the review of income and wealth

Review of Income and Wealth
Series 66, Number 3, September 2020
DOI: 10.1111/roiw.12424

MEASURING THE LABOR INCOME SHARE OF DEVELOPING COUNTRIES: LESSONS FROM SOCIAL ACCOUNTING MATRICES

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This paper addresses the challenges of measuring the labor income share of developing countries. The poor availability and reliability of national account data as well as the fact that self-employed—whose labor income is hard to capture—account for a major share of the workforce and often work in the informal sector render its computation difficult. Consequently, measuring the labor share requires assumptions. I consult social accounting matrices in addition to national account data to gain information on the production structure and self-employed incomes in developing countries. The final data set covers about 90 developing countries from 1990 to 2011. The data suggest that the finding of declining labor shares of previous studies also applies to the sample of low and middle-income countries. Furthermore, I find the labor share in developing countries to be about one-half in size and hence less than the standard "two-thirds" in economic literature.

JEL Codes: D33, E01, O10

Keywords: factor income distribution, economic development, labor share, national accounts

1. INTRODUCTION

The labor income share is a measure of the factor income distribution and reflects how much of national value added accrues to labor (as opposed to capital and land). Dynamics in the factor income distribution are of particular relevance for developing countries, especially in their effort to fight poverty. The main asset of the poor certainly is labor, usually in form of agricultural self-employment (Fields, 2014, WB, 2006 and 2013). Hence, regressive redistribution of factors and their remuneration will be felt strongly in these countries due to weak social safety nets and limited capital access of the poor.

Measuring the labor share, however, is notoriously difficult in the context of low and middle-income countries. Most studies rely on the relation of compensation of employees (CoE) to GDP from national account statistics when measuring the labor share. A key problem of this simple definition is the fact that CoE does not include the labor income of the self-employed. They, however, account for the major fraction of the labor force in developing countries[1] (WB, 2013, ILO, 2015). An additional difficulty arises from the fact that self-employment in developing

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[1]In this paper, the term "developing countries" refers to both low and middle-income countries.

countries is often located in the informal sector. As data on the number of self-employed, their income and labor component is deficient for these countries, adjusting the labor share for the self-employment sector requires making assumptions. The fact that the economic structure of developing countries fundamentally differs from the ones of high-income economies makes separate assumptions necessary. For example, self-employed in OECD countries are more likely to have consciously decided to enter self-employment while it may well be a business out of necessity for workers in the developing world (Günter and Launov, 2012). Eventually, developing countries give reason for concern about the scope, detail and quality of their national accounts (UN, 2012). The adjustment of the labor share hence requires more prudent handling in the case of low and middle-income countries.

This paper presents a data set on the labor income share in developing countries, which addresses these issues. As national accounts have data gaps regarding the (informal) self-employment sector and may suffer from measurement errors, I consult social accounting matrices (SAMs) as additional source of information to increase the reliability of labor share data constructed at the aggregate level. SAMs represent the economic cycle in matrix form and integrate information from various data sources besides national accounts, such as input-output tables and household surveys. As they keep disaggregated information (e.g. income by household group or industry), they reveal more information on distributional aspects than national accounts. SAMs further connect the distribution of incomes with the production structure of an economy and hence deliver insights into the contribution of each production factor to national income (Keuning and de Ruuter, 1988). This paper uses SAMs to give guidance in two ways: First, three representative SAMs serve as case studies to open the "black box" of national accounts, to obtain knowledge about the revenues of self-employed in developing countries and how these break down into capital and labor income. These insights are used to formulate assumptions that are necessary to compute labor share data at the aggregate level. This leads to the choice of agricultural employment share as a proxy for self-employed workers, assuming that they earn the same average wage as wage employees or—in case of low and lower middle income countries in South Asia and Sub-Saharan Africa—half of the average wage. Second, a pool of 51 SAMs for 45 developing countries (taken from UN DESA and IFPRI) covering the period 1991-2008 is compared to the final labor share data set to check the validity of estimates obtained from national account data. By this means, the information content of national accounts and SAMs can be exploited in a meaningful manner.

The final data set covers about 90 developing countries spanning the period 1990–2011. The recent economic literature identified a decline in labor shares in high-income countries and on the global level. This finding also applies to the specific sample of low and middle-income countries as the data suggest that labor's relative income in developing countries has been declining by on average 11 percentage points since the early 1990s. While this seems to be independent of a country's development stage, a high share of natural resource rents in GDP has a significant negative impact. Furthermore, I find the labor share in developing countries to be about one-half in size and hence lower than in high-income countries.

The paper is organized as follows. Section 2 presents the concept of the labor share and elaborates on its measurement using national accounts. Existing data sets are reviewed in section 3. Section 4 discusses the challenges associated with measuring the labor share of developing countries from national accounts. Section 5 performs three case studies using SAMs to extract information about the self-employed and their labor income. Findings are used to formulate the necessary assumptions when constructing labor share data from national accounts in the following step (section 6). Section 7 validates the data by comparing it to a pool of 51 SAMs and section 8 presents some properties of the data set. Section 9 concludes.

2. The Labor Share: Concept and Measurement

The labor share reflects how much of national income is earned by labor. Assuming that value added, or production output, is given by $Y = f(K, L)$, where K is capital (including land) and L labor (including human capital) used in production, the income distribution between production factors is given by:

$$Y = \frac{w}{P} \times L + \frac{i}{P} \times K, \tag{1}$$

where w is wage, i the interest rate, and P the price level. The labor share LS then can be expressed as:

$$\mathrm{LS} = \frac{w \times L}{P \times Y} \tag{2}$$

The labor share can be computed from national accounts. The empirical literature usually starts out from the relation of CoE to total value added produced in the respective country (GDP):

$$\mathrm{LS_n} = \frac{\mathrm{CoE}}{\mathrm{GDP}} \tag{3}$$

Data is provided by the United Nations System of National Accounts (UN SNA) and is accessible through the National Accounts Official Country data.[2] This simple measurement, however, tells only half the story and is often referred to as the *naïve labor share* (LS_n). As pointed out by Krueger (1998) and Gollin (2002), CoE merely covers wage earners in the corporate sector and ignores self-employment. The challenge with self-employed income is that it consists of income from labor as well as from capital so that its labor component needs to be filtered out in a first step. Due to the poor data situation in developing countries, this is a tricky task. If it is not corrected for self-employment, however, self-employed income would be mistakenly treated as only consisting of capital income, resulting in a downward bias of the labor share. Furthermore, in a dynamic perspective,

[2]The UN SNA has undergone several revisions (1968, 1993 and 2008). These always came along with new standards, also affecting major aggregates such as GDP and its income components. Different series hence might imply different data.

ceteris paribus shifts in the composition of employment would automatically change the labor share. For example, when formerly self-employed enter wage employment—in developing countries, this typically is the movement away from subsistence agriculture to the corporate sector—their labor income suddenly appears in employee compensation statistics, raising the labor share, even though their labor income has effectively not changed (or only very little). Gollin (2002) therefore came up with three possible approaches to adjust the naïve labor share for self-employed labor income, relying on three different assumptions.

Gollin's first two adjustments make use of the item mixed (MI) income listed in the UN SNA. MI refers to the remuneration of the self-employed and—as the term already suggests—includes income from labor and capital (UN, 2009). By using this item and filtering out its labor income component, which is then added to employee compensation, a meaningful measure of the labor share can be obtained.

In his *first adjustment*, MI is simply added to CoE, assuming income of the self-employed to be only composed of labor income:

$$LS_{G1} = \frac{\text{CoE} + \text{MI}}{\text{GDP}} \tag{4}$$

As this procedure ignores self-employed income from other factors of production than labor, it is likely to overestimate the labor share.

His *second adjustment* assumes self-employed income to consist of the same mix of labor and non-labor income as the rest of the economy:

$$LS_{G2} = \frac{\text{CoE}}{\text{GDP - MI}} \tag{5}$$

This approach is more straightforward but disregards that capital and labor shares might vary substantially across sectors and with the size and structure of businesses.

Gollin's *third adjustment* draws on data on the employment structure of a country. Relying on the assumption that self-employed earn the same labor income as employees, it imputes the average wage bill of employees (*E*) to the self-employed. Only income of the self-employed that exceeds the mean wage sum is counted as income from capital:

$$LS_{G3} = \frac{\frac{\text{COE}}{\text{E}}}{\frac{\text{GDP}}{\text{TE}}} = \frac{\text{COE}}{\text{GDP}} \times \frac{\text{TE}}{\text{E}}, \tag{6}$$

where TE is total employment. This adjustment does not take into consideration that self-employed and wage earners might work in different sectors, realizing different labor productivities. For example, if self-employment mainly occurs in subsistence farming and other low-productive activities, as it is typically the case in developing countries, this equation systematically overestimates the labor share. To account for such systematic differences, some studies (Arpaia *et al.*, 2009, OECD, 2012, and others) use average sector wages to impute the income of the self-employed per sector. Such detailed data is, however, only available for OECD countries (for example in the EU KLEMS data).

Gollin (2002) finds labor shares to be more or less constant across time and space when applying his adjustments and therefore suggests to adhere to models using a Cobb-Douglas production technology.[3] He finds the labor share to range between 60 and 85 percent. His results are, however, based on a small sample of 31 high and low income countries observed at only one point in time. Recent studies challenge these findings, as reviewed in the next section.

3. Data Review

Aside from Gollin (2002), various international organizations as well as researchers have taken up the analysis of trends in labor shares. The majority of the empirical literature (Arpaia *et al.*, 2009; Bentolila and Saint-Paul, 2003; Blanchard, 1997; Daudey and García-Peñalosa, 2010; Ellis and Smith, 2007; Elsby *et al.*, 2013; Guscina, 2006; Hutchinson and Persyn, 2012; IMF, 2007; Jaumotte and Tytell, 2007; OECD, 2012 and Slaughter, 2001) is restricted to OECD countries, where data quality as well as coverage is high and data on employment structure and mixed income available. They rely on the naïve labor share or, additionally, Gollin's third adjustment, as it is for example provided in the European Commission's AMECO database. Piketty (2014) adopts an entirely different approach and uses tax data to study the distribution of top incomes and capital gains.[4] His study is restricted to around 30 countries, mainly from the Western Hemisphere that provide income tax data. When he splits mixed income between capital and labor income, he relies on Gollin's second adjustment.

There are some broader studies (for example, Bernanke and Gürkaynak, 2001, Diwan, 2001, Guerriero and Sen, 2012, Harrison, 2005, Jayadev, 2007, Karabarbounis and Neiman, 2014, Rodriguez and Jayadev, 2010, Stockhammer, 2013) that conduct worldwide analyses including a number of developing countries. Like the recent study by Karabarbounis and Neiman (2014), they mainly base their analysis on the naïve labor share. As data are lacking, applying one of Gollin's adjustments (usually, the first or third) comes with the consequence that only a few developing countries remain in the sample.[5] Some other studies (Ortega and Rodriguez, 2001; Decreuse and Mareek, 2015) use the UNIDO INDSTAT dataset that, however, only measures the labor share in the corporate manufacturing sector. The ILO Global Wage Database, the ILO/IILS data and the Socio Economic Accounts of the World Input Output Database [WIOD SEA] are additional data sources. Likewise, they provide adjusted labor shares only for a handful of developing countries.

With adjusted labor share data for 127 low, middle and high-income countries for at least 20 years, the Penn World Table (PWT) is the largest provider of data on global labor share trends.[6] By using data on total agricultural value added as a

[3]Due to its assumption of constant output elasticities and factor remuneration according to productivity, the Cobb-Douglas production technology predicts factor shares to be constant over time.

[4]Available in the World Top Income Database.

[5]For example, when Rodriguez and Jayadev (2010) adjust their naïve labor share dataset of 135 countries for mixed income, their sample size sharply reduces to 59 (mainly high-income) countries.

[6]It publishes labor share data since its version 8.0 released in 2013.

proxy for the labor component of MI, Feenstra, Inklaar and Timmer (2015) are able to increase the number of sample countries by about 60. Time and country coverage is further extended by interpolating and keeping labor shares constant over time. They develop a "best estimate" labor share that chooses the most appropriate from the three Gollin adjustments according to three rules, which are based on a country's data availability and plausibility. The final labor share data for low and middle-income countries eventually mainly relies on LS_{G2}. In 45 percent of cases, mixed income is available and used, assuming that self-employed mixed income has the same labor share. Where MI is not available (in 49 percent of cases), agricultural value added is taken as proxy for the labor component of mixed income (see Section 4 for a discussion of the suitability of this proxy). In the few remaining cases, they hold on to the naïve share when it exceeds 70 percent and prefer LS_{G3} in case this yields lower estimates than LS_{G1} (given the risk of overestimation).

In contrast to Gollin's results, all studies find the labor share to be decreasing in most of the high income countries in the past forty years, regardless of how labor's share in national income is measured. The global studies confirm this decline and hence indicate also a negative trend for the developing world since 1990. The labor share is also found to be less than the ubiquitous "two thirds" on the global level. For example, it averages 52 percent and 46 percent in the PWT and in Harrison (2005), respectively.

To date, the PWT are the most comprehensive data set for labor shares of developing countries. They are a good starting point, but there is room for precision for the specific sample of low and middle-income countries: Most importantly, as measuring the labor share of developing countries depends on deficient national account data and necessitates making a set of assumptions, databases should verify their results, for example by checking them against country- or region-specific data (especially when proxies are used). Furthermore, studies may not adequately account for systematic differences between industrialized and developing economies when applying the same assumptions for a global sample. Therefore, value may be added to the existing data by using a separate empirical investigation.

In view of this, my dataset contributes to the literature in three respects: First, it draws upon additional information from SAMs to increase the reliability of data on the labor share based on national accounts. Qualitative information from case studies and quantitative information from cross-country data is used to formulate assumptions and to check the validity of the final data. Second, my data builds on as few assumptions as possible. The PWT interpolates missing observations and assumes labor shares to be constant at the start and end points. Especially the latter can be misleading in light of the increasing evidence of non-constant labor shares.[7] Third, my data set is limited to low and middle-income countries, allowing to better consider differences owed to a country's development status when constructing the labor share. Besides, I provide additional information on the series of the UN SNA used to take the differences between the 1968, 1993 and 2008 series into account.

[7]Users of the data set should therefore consider to drop inter- and extrapolated data points.

4. Measurement Challenges

Constructing a macro-level panel data set on the labor share of developing countries is hampered by the limited availability and reliability of national account data in these countries. Data on MI (required for LS_{G1} and LS_{G2}) is only provided by about one third of low and middle-income countries that also report CoE; and even basic figures such as the self-employment share (required for LS_{G3}) are scarce. This is not surprising in view of the fact that the most prevailing forms of self-employment in developing countries are micro and small enterprises (typically street vendors) and subsistence farmers. These forms of self-employment mostly coincide with informality and therefore usually remain statistically unobserved. UN SNA standards demand to record the so-called shadow economy but due to its very nature national accounting often fails to do so (OECD, 2004). As a consequence, especially national income accounting in Sub-Saharan Africa is fraught with data gaps and inconsistencies which impairs cross-country comparability (Jerven, 2012).

These data constraints require to select proxy variables for either self-employed income or their employment share. This, in turn, involves making assumptions about the composition of total employment or self-employed value added. To extract the labor income of the self-employed and to decide for one of Gollin's adjustments, further assumptions are needed concerning self-employed factor intensities and productivities. This dependence on assumptions, coupled with the poor data situation, suggests that data compilation at the macro-level is a delicate issue and may benefit from additional information sources.

Choosing a proxy in the context of developing countries takes place against the background that an average of about two thirds and up to 90% of the working population is self-employed, with most of them being vulnerable and belonging to the informal sector (ILO, 2014). The PWT use total value added in agriculture as proxy for self-employed labor income, building on the assumption that most of self-employed income stems from agricultural production, with labor being by far the most important input factor (Feenstra *et al.*, 2015). This proxy is plausible, yet it disregards capital, especially land, as agricultural production factor and counts labor income of agricultural employees twice (Feenstra *et al.*, 2015). In a dynamic perspective, it cannot capture the process of industrialization of agriculture, resulting in an increasing capital share in agricultural value added over time. This proxy hence is likely to lead to an overestimation of the labor share. On the downside, this proxy leaves aside labor income from other forms of self-employment, which scope should be, however, relatively low in the developing world.

To meet these challenges, the next section explores SAMs as additional sources of information before turning to the formulation of assumptions and deciding on proxies.

5. Social Accounting Matrices

In contrast to national accounts, which represent the economy in the form of double entry bookkeeping, a SAM displays flows of all economic transactions in a matrix representation. SAMs are constructed by matching, complementing and balancing various data sources, such as national accounts, input-output tables, labor force surveys and household surveys. SAMs hence bridge production and income data collected from various origins at the meso- and macro level. Pyatt, who introduced SAMs to the World Bank in the 1960s, and others therefore stress the role SAMs can play in improving the quality of national accounts (Pyatt and Round, 1985) and supplying additional information on distributional issues (Keuning and de Ruuter, 1988).

The composition of SAMs often starts out from input-output tables that are then supplemented in various ways: National accounts and balance-of-payments data contribute national aggregates, expenditure flows in the input-output table are usually linked to labor force surveys and income flows to household surveys (Keuning and de Ruuter, 1988). This also allows determining the factor shares of an economy—an important advantage of SAMs when measuring the factor income distribution. National accounts should deliver information on compensation of employees, mixed income of self-employed and property and transfer incomes. However, as has been mentioned before, mixed income is not split into capital and labor income and especially data on mixed, property and transfer income is often not available for developing countries. By using additional data sources and sector-specific technology coefficients from input-output tables and information on sectoral output from national accounts, SAMs can split value added into capital and labor income (Breisinger *et al.*, 2010). This cannot only be done for the corporate sector but also for the self-employed given that labor force surveys can identify the sectors of the self-employed and household surveys how much self-employed earn with their businesses. This information can be used as basis for estimating the labor income of the self-employed. Another method to split mixed income into its capital and labor component—which GTAP (Ivanic, 2004 and Yusuf, 2006) prefer—is to impute wages of employees to the self-employed when working hours, sector and qualification of both are available.

In theory, a SAM always balances, but in the empirical practice, it never does from the outset. This is due to several reasons: (1) The data stems from different sources, (2) national accounts are often inconsistent in developing countries and (3) SAMs require converting every item into money flows. For this reason, statistical methods are needed to adjust the unbalanced SAM. The fact that SAMs reveal inconsistencies and require reconciling different data sources can constitute an important advantage over national accounts. Given that balancing methods can minimize measurement errors and other sources of inaccuracy, their comparative reliability is likely to be higher. The most frequent method to balance inconsistencies in the data is the cross-entropy approach. This method is based on information theory and minimizes the cross-entropy of the distance between the original and a newly estimated SAM (Fofana et al., 2005). The advantage of this method is that it can start from inconsistent data (estimated with error) and thus can deal with the poor data situation of developing countries (Robinson *et al.*, 2001). Furthermore, the approach makes use of all available information and not only the sums of rows and columns (ibid.). It hence can balance a SAM in a flexible and efficient way when facing scattered, sparse and even inconsistent data. A drawback of this method is that it does not allow including judgments on the relative reliability of the various data sources used, as for example the Stone-Byron method does

(Round, 2001). Round (2001) and Fofana et al. (2005), who discuss different balancing methods, conclude that neither method is perfect and that users should consider it together with the source data.

A disadvantage of SAMs is that their comparability across countries is limited (Pyatt and Round, 1985). This is because SAMs are composed individually by country, according to available data sources. Hence, also SAMs, which stem from the same origin that has applied the same rules and balancing methods, are only partially comparable. Unfortunately, SAMs are also not available at large scale. But the International Food Policy Research Institute (IFPRI) and the UN Development and Analysis Division (UN DESA) provide data for several developing countries. In addition, there are a number of country case studies available from various sources.

5.1. *Three case studies: Indonesia, Zambia and Bolivia*

In a first step, I take a closer look at three SAM case studies that have a distributional focus, include an analysis of self-employed and their factor income and hence are a useful source of qualitative information on self-employment in developing countries. Studies on Zambia (Thurlow et al., 2004), Indonesia (Yusuf, 2006) and Bolivia (Thiele and Piazolo, 2002), which represent the three major developing regions Africa, Asia and Latin America, are chosen for this exercise.

The Bolivian SAM indicates how the labor income of the self-employed compares to employees' wages. It does, however, not split mixed income of the self-employed into capital and labor income as the SAMs for Indonesia and Zambia do. The Indonesian SAM calculates the labor income of the self-employed by wage imputation (Yusuf, 2006). To do so, the work time of the self-employed is multiplied by the average wage of employees for that time who work in the corresponding sector and have the same type of skill. Capital income is the residual when subtracting this amount from household business net revenue. This procedure yields a relatively low labor share for the self-employed of 45 percent. Self-employed mixed income makes up 40 percent of total household incomes and their labor share in the whole economy hence amounts to 18 percent (see Table 1). By contrast, the national labor share is 65 percent. In case of the Zambian SAM, self-employed labor income is determined by applying the sectoral capital-labor ratios taken from the input-output table to mixed income, unfortunately without reporting the disaggregated results (Thurlow *et al.*, 2004). The economy-wide labor share amounts to 46 percent (see Figure 1).

As can be seen in the SAM of Bolivia for 1997 (Table 2), self-employed earning mixed income mostly work in traditional agriculture, they are smallholder farmers. Outside agriculture, self-employed primarily work in the service sector. There, it usually takes the form of own-account enterprises that engage in wholesale, retail or hospitality. A smaller share earns income from light manufacturing (for example of consumer goods), especially in rural areas where processing of agricultural products is common. Self-employed earning profits (i.e. employers) are mostly active in modern agriculture, light manufacturing and the service sector (mainly

TABLE 1
Factor Incomes and Shares of the Self-Employed (%) Across Sectors in Indonesia, 1997

Income source	Income shares	Factor shares
Labor	*82.4*	*65.4*
Wage employment	42.2	47.9
Agriculture		4.9
Production		16.8
Services		16.1
Professional		10.1
Self-employment	40.2	17.6
Agriculture		6.8
Production		4.0
Services		6.5
Professional		0.3
Non-labor	*17.6*	*23.6*
Total (%)	100	100

Source: Author's calculation [based on Yusuf (2006), Table 4].

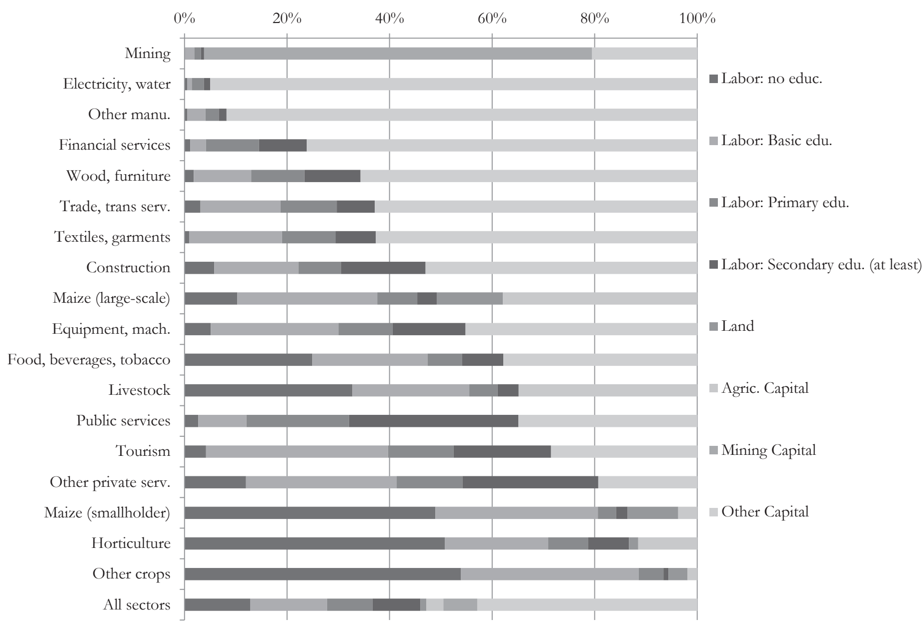

Figure 1. Factor employment across sectors in Zambia, 2001.
Source: Author's illustration [based on Thurlow et al. (2004), Table 5.6].

transport and finances). On the other hand, self-employment hardly appears in the sectors of heavy manufacturing and processing of fossil resources.

It is furthermore observed that sectors in which self-employment prevails are labor-intensive sectors. For example, in the Indonesian SAM for 2003, the labor share in the hospitality sector is 80 percent, in the agricultural sector 65 percent and in the retail sector 58 percent (Yusuf, 2006). At the same time, mining has with 15 percent the lowest labor share (Yusuf, 2006). A similar picture emerges from the SAM of Zambia for 2001 (see Figure 1). Furthermore, in a given sector, the

TABLE 2
Distribution of Factor Incomes (%) Across Sectors in Bolivia, 1997

Sector	Mixed income	Employers' profits	Salary and wages	Capital income
Trad. Agriculture	38	0	0	0
Modern Agriculture	0	11	9	8
Informal service sector	28	0	0	0
Formal service sector	16	55	22	44
Capital goods	0	0	1	0
Consumer goods	8	17	13.5	14
Intermediate goods	1	9	6	7
Construction	4	2	6.5	2
Mining	5	7	5	5
Oil and gas	0	0	4	7
Electricity, gas and water	0	0	2	13
Public sector	0	0	31	0
Total (%)	100	100	100	100
Total (Mio. Bolivianos)	10766	7156	12156	5839

Source: Author's calculation [based on Thiele and Piazolo (2002), Table 6].

self-employed seem to pursue a more labor-intensive strategy than larger firms. The employment of agricultural capital and hence the capital share increases with farm size: In the case of maize agriculture, labor makes up 87 percent of all factor inputs on small-scale farms but only 49.2 percent on large-scale farms.[8] Assessing skills, there is evidence that self-employed are less educated than the rest of the workforce, suggesting that they are less productive per unit of labor. First, within the same sector, own-account workers pursue a less skill-intensive strategy than large firms. As can be seen in Figure 1, most of labor in smallholder farming is uneducated, whereas the skill content of labor is higher for larger farms. Second, self-employed work in sectors where unskilled labor prevails (Yusuf, 2006).

As can be seen in Figure 2, smallholders and urban own-account workers—who represent the bulk of self-employed—are the most worst off, suggesting a relatively low labor income (besides a low income from capital). An exception are urban employers who realize the highest income, mainly from capital; they are small in number though. The average wage employee earns more than the average self-employed, suggesting that own-account enterprises are less productive than their larger counterparts (which is mainly due to their low educational attainment and limited access to capital).

What can be learnt from these case studies regarding self-employed labor income? Most importantly, the level of self-employed labor-income primarily depends on the type of self-employment. Rural own-account workers have high labor shares but earn relatively low incomes, such that their labor income is likely to be lower than that of wage employees. Urban own-account workers earn more than their rural counterparts, their labor shares are high when they work for example in the service sector and lower if they are manufacturing entrepreneurs. Employers seem to be above average earners; they do not only earn mixed income but also profits. How high the labor incomes of employers and urban own account workers are in relation to employees hence is not clear from the outset, they could be higher, equal or lower, depending on their skills and the sector in which they work. How employees' labor incomes relate to self-employed labor income on the national level hence crucially depends on the employment structure of an economy. Figure 3 therefore shows the share of employees, employers, own-account and contributing family workers across income groups and regions in 2010. As can be seen, the share of vulnerable (self-)employment (i.e. own-account and contributing family workers) is about 80 percent in low-income countries; here only 2 percent of all self-employed are employers. The share of self-employment (and its vulnerability share) decreases in the course of development such that in upper middle-income countries, self-employed only make up 36 percent of all employed, about 6 percent of them being employers. The share of vulnerable self-employment is especially high in Sub-Saharan Africa and South Asia. Furthermore, own-account workers in low-income countries mostly run rural subsistence businesses, whereas own-account workers in upper middle-income countries are more likely to be urban entrepreneurs, with a high degree of similarity to employers (Cho *et al.*, 2015).

[8]The reason of higher labor intensities in small farms is often seen in the availability of family labor, which gives smallholders easy access to manpower (Wiggins *et al.,* 2010; WB, 2013).

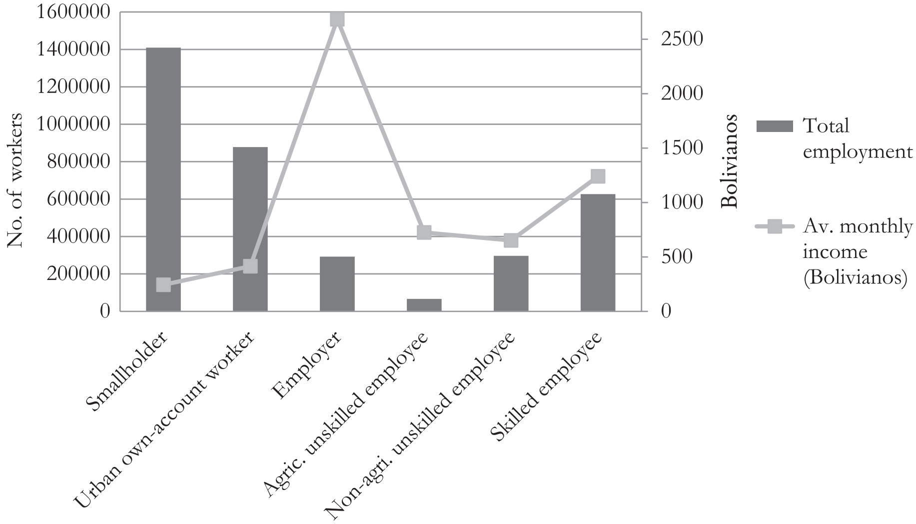

Figure 2. Employment and income by household group in Bolivia, 1997.
Source: Author's illustration [based on Thiele and Piazolo (2002), Table 8].

Of course, these are just individual cases but findings are consistent with the general literature on self-employment in developing countries (for example, Bargain and Kwenda, 2011, Cho *et al.*, 2015, Fields, 2014, Fox and Sohnesen, 2012, ILO, 2016, Kapsos and Bourmpoula, 2013, Mead and Liedholm, 1998 and WB, 2013).

6. Measuring the Labor Share: Steps of Construction

Now having a more precise understanding of self-employment in low and middle-income countries, I turn to the construction of an aggregate labor share data set. As illustrated above, there are mainly three alternatives to adjust the naïve labor share for self-employment, relying on three different assumptions.

As a basis, the naïve labor share is computed from the UN SNA with Formula (3).[9] Data is retrieved from the most recent UN SNA series available.[10] The final labor share data set includes information on the UN SNA series used, as there can be substantial differences between them.

In a next step, the naïve labor share is adjusted for self-employment. *Gollin's first adjustment* treats all self-employed income as labor income. Although SAMs have shown that typical self-employed activities are associated with high labor shares, this approach tends to overestimate the labor share. Studying

[9]National income data can be determined by the income, expenditure or production approach. Data on CoE is calculated by the income approach (or, more precisely, the primary distribution of income accounts). Conversely, I take GDP from the expenditure side, although theoretically producing the same result as GDP coming from the income side. The reason behind is that when using expenditure components (rather than income components) to measure GDP, there is a higher reliability that the informal sector is covered as well (Schneider and Buehn, 2016; US BEA, 2009).

[10]Within a series (1968, 1993 or 2008), I chose the sub-series with the lowest number available. In case this procedure results in different series for compensation of employees and GDP, I adapt case by case to make sure that the same series is used for both items.

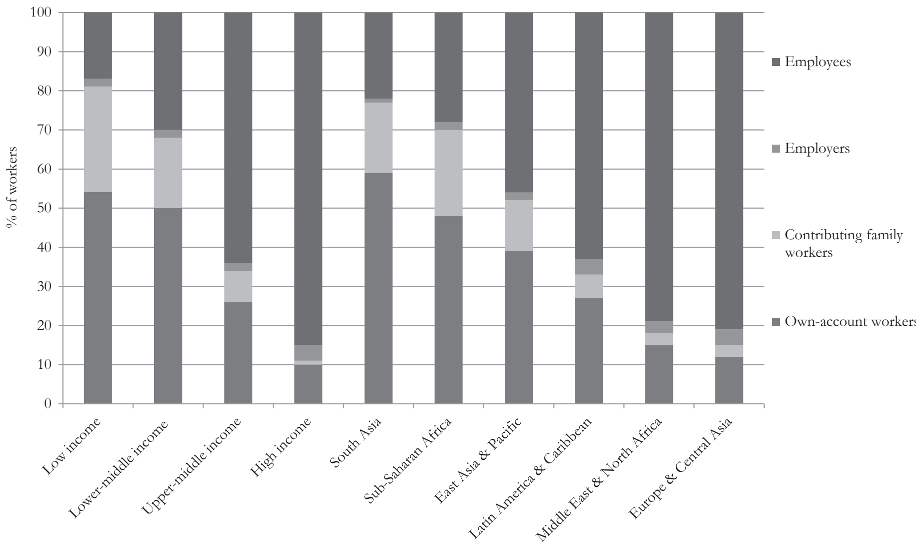

Figure 3. Status in employment across income groups and regions, 2010.
Source: Author's illustration [based on ILOSTAT modeled estimates, 2017].
Note: Self-employment = Own-account workers + Contributing family workers + Employers; Vulnerable employment = Own-account workers + Contributing family workers.

SAMs revealed that there is an (albeit small) non-labor share in smallholder agriculture and that the higher the share of urban own-account workers and employers, the higher the capital share. The next option—*Gollin's second adjustment* – assumes self-employed income to contain the same mix of capital and labor income as the rest of the economy. This, by contrast, rather understates the labor share. It might be appropriate for urban own-account workers and employers but smallholder farmers have much higher labor shares than incorporated businesses. Furthermore, as mentioned above, applying either of these two adjustments shrinks the sample size as only a few developing countries report data on mixed income. *Gollin's third suggestion* uses the share of self-employment in total employment to impute the average wage sum of employees to the self-employed (Formula 6). On the one hand, this method might be appropriate for employers and (successful) urban own-account workers, as it assumes that they earn the same labor income as wage employees. On the other hand, it probably overestimates the labor share in case self-employment mainly occurs in the form of small-scale agriculture. However, by imputing not the total but just a share of employees' wage bill, it can be a meaningful starting point. Data on the self-employment share (not to mention on the types of self-employment) is not available for all low and middle-income countries. Implementing this adjustment therefore requires choosing a proxy that can serve as indirect measure. Building on the analysis above, I select agricultural employment as proxy variable, assuming that most of the self-employed in poor countries are smallholders and most of the farm labor force is self-employed. Certainly, this proxy is more appropriate in

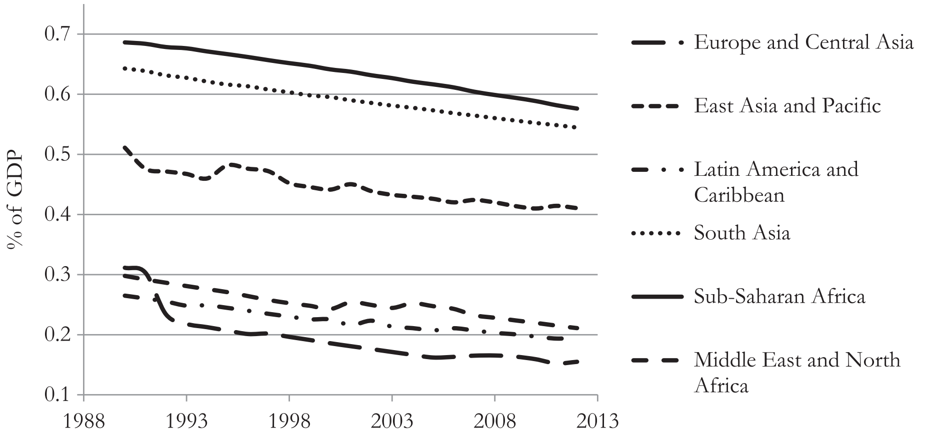

Figure 4. Agricultural employment shares by region, 1990–2012.
Source: Author's illustration [based on FAOStat and WB WDI].

some regions (especially low-income countries) than in others, depending on the sectoral composition of an economy, and disregards self-employed activities other than in agriculture. But the correlation of 0.80 between the self-employment share (taken from ILOSTAT) and the agricultural employment share suggests that it serves as a good proxy. Aside from the high congruence, another strength of this proxy variable is the high availability and quality of data. Data on agricultural employment is provided for almost all developing countries by either the World Bank World Development Indicators (WB WDI) or UN's Food and Agricultural Organization (FAOStat). Figure 4 illustrates the development of the agriculture employment share by region over time. Similar to what we know about self-employment in the developing world, it shows how the importance of agriculture varies across regions and how it declines with the economic development of a country.

The labor income of employees can now be imputed to the self-employed:

$$LS_{G3'} = \frac{\text{CoE}}{\text{GDP}} \times \frac{\text{TE}}{\text{TE - AE}}, \tag{7}$$

where agricultural employment (AE) serves as proxy for self-employment. The full imputation seems to be suitable for many countries: In Eastern Europe, Central and East Asia, Middle East, North Africa, Latin America and the Caribbean this adjustment yields labor shares that range between 17 and 82 percent and average at 50 percent or below. Furthermore, it ranges between Gollin's first and second adjustment for most countries that report MI. I therefore hold on to this adjustment in these countries. At the same time, however, it yields implausibly high values for other countries (for example, 208 percent in China, 1200 percent in Bhutan or 148 percent in the case of Niger). There may be three reasons for this:

(1) countries might already correct for labor income of the self-employed in their reported CoE such that any further amendment would mean a double adjustment; (2) the national account data may contain errors or agricultural employment may be an inappropriate proxy; (3) the assumption behind this adjustment might not hold for all countries.

Bhutan is certainly a case where the national statistics office—contrary to general accounting rules—already corrected for the labor income of the self-employed: Their reported naïve labor share amounts to 91percent. This seems also to be the case for a few other countries. So no further modification is done in countries, where the naïve labor share is already reasonably high (greater than 21 percent) and an imputation of wages would overshoot (greater than 91 percent).[11] A special case are post-Soviet states as they all show a considerable plunge in the naïve labor share in the early 1990s. Behind this fall is not only the heavy economic transformation but also stagnant statistics: suddenly, a previously non-existing shadow economy sprang up in the former Soviet republics which the national statistics offices were not able to capture (Kaufman and Kaliberda, 1996, Johnson *et al.*, 1997). Many formerly official workers began to work as self-employed in the informal economy and no longer appeared in official statistics. To correct for the increasing shadow economy and the related drop in the naïve labor share, I leave the naïve labor share in the years before the plunge so that incorrect upward adjustments are avoided. Most observations with implausibly high labor shares, however, give reason to conclude that the underlying assumption (same labor income of self-employed and employees) is not appropriate. The wage imputation yields very high adjusted labor shares (above 75 percent or even above 100 percent), while the unadjusted shares give reason to conclude that they do not incorporate the self-employment sector (estimates are below 25 percent). This suggests that the actual labor share lies somewhere in between. The cases concerned are the most backward economies—basically countries in Sub-Saharan Africa and South Asia—where most self-employed are low-productive subsistence farmers (Figure 3, FAO, 2012, WB, 2013). For the low and lower middle-income countries from these two regions, it therefore seems reasonable not to impute the full wage sum, but only a share of employees' wages:

$$LS_{G3''} = \frac{\text{CoE} + \frac{\text{CoE} \times \text{AE}}{\text{E}}}{\text{GDP}} \tag{8}$$

Following the insights from SAMs, the self-employed workers are assumed to earn on average half of employees' income. Most of them belong to the vulnerable self-employment sector where workers earn very low (labor) incomes. This assumption is of arbitrary kind, as the exact magnitude of the share depends on the self-employment structure and the corresponding productivity levels in each country, for which data is not available on large scale. However, the resulting estimates appear reliable: They range between 11 and 86 percent in Sub-Saharan Africa and

[11]These marking values stem from the most extreme labor shares observed in SAMs, the naïve share and after Gollin's first and second adjustment.

43 and 74 percent in South Asia, and, where available, move between Gollin's first and second adjustment. Furthermore, the assumption fits to the insights from the analysis of SAMs (see Figure 2). Equation (8) hence provides a practical solution for the above-outlined problems.

After completing these steps, Gollin's first adjustment functions as upper and his second adjustment as lower bound in countries which report MI and in case the so far adjusted labor share exceeds either of these limits.

Table 3 summarizes the resulting labor share and its components. The final data set covers 93 low and middle-income countries from 1990 until 2011 (see Appendix for a list of countries included and the Online Appendix for the final data set). It is an unbalanced panel with in total 1396 observations.[12] The labor share ranges from 6 to 91 percent with a mean and a median of 47 percent. While the PWT labor share is based mainly on LS_{G2}, using in more or less equal parts mixed income and agricultural value added as a proxy for the labor component of MI, my data relies in the majority of cases (two-thirds) on LS_{G3}. LS_{G3} is computed using agricultural employment as proxy and imputing the full average wage of employees to the self-employed in the emerging regions and a fraction of one-half in the less developed regions of South Asia and Sub-Saharan Africa. LS_n is taken in the few cases where it seemingly already has been adjusted for self-employed income. Finally, the data is framed with LS_{G1} and LS_{G2} where available. Due to the systematic differences between self-employed and employees in developing countries, relying on Gollin's third assumption might overestimate the labor share of developing countries (Feenstra *et al.*, 2015). The summary statistics suggest that this is not the case given that in 21 percent of cases LS_{G2} serves as a boundary.

7. Validation of Data

To check the reliability and validity of the macro-level estimates, they are checked against information from SAMs. IFPRI and UN DESA provide 51 SAMs for 45 developing countries.[13] As SAMs disaggregate by production factors, the labor share can be easily extracted by dividing the sum of labor incomes by total factor income. Unfortunately, the size of the data pool is too small to conduct large-scale data analyses across time and space. Nevertheless, the SAMs provide some usable quantitative information about the size and distribution of labor shares in developing countries, which can serve as benchmark. The SAM labor share data (in total 51 observations) range between 24 and 71 percent, with a mean and a median of 46 percent. Figures 5 and 6 provide the probability density function for the SAM data pool, as well as for the naïve, composed and PWT labor share, obtained from Epachenikov kernel density estimates. Figure 5 shows the distribution for a common set of country-year observations (in total 33 observations), whereas Figure 6 shows the same for all available observations. As expected, the distribution of the unadjusted labor share is to the left of the

[12]The PWT data set has more than 50 percent more observations in its sample of low and middle-income countries but this is due to inter- and extrapolation.

[13]To ensure comparability, I restrict the data to SAMs from IFPRI and UN DESA that both apply the cross-entropy approach for balancing inconsistencies between different data sources.

TABLE 3
The Final Labor Share (in %) and its Components

Adjustment	Range	Mean	Median	Obs.	Comments
Final labor share	6.0-90.7	46.5	46.5	1396 (100%)	Composition of the below adjustments
1. Step: Gollin's 3rd adjustment (with agricultural employment as proxy for self-employment)					
a) $LS_{G3'}$	6.0-80.9	46.5	46.3	702 (50.3%)	
b) $LS_{G3''}$	10.5-86.2	47.3	47.4	208 (14.9%)	In low and lower middle-income countries in SA and SSA
2. Step: Use naïve labor share in case it already covers self-employment					
LS_n	13.9-90.7	44.5	40.6	134 (9.6%)	
3. Step: Framing the data with Gollin's 1st adjustment (upper bound) and 2nd adjustment (lower bound)					
a) LS_{G1}	26.2-72.3	51.0	52.9	61 (4.4%)	
b) LS_{G2}	21.0-73.4	46.2	46.3	291 (20.9%)	

Source: Author's calculation [based on UN SNA, FAOStat and WB WDI].

TABLE 4
Regression of Labor Share

Variable	Composed LS	Naïve LS	Composed LS	Composed LS
Fixed effects model				
Time trend	−0.513***[0.080]	−0.252***[0.069]	−0.584***[0.080]	−0.515***[0.076]
GDP p.c. (log)			−0.182 [0.430]	−0.271 [0.474]
Natural resource rents(% of GDP)				−0.197** [0.076]
SNA series	−0.869 [2.380]	−0.987 [1.923]	1.309 [2.021]	0.480 [2.113]
Random effects model				
Time trend	−0.517***[0.079]	−0.256***[0.068]	−0.580***[0.079]	−0.507***[0.075]
GDP p.c. (log)			−0.0824 [0.400]	−0.176 [0.440]
Natural resource rents(% of GDP)				−0.205*** [0.069]
SNA series	−0.575 [2.295]	−0.787 [1.885]	1.589 [1.951]	0.699 [2.048]
Observations	1,396	1,396	1,239	1,218
Number of countries	93	93	89	87
Av. obs. per country	15	15	14	14

Source: Author's calculation [based on UN SNA, FAOStat and WB WDI].
Note: SNA system is a categorical variable (=0 if 1968 series, =1 if 1993 series and = 2 if 2008 series). Cluster-robust standard errors in brackets.
****p*-value < 0.01, ***p*-value < 0.05,

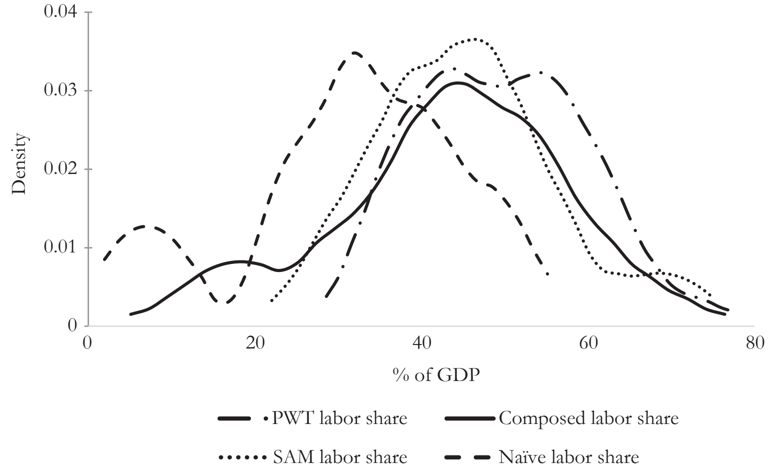

Figure 5. Distribution of labor share data (common set of country-year observations).
Source: Author's illustration [based on UN SNA, FAOStat, WB WDI, IFPRI, UN DESA and PWT].
Note: Kernel density estimates.

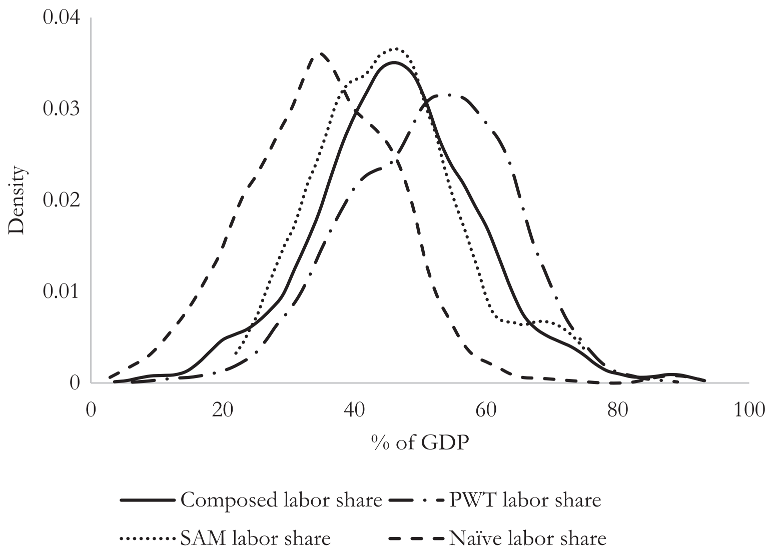

Figure 6. Distribution of labor share data (all available observations).
Source: Author's illustration [based on UN SNA, FAOStat, WB WDI, IFPRI, UN DESA and PWT].
Note: Kernel density estimates.

adjusted estimates. In Figure 5, it ranges between 6 and 51 percent, with a mean of 32 percent and a median of 34 percent. The corresponding values of the composed labor share range between 11 and 71 percent, with a mean of 44 percent and a median of 46 percent. The distribution of the composed labor share resembles that of the SAM labor share in Figures 5 and 6, giving support to the way of construction. With a mean and median of 50 percent and a range between 33 and

73 percent (in Figure 5), the PWT estimates are slightly higher. This is mainly due to the primary reliance of these observations on Gollin's second adjustment using agricultural value added as a proxy for the labor component of MI (in 58 percent of cases). As argued in section 4, relying on this proxy is likely to overestimate the labor share. As the PWT data set in about half of all cases for low and middle-income countries relies on this proxy, its estimates run risk to overestimate the labor share (see Figure 6).

SAMs only offer limited possibility to check the validity of the composed data set in a dynamic perspective since SAMs are usually constructed at large time intervals; in most cases, there is just one observation per country available. However, some insights can be gained from the example of South Africa, which is the only country for which at least three SAMs covering a time span of more than ten years are available. According to the SAM estimates (see Figure 7), the country's labor share decreased by 7 percentage points between 1993 and 2005 (from 56.3 to 49.8 percent). The composed labor share (here $LS_{G3'}$) shows a similar pattern, suggesting that this is an appropriate way of proceeding for this country. Leaving the naïve share as it is, on the other hand, would understate the labor share while the PWT labor share yields comparably high estimates.

We can also learn from looking at the components of the composed labor share (see Figure 8). From mid-1990s onwards, the composed labor share is just about the same level as LS_{G2}, indicating that the adjustment process results in an average capital-labor mix of self-employment like in the rest of the economy. The composed labor share is centered between the LS_n (no self-employed income) and LS_{G1} (all self-employed income treated as labor income) which further suggests that the labor share of self-employment is on average close to one half (as is the labor share in national income). LS_{G3} (using agricultural employment) lies in between LS_{G1} and LS_{G2}. As the former rather overestimates and the latter rather underestimates the labor share, it seems to be reasonable to use the third adjustment as a basis. The naïve labor share is much lower than the adjusted alternatives, which stresses the importance of adjusting the labor share in the context of developing

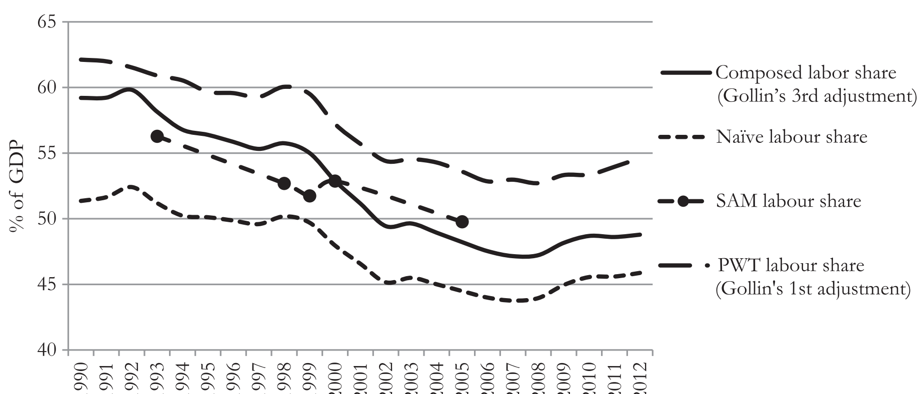

Figure 7. Labor share of South Africa, 1990–2012.
Source: Author's illustration [based on UN SNA, FAOStat, WB WDI, IFPRI, UN DESA and PWT].
Note: PWT uses agricultural value added as a proxy for self-employed labor income, the composed labor share uses agricultural employment as a proxy for self-employment.

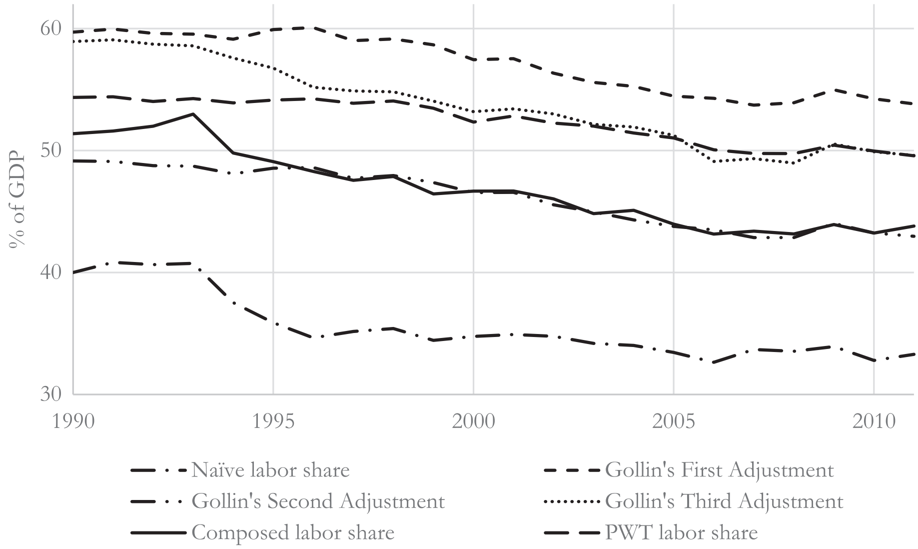

Figure 8. Different labor share adjustments, 1990–2011.
Source: Author's illustration [based on UN SNA, FAOStat, WB WDI and PWT].
Note: Data on Gollin's first, second and third adjustment is interpolated and kept constant beyond start and end points for this illustration to deal with unbalanced panel data.

countries. There is a sharp drop in the naïve share in the early 1990s. This partly stems from the post-Soviet states in transition, supporting the procedure described above for these cases. The PWT labor share relies on Gollin second adjustment, using mixed income and – where not available – agricultural value added as a proxy for self-employed labor income. The fact that its estimates are located well above LS_{G2} (programmed with mixed income) indicates that the proxy probably overestimates self-employed labor income and hence the labor share. The PWT estimates hence yield comparatively high labor shares.

8. Properties of the Data Set

8.1. *Descriptives on the labor share*

Consistent with findings of other recent studies, my results provide evidence against the hypothesis of constant labor shares. As can be seen in Figure 8, I find the labor share data to be also declining in developing countries since 1990. It is stable in the early 1990s but starts declining sharply with the end of the Cold War. The labor share recovers slightly in the late 2000s in the course of the Global Financial Crisis of 2007-8 but falls back to the pre-crisis level afterwards.[14] The negative trend in the labor share is robust to different forms of measurement. It should be emphasized that even the naïve share, which only captures wage

[14]This temporarily reversed trend mainly goes back to the countercyclical movement of the labor share, meaning that capital owners usually loose more than wage earners do during crises (ILO, 2013).

employment, is decreasing significantly over time. It is a well-known fact that the labor share has fallen in most high-income economies over the last two decades. This is mainly explained with capital-augmenting technological progress and the specialization into capital-intensive commodities in the course of globalization—an argument based on the Heckscher-Ohlin model and Stolper-Samuelson theorem. To the extent that labor is abundant in developing countries, one would rather expect the labor share in developing countries to rise with international integration. This should be especially the case for the naïve share, expecting trade and development to expand the (assumingly labor intensive) corporate sector. Findings, however, show that also the corporate share, which only covers wage employment, is decreasing, confirming the results of other studies such as that of Karabarbounis and Neiman (2014). This paper yields another interesting finding in that regard: Given that the economy-wide labor share has been decreasing slightly faster than the naïve labor share between 1990 and 2010 (see Figure 8), also the share of self-employed labor income in national income must have been declining during that period. The share of self-employed in the workforce decreased since 1990 (ILO, 2015), and correspondingly the labor share of the self-employment sector, given that fewer workers earn self-employed labor income (see also van Treeck, 2017). This decline, however, has not been compensated by an increase in the labor share of the wage employment sector: Although increasingly more people entered wage employment over the period examined, the increasing number of wage earners did not lift the labor share of the wage employment sector (van Treeck, 2017). By contrast, on average, it even decreased—and the picture of a decreasing corporate wage share, as for example Karabarbounis and Neiman (2014) draw it, is looking even worse. The reasons for the decreasing labor share might be different in various contexts. The literature mainly discusses the effects of technological change, financialization, worldwide competition, unemployment and the decreasing bargaining power of labor (Stockhammer, 2013; Karabarbounis and Neiman, 2014).

The significant downward trend is also seen when regressing the composed and the naïve labor share on time, real GDP per capita (taken from SNA), the share of natural resource rents in GDP (taken from WDI) and the SNA system in a fixed and random effects model (see Table 4). The composed labor share on average decreases by 0.51–0.58 and the naïve share by 0.25–.26 percentage points per year over the observed period (i.e. in total by about 11 and by 5 percentage points respectively). There is no significant relationship between a country's GDP per capita and its labor share. This is also confirmed by Figure 9, which displays labor shares for different income groups (low, lower-middle and upper-middle-income) according to World Bank's country classification in 2000. Equally, an interaction term between the time trend and GDP per capita reveals that there is no systematic difference in the time trends of different income groups as it yields insignificant results. By contrast, the share of natural resource rents (as percent of GDP) has a significant negative impact on the labor share. On average, the composed labor share is 0.20 (in fixed effects model) and 0.21 (in random effects model) percentage points lower, when the share of natural resource rents in GDP increases by one percentage points. As the share of natural resource rents varies between 0 and 68 percent in the sample, this is quite a huge effect. In addition, the very low labor

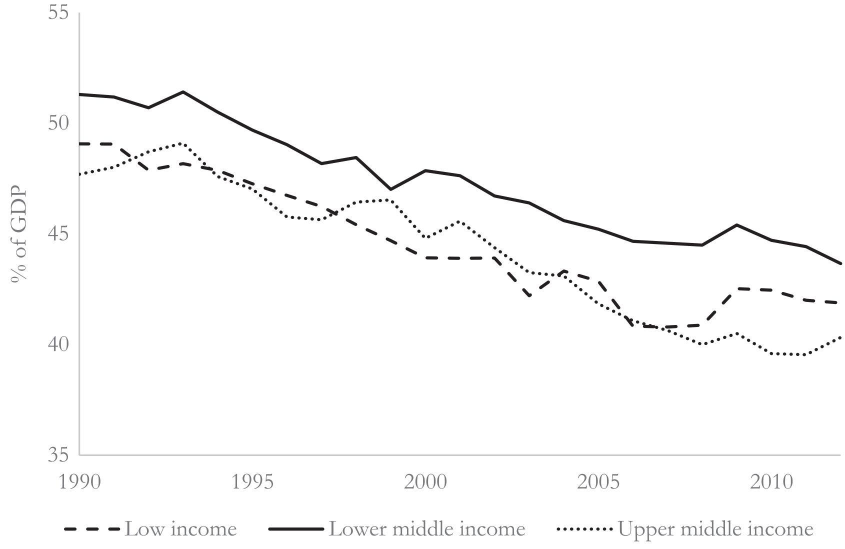

Figure 9. Labor shares by income classification, 1990–2011.
Source: Author's illustration [based on UN SNA, FAOStat and WB WDI].
Note: Income classification according to 2000. Data is interpolated and kept constant beyond start and end points for this illustration to deal with unbalanced panel data.

share values at the lower end of the distribution (see Table 3) can be explained with high natural resource rents. When dropping countries where up to two thirds of GDP come from natural resources, the very low values of the composed labor share (below 12 percent) disappear and the mean and media of the labor share slightly increases up to 47 percent. Furthermore, descriptives show that the labor shares are lowest in the Middle East and North Africa (about 40 percent) which is expected as most of the oil-producing countries are located in this region. The regression further shows that the SNA series has a negative but insignificant influence on the resulting data.[15]

Finally, the descriptive statistics show that the average level of the labor share is well below the standard of "two-thirds". This finding corresponds to recent economic studies which argue that the labor income share in developing countries is significantly lower than that in high income economies and about one-half in size (for example, Chen *et al.*, 2010, Imrohoroğlu and Üngör, 2016, Izyumov and Vahaly, 2015, Young and Lawson, 2014).

8.2. *Unit roots*

Descriptives on labor share data already provide evidence against the long-prevailing hypothesis of constant factor shares. Nevertheless, many theoretical models are still based on the Cobb-Douglas production technology or similar models that treat the labor share as a persistent variable. For future applications, it is therefore important to be on notice of the possible presence of unit

[15]In many cases, data is available from different series.

TABLE 5
Augmented Dickey-Fuller Tests of Labor Share Data

Lags	No Trend	With Trend	With Constant
1	$\chi^2(174) = 280.4$***	$\chi^2(174) = 432.2$***	$\chi^2(164) = 487.2$***
2	$\chi^2(170) = 298.8$***	$\chi^2(170) = 382.1$***	$\chi^2(154) = 410.9$***
3	$\chi^2(164) = 317.7$***	$\chi^2(164) = 252.0$***	$\chi^2(144) = 367.2$***

Note: Degrees of freedom in parentheses.
***p-value < 0.01.

roots in the labor share data as the problem of spurious regression may arise (Granger and Newbold, 1974; Kao, 1999). I therefore test for the presence of unit roots, using a Fisher test statistic as presented in Maddala and Wu (1999):

$$\lambda = -2 \sum_{i=1}^{N} \ln(\pi_i) \tag{9}$$

where π_i is the p-value of any unit root test for each cross section i.[16] Within this framework, the augmented Dickey-Fuller (1979) test is performed which can be considered as the most common method, testing the null hypothesis of unit root against the alternative of stationarity. The Fisher test statistic is preferred over other test statistics, such as Im-Pesaran-Shin, as it is not an asymptotic but an exact test which does not require a balanced panel. The results, however, should still be treated with caution, given the low power of unit root tests in finite samples like here (Blander and Dhaene, 2012).

Table 5 shows the test results for the composed labor share data. The test comes in three versions (without constant and trend, with trend and with constant) and is run on the first, second and third lag which are appropriate lag lengths for annual data. The null of unit root is rejected in all nine tests at the one per cent level of statistical significance, thus providing strong evidence against the persistence of the labor share in developing countries.[17] Conducting the same tests for the PWT labor share data allows to reject the null hypothesis in only six (out of nine) versions, which might be due to the inter- and extrapolations in the data set.

9. Conclusion

This paper reveals that measuring the labor share of low and middle-income countries is neither direct nor straightforward. There clearly is a quality-coverage trade-off regarding its computation: The more global the coverage, the greater the prevalence of poor quality data and the more questionable the comparability between countries. However, giving up on its cross-country measurement and simply assigning "two-thirds" to the labor share cannot be the consequence. Although different developing regions can hardly be measured with the same

[16]The test is χ^2-distributed with 2N degrees of freedom.
[17]The degrees of freedom equal the number of countries in the data times two. This number, however, varies across the different tests because data gaps prevent to perform the test on all countries.

yardstick, broad data sets are required to analyze comprehensive trends in labor shares.

Up to date, labor's share in income in the specific sample of low and middle-income countries remains underexplored. This paper contributes to the literature by providing a macro-level labor share data set which integrates information from SAMs to underpin the results and mitigate methodological problems such as the necessary specification of assumptions. Unfortunately, there is only a limited set of SAMs available which I do not claim to be statistically representative. But the additional information can give guidance in the data processing and validates the distribution of the final estimates. Future research on the labor share depends crucially on more valid and robust (national accounting) data. Counter-checking national accounts with additional data can only be a second best option. It is hence recommended that national statistics offices increase their effort in gathering data on the (informal) self-employment sector. In a first step, data acquisition should focus on types and sector composition of the self-employed. For this more funding and qualified personnel directed towards reliable and regular data collection will be necessary (Jerven, 2012). Until high quality data is available, it is inevitable to conduct robustness checks on national account data, with SAMs being just one possibility.

The data set confirms the finding of previous studies of the downward trend in labor shares also for the developing world. Furthermore, the labor share is found to have an average level of one-half. Future research hence should develop new economic models which move beyond the constancy of factor shares and assumption of "two-thirds" (Kanbur and Stiglitz, 2015).

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Appendix. Countries included in data set.