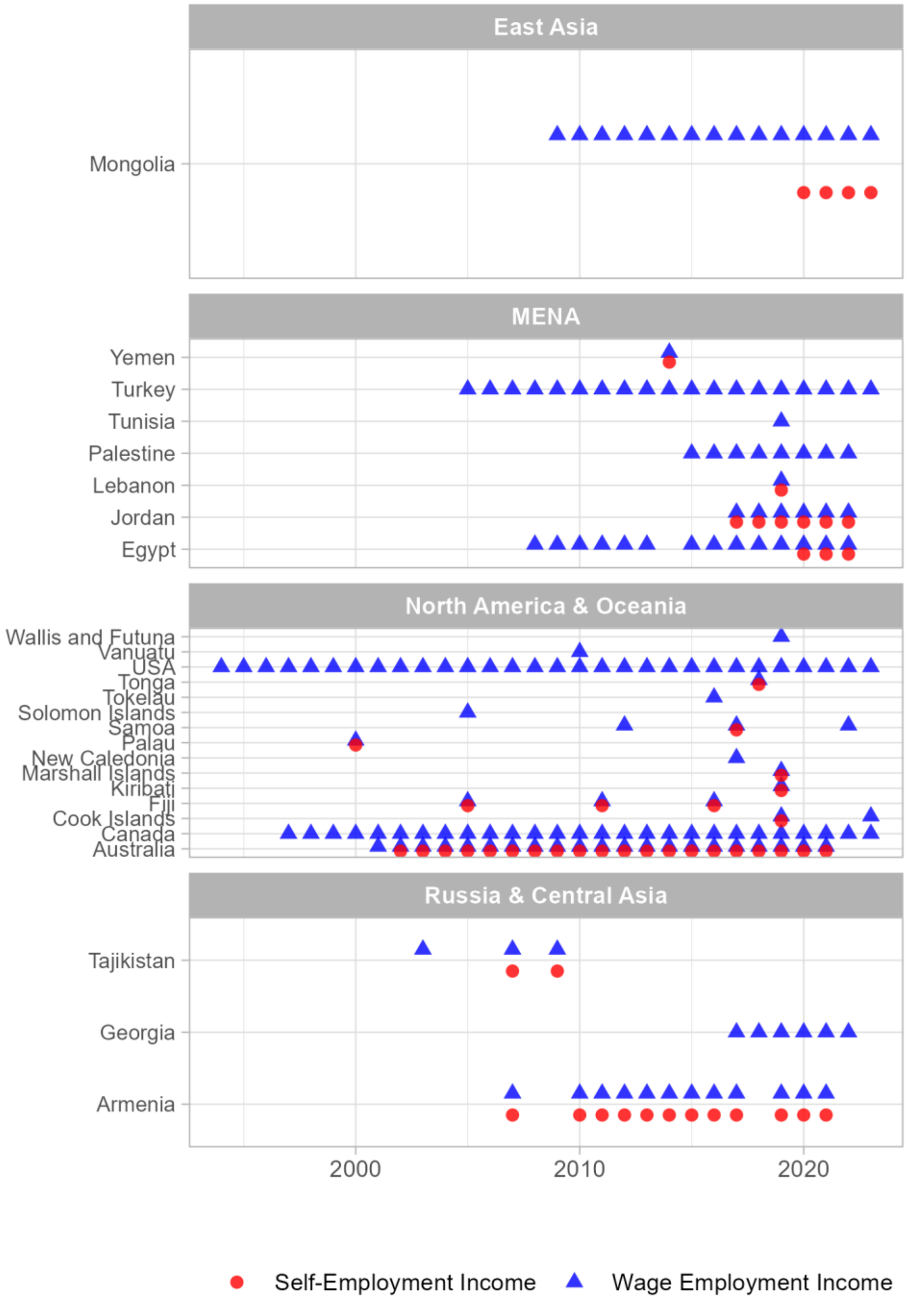
Figure A.3: ILO Harmonized Microdata Repository: Coverage individualized wage and self-employment income data

Panel A.

Panel B


South & South-East Asia
Viet Nam
Timor-Leste
Thailand
Sri Lanka
Philippines
Pakistan
Nepal
Myanmar
Maldives
Lao PDR
Indonesia
India
Cambodia
Brunei Darussalam
Bhutan
Bangladesh
Afghanistan
Sub-Saharan Africa
Zimbabwe
Zambia
Uganda
Togo
Tanzania
Sudan
South Africa
Sierra Leone
Senegal
Sao Tome and Principe
Rwanda
Nigeria
Niger
Namibia
Mauritius
Mauritania
Mali
Malawi
Madagascar
Liberia
Lesotho
Kenya
Guinea-Bissau
Guinea
Ghana
Gambia
Ethiopia
Eswatini
DR Congo
Djibouti
Cote d'Ivoire
Congo
Comoros
Chad
Cameroon
Cabo Verde
Burundi
Burkina Faso
Botswana
Benin
Angola
1990
2000
2010
2020
Self-Employment Income
Wage Employment Income

Panel C



Notes: This figure shows country-year observations with information on wage income (red) and self-employed income (blue) available in the ILO Harmonized Microdata Repository. Individualized income data is available for 144 countries, covering various years between 1990 and 2024.

Appendix B: Methodological Discussion China

B.1: CHIP Raw Variables Definitions

1988 Rural

wage: indicates wage income from employer
typeem: type of employment (5 = self-employed, 9 = farmer)
ami88, tnri88, oci88, olci88: monthly and irregular wage income components
grost: gross income from farming
gsidei: gross income from sideline activities

1988 Urban

v112: current employment status
v115: type of employment
v201–v207: monthly wage components
v208–v212: annual bonus/allowance/cash-in-kind components
v218: net income before taxes from self-employment

1995 Rural

b107: employment activity
b113: workplace ownership (1 = farm, 3 = self-employed)
b201–b208: wage income components
b501_1/2: farming gross income and costs
b502_1/2: non-farm self-employment gross income and costs

1995 Urban

a6: employment status
a29: tenure of employment
a52, a62: wage components
a64–a66: self-employment income

2002 Rural

p1_7: employment status
p1_67_1: occupation code
p1_30/32/34/36: agriculture time indicators
p1_43: total wage income
h1_401_1/2: farming income and cost
h1_402_1/2: non-farming self-employment income and cost

2002 Urban

p107: employment status
p141: occupation category
p201: declared income (used for pwage/pself)

2007 Rural

a17: employment status
c26: type of non-agricultural job
c07: industry (used to infer farming)
c18: monthly income

2007 Urban

a17: employment status

c22: job contract type

c17: total monthly income (in yuan)

g105: family business income

2013 Rural

a19: employment status

b01_1: engaged in farming

b02_1: engaged in wage work

b03_1: engaged in business

b01_2/3, b02_2/3, b03_2/3: hours and days for share calculation

c05_1: total income from job

2013 Urban

a19: employment status

c03_1: employment type

c03_3: industry (1 = agri/fish/etc)

c05_1: income from job

2018 Rural

a20: employment status

b01_1: engaged in farming

b02_1: engaged in wage work

b03_1: engaged in business

b01_2/3, b02_2/3, b03_2/3: time/hours for income share

c05_1: income from job

2018 Urban

a20: employment status

c03_1: employment type

c03_3: industry (1 = agri/fish/etc)

c05_1: income from job

B.2: Harmonized Variable Construction

Year	Area	Variable	Definition
1988	Rural	wage	original variable
1988	Rural	self	typeem == 5
1988	Rural	farm	typeem == 9
1988	Rural	pwage	12*ami88 + tnri88 + oci88 + olci88
1988	Rural	pself	selfadult*gsidei / sum(selfadult)
1988	Rural	pfarm	farmadult*grost / sum(farmadult)
1988	Urban	wage	v115 in (3,4,6,7)
1988	Urban	self	v115 in (1,2,5)
1988	Urban	pwage	12*(v201+v202+v203+v204+v205+v206+v207)+v208+v209+v212
1988	Urban	pself	v218
1995	Rural	wage	b107==2
1995	Rural	self	b107==1 & b113==3
1995	Rural	farm	b107==1 & b113==1
1995	Rural	pwage	b201 + 12*b202 + b203 + b204 + b205 + b206 + b207 + b208
1995	Rural	pself	selfadult*(b502_1 - b502_2) / sum(selfadult)
1995	Rural	pfarm	farmadult*(b501_1 - b501_2) /sum(farmadult)
1995	Urban	wage	a29 in (1,2,3)
1995	Urban	self	a29 == 4
1995	Urban	pwage	a52 + a62
1995	Urban	pself	a64 + a65 + a66
2002	Rural	wage	p1_67_1 in (2,3,4,6,7,8,9,10,12)
2002	Rural	self	p1_67_1 in (5,11)
2002	Rural	farm	(p1_30 + p1_32 + p1_34 + p1_36) > 0
2002	Rural	pwage	p1_43
2002	Rural	pself	selfadult*(h1_402_1 - h1_402_2) / sum(selfadult)
2002	Rural	pfarm	farmadult*(h1_401_1 - h1_401_2) / sum(farmadult)
2002	Urban	wage	p141 in (3,4,5,6,7,8,9)
2002	Urban	self	p141 in (1,2,10)
2002	Urban	pwage	wage*p201
2002	Urban	pself	self*p201
2007	Rural	wage	c26 == 2
2007	Rural	self	c26 in (1,3)
2007	Rural	farm	a17 == 1 & c07 in (2,3)
2007	Rural	pwage	12*c18
2007	Rural	pself	12*c18 (self-employed only)
2007	Rural	pfarm	not available => imputed

2007	Urban	wage	c22 in (1,2,3,4,5,7)
2007	Urban	self	c22 == 6
2007	Urban	pwage	12*c17
2007	Urban	pself	selfadult*g105 / sum(selfadult)
Year	**Area**	**Variable**	**Definition**
2013	Rural	wage	b02_1 == 1
2013	Rural	self	b03_1 == 1
2013	Rural	farm	b01_1 == 1
2013	Rural	pwage	wage*c05_1
2013	Rural	pself	selfadult * sum(selfadult*c05_1) / sum(selfadult)
2013	Rural	pfarm	not available => imputed
2013	Urban	wage	c03_1 == 2
2013	Urban	self	c03_1 in (1,3,4)
2013	Urban	pwage	wage*c05_1
2013	Urban	pself	selfadult * sum(selfadult*c05_1) / sum(selfadult)
2018	Rural	wage	b02_1 == 1
2018	Rural	self	b03_1 == 1
2018	Rural	farm	b01_1 == 1
2018	Rural	pwage	wage*c05_1
2018	Rural	pself	selfadult * sum(selfadult*c05_1) / sum(selfadult)
2018	Rural	pfarm	not available => imputed
2018	Urban	wage	c03_1 == 2
2018	Urban	self	c03_1 in (1,3,4)
2018	Urban	pwage	wage*c05_1
2018	Urban	pself	selfadult * sum(selfadult*c05_1) / sum(selfadult)

B.3: Estimated aggregate values for employment and incomes

Table B1: Employment by sex and employment type

```
. tabstat wage farm self if male==0 [fw=round(weight)], by(year) s(sum)

Summary statistics: Sum
Group variable: year
```

year	wage	farm	self
1988	8.47e+07	2.25e+08	2563770
1995	1.53e+08	1.95e+08	3513880
2002	1.43e+08	1.59e+08	1.21e+07
2007	1.94e+08	1.28e+08	2.13e+07
2013	2.18e+08	6.56e+07	4.04e+07
2018	2.26e+08	5.87e+07	5.08e+07
Total	1.02e+09	8.31e+08	1.31e+08

```
. tabstat wage farm self if male==1 [fw=round(weight)], by(year) s(sum)

Summary statistics: Sum
Group variable: year
```

year	wage	farm	self
1988	1.02e+08	2.14e+08	8184395
1995	1.89e+08	1.93e+08	6485432
2002	2.28e+08	1.37e+08	2.28e+07
2007	2.74e+08	1.16e+08	3.85e+07
2013	3.23e+08	4.47e+07	5.84e+07
2018	3.28e+08	4.31e+07	7.27e+07
Total	1.44e+09	7.48e+08	2.07e+08

Table B2: Incomes by sex and employment type

```
. tabstat pwage pfarm pself if male==0, by(year) s(sum) f(%15.0fc)

Summary statistics: Sum
Group variable: year
```

year	pwage	pfarm	pself
1988	142,682	152,585	2,789
1995	687,663	430,459	14,086
2002	1,295,651	489,769	76,284
2007	3,948,794	1,109,154	401,657
2013	6,136,903	847,209	1,278,591
2018	9,290,189	973,084	2,317,870
Total	21,501,882	4,002,260	4,091,276

```
. tabstat pwage pfarm pself if male==1, by(year) s(sum) f(%15.0fc)

Summary statistics: Sum
Group variable: year
```

year	pwage	pfarm	pself
1988	205,845	138,704	12,462
1995	1,124,136	417,296	32,695
2002	2,260,621	395,222	178,236
2007	7,228,751	983,239	1,126,666
2013	11,162,318	575,694	2,362,169
2018	16,792,529	742,035	4,506,120
Total	38,774,201	3,252,189	8,218,346

Source : CHIP data and authors' computation.