The Role of Labor in Sustainable Development

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Chapter 1

Motivation and Overview

> *"The production of wealth is the result of agreement between labor and capital, between employer and employed. Its distribution, therefore, will follow the law of its creation, or great injustice will be done."*
>
> Leland Stanford (1824-1893) – founder of Stanford University

1.1 The role of labor in sustainable development

1.1.1 On the emergence of sustainable development

The field of development economics is not limited to the analysis of economic growth in the developing world, as one might initially believe. The narrow perception of development as purely economic development – with the growth of gross domestic product (GDP) as ultimate goal – was widely abandoned in the 1980s and 1990s when it was replaced by the broader concept of human development (Todaro and Smith, 2009).[1] Especially thanks to the work of the philosopher and economist Amartya Sen, income was no longer seen as an end

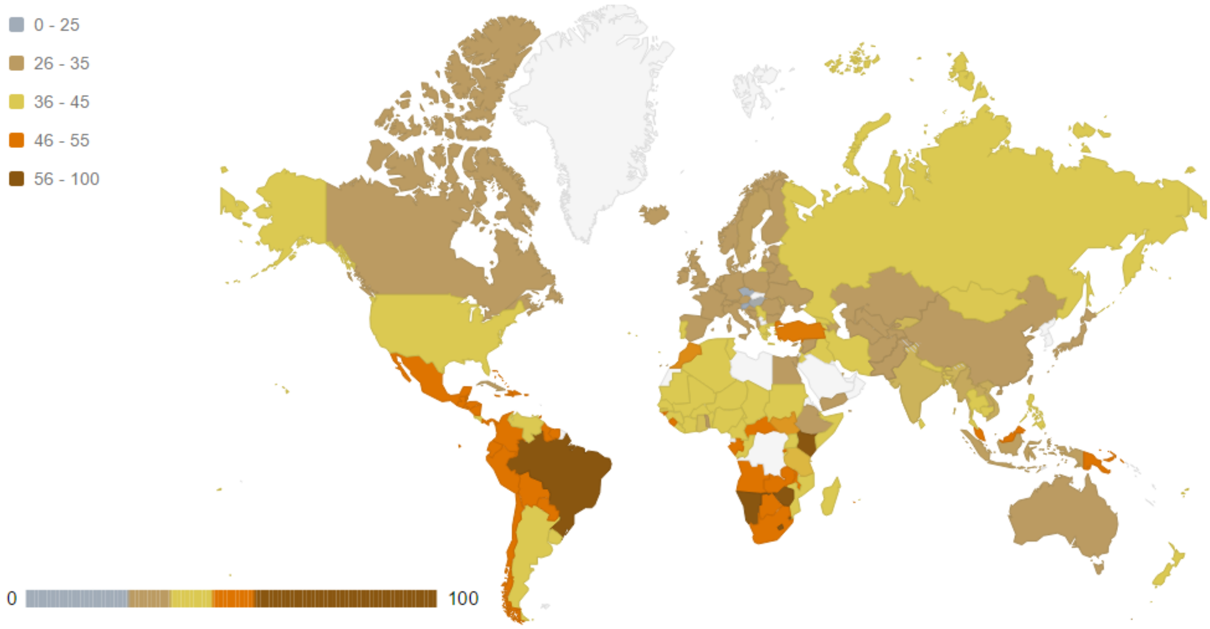
[1] The division of the world into 'developed countries' and 'developing countries' can be criticized for the hierarchy it implies between 'advanced' and 'backward' countries, as argued by the post-development school (for example, Escobar, 2000, Sachs, 1992 and Ziai, 2012). Similarly, this school questions the concept of 'development' as a whole since it aims at a form of development that is universal and usually exclusively based on western ideas of industrialization (e.g. consumerism). In this dissertation, I stick to the terms 'development' and 'developing countries' as they are common concepts in development economics and since their perception also has broadened among development economists in the last decades. However, I would like to emphasize that I interpret 'development' as a transformation process that involves a pluralism of ideas and that I use the country classification 'developing country' to be able to clearly define the study area of this work (and not to indicate any order of countries). An alternative term in this context is 'Global South', which is, however, rarely used in the field of development economics.

in itself but as a means of expanding people's choices (UNDP, 1997). Poverty alleviation and aspects such as health, education and political freedom and hence the multidimensional nature of development were increasingly acknowledged. In 2000, the international community adopted the by then broadest program for human development, the Millennium Development Goals (MDGs). 189 member countries of the United Nations agreed to implement eight goals to fight poverty in its various facets, including eradicating extreme poverty and hunger, achieving universal education and reducing child mortality by 2015 (UN, 2016). These ambitious goals were not fully achieved, one reason being that the program left aside the issue of inequality (UN, 2015); Vandemoortele (2011) therefore even speaks of "Minding Development Gaps" (p.1).

In fact, high inequality threatens the social inclusiveness of education and health programs and aggravates the fight against poverty since economic growth is not specifically targeted at the poor. Furthermore, distributional impacts of development policies have to be understood to assess their impact on the poor (Ravallion, 2001). But inequality in incomes – and even more so in wealth – is immense, especially in poor countries (see figure 1.1), thus threatening human development. In the last three decades, and over the MDG period, income inequality has increased *within* most countries, not only in high income regions, but also across the developing world (Atkinson and Bourguignon, 2015, Dabla-Norris, 2015, Goldberg and Pavcnik, 2007, Milanovic, 2015, UNDP, 2013, WB, 2016d). As a result of these trends, especially global interpersonal inequality – i.e. inequality between individuals worldwide – is still very high and on similar levels with the most unequal societies in the world such as Brazil (Milanovic, 2012). Equivalently, the gaps in terms of health, education and nourishment remain large in many countries (Klasen, 2016, UN, 2015). Many economies achieved progress in human development on average but were at the same time confronted with persistent or even increasing disparities (UNDP, 2013). These inequities, however, were not captured by the MDGs that only measured global and national averages (van Bergeijk and van der Hoeven, 2017, Melamed, 2012).

Until the 2000s, the distribution of income has been left largely unattended by the economic discipline, including many development economists. But the persistence of poverty in many developing countries and indications of historically high levels of inequality, for example that "the top decile owns[ed] 71 % of global wealth" (Davies et al., 2011, p. 223), continues to draw the interest of social scientists. Since the late 2000s, questions of inequality are increasingly placed on the international research agenda. It has become clear that to achieve the goals of human development, such as improved health and access to education, distributional patterns need to change. Most importantly, fighting poverty through

Figure 1.1: **Gini index of national income distribution around the world**



Note: The Gini index measures the statistical dispersion of a country's income distribution and ranges between 0 (perfect equality) and 100 % (perfect inequality).
Source: UNU-WIDER 2017.

economic growth can hardly be achieved when income inequality remains at such high levels (van Bergeijk and van der Hoeven, 2017, Lübker, 2002).[2]

In order to respond to the challenges and limitations of the MDGs, inequality played an increasing role when the international community negotiated the follow-up development agenda, the 2030 Agenda for Sustainable Development, which was adopted by 193 UN member states in 2015. Amongst the set of 17 goals – the Sustainable Development Goals (SDGs) – is also goal 10, which calls for "reduced inequalities – reduce inequalities within and among countries" (UNSD, 2016).

The SDGs are much more comprehensive than the MDGs and based on the concept of sustainable development (UNCTAD, 2014). Sustainable development combines the goals of economic development, social inclusion and environmental sustainability (see figure 1.2). It hence incorporates human development but has an additional focus of eliminating inequalities and further emphasizes environmental impacts, which the expansion of human development might entail, demanding that natural, man-made and human capital should be

[2]For example, Lübker (2002) calculated that "if countries had managed to maintain the most favorable income distributions of the past three to five decades, this would have reduced the number of people living on less than a Dollar per day from the present figure [1998] of 1.2 billion to 900 million" (p. 22).

sustained for current and future generations (Sachs, 2015).[3] In contrast to the MDGs, the SDGs therefore also encompass several goals on sustainable consumption and production as well as on environmental conservation.

The more comprehensive approach of sustainable development provides further reason to reduce income disparities – apart from contributing to the fight against poverty. The last decades were not only characterized by high inequalities but also by human-induced climate change, environmental degradation (such as the loss of biodiversity) and resource pressure, threatening the livelihood of societies worldwide (IPCC, 2007). Inequality in incomes usually entails inequality in resource use, on the global level as well as within developing countries (Seyfang and Paavola, 2008). Although the same size of an economy can have varying degrees of environmental impact, a larger economy in monetary terms also tends to have a larger material basis (Behrens et al., 2007, Jakob et al., 2014, Ravallion et al., 2000). To achieve sustainable development, a major challenge for the international community therefore is to increase the incomes of the poor while at the same time mitigating environmental degradation. Against this background and from a climate justice[4] point of view, it is necessary to not only promote low-material growth but also to make economic growth pro-poor. If mankind wishes to successfully combat poverty within planetary boundaries, (limited) natural resources need to be distributed more fairly and the use of natural sinks, such as forests, for waste disposal and emissions more balanced (Sachs and Someshwar, 2012, Steffen et al., 2015).

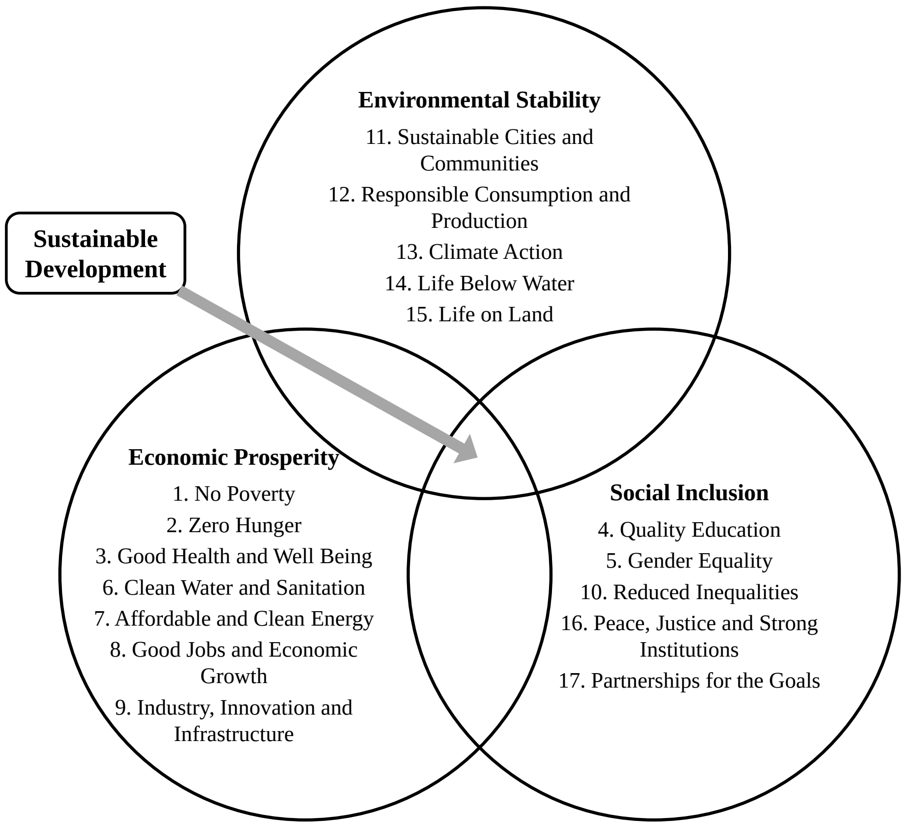
1.1.2 The concept of the labor share

Employment and the quality of employment – decent work – plays a significant role in the promotion of sustainable development. Productive and remunerative work is the main route out of poverty and the creation of decent employment is vitally important to make growth pro-poor (OECD, 2009, WB, 2013). The poor mostly only have their labor force to generate income; other income sources – returns on capital or public and private transfers – only make up a small proportion of their incomes (Besley and Cord, 2007). In contrast to labor income, income from capital assets is generally much more concentrated and earned by top income groups. Giving labor a fair share in economic prosperity therefore is key to

[3]It is further distinguished between strong and weak sustainability. While weak sustainability assumes that the three different forms of capital (natural, man-made and human capital) are substitutable and only the total stock of capital matters, the concept of strong sustainability argues that natural capital has unique features and cannot be replaced by other forms of capital (Stiglitz and Fitoussi, 2009).

[4]The concept of 'climate justice' emphasizes that the burdens and benefits of climate change affect people and regions to different degrees.

Figure 1.2: **The 17 Sustainable Development Goals and their primary dimension of sustainability**



Source: Adapted from Barbier and Burgess (2017).

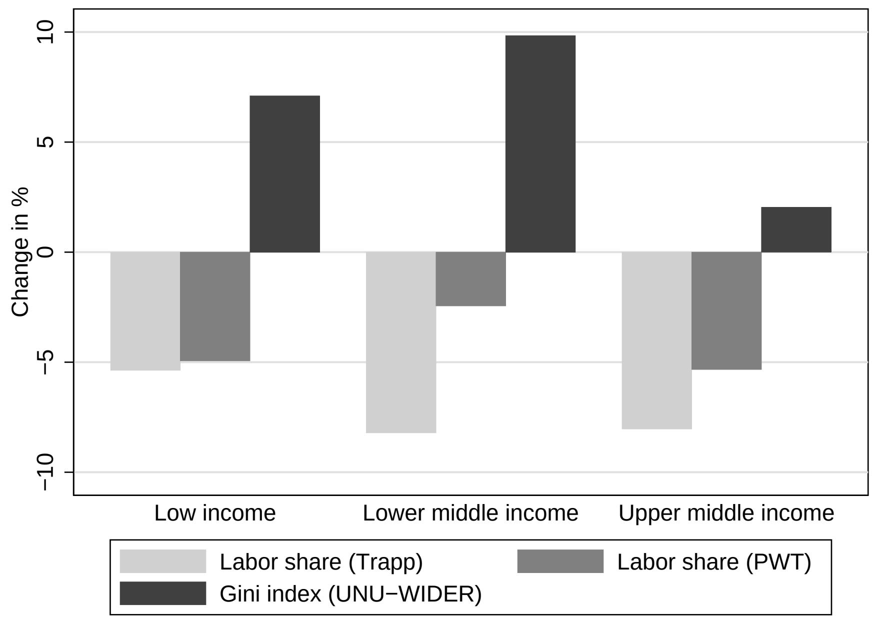
fighting poverty and further reducing inequality in income.

To be able to assess how far an economy spreads its income achievements amongst its working population, overall productivity trends of an economy have to be related to developments in the labor market. The factor (or functional) income distribution enables to do so by measuring how aggregate income is distributed between the factors of production: Labor (including human capital) and capital (including land). The labor's share in income of a country then shows how much of national income is earned by labor. Its size depends on the labor-intensity with which economic output is produced and on how labor productivity is reflected in labor incomes. If labor income and economic output develop in tandem, the labor share remains constant. If, however, labor income is increasing but overall income is increasing faster, the labor share declines (and vice versa). The labor share thus indicates in how far an economy manages to translate income gains also into higher wages and whether it develops in an inclusive and equitable manner. For this reason, the labor share was implemented within the 10th SDG on "reduced inequalities" as an indicator for target 10.4 ("Adopt policies, especially fiscal, wage and social protection policies, and progressively achieve greater equality").

For a long time, the labor share was assumed to be constant and about two-thirds in size. This primarily goes back to the work of Cobb and Douglas (1928) who presented a production function which implied constant factor shares and yielded empirical estimations of the labor share between 60 and 75 % in the United States and other high income countries countries (Douglas, 1967, 1976). Assuming that wages are paid according to labor productivity, their model predicts that only non-neutral technological progress and a shift to sectors that use one of the production factors with relative intensity (for example through trade) will cause movements in factor shares (Bentolila and Saint-Paul, 2003). The Cobb-Douglas production function is also at the center of the prominent neoclassical growth model by Solow (1956) and Swan (1956), which gave further support to the proposition of constant factor shares in the context of economic development. The long-term stability of factor shares thus became one of the "stylized facts" of economic growth put forward by Kaldor in 1957. As a consequence, the economic discipline put the distribution of income between factors of production aside and turned to the distribution of income between individuals instead (Sandmo, 2015).

Data, however, began to deviate from these 'facts' in the early 1990s, bringing the labor share back on the research agenda in the mid-2000s (Giovannoni, 2014). There were growing signs that overall productivity had disconnected from labor income and that the labor share had declined across the globe. Most prominently, Piketty (2014) presented data on the rising capital share in high income countries and a few global studies also found a similar trend in low and middle income countries (Harrison, 2005, Karabarbounis and Neiman, 2014, Rodriguez and Jayadev, 2010, Stockhammer, 2013). These developments posed a puzzle to economists: They had expected the labor share to rise in developing countries in the last decades, a period of increased globalization (Stockhammer, 2013). This is because classical trade theory (mainly the Heckscher-Ohlin model and Stolper-Samuelson theorem) predicts the labor share of developing countries to rise with trade: Since poor countries are relatively labor-abundant, trade will boost the demand for labor-intensive goods in these countries. This, in turn, is predicted to translate into higher wages and a higher labor share. However, there is evidence that the opposite occurred in the last three decades, which has serious implications for inequality, poverty as well as overall political stability and hence sustainable development.

Figure 1.3: **Change in labor share and income distribution by country income group, 1990-2011**



Note: Figures are unweighted averages. Income distribution measured by within country Gini indices following the first concept of Milanovic. Income group according to the World Bank country classification in 2000. *Source*: PWT (2015), Trapp (2015) and UNU-WIDER (2017).

1.1.3 The labor share in the context of sustainable development

As mentioned above, sustainable development covers the economic, social and environmental system. Each of the 17 SDGs can be primarily attributed to one of the systems, but they also touch the other dimensions to a greater or lesser extent. The dimensions of sustainability and the several SDGs are therefore connected to each other in multiple ways and build an integrated system and network of goals (Barbier and Burgess, 2017, Le Blanc, 2015). The links between the goals can be positive as well as negative, creating synergies and trade-offs. Thus, although the labor share primarily refers to inequality and hence the social system, it further affects the economic system (through its impact on income and poverty) and to some degree also the environmental system.

The fact that labor has been losing ground against capital since the early 1990s, not only in high income countries but also in the developing world, can in part explain the substantial increase in **personal income inequality**, i.e. inequality in income between individuals, that is observed in many developing countries. The personal income distribution is linked to the factor income distribution through factor ownership and can be derived from it once it is known how capital and labor are distributed among people (Ray, 1998). The factor income distribution is therefore a statistical determinant of the personal income distribution. The relationship between the personal and factor income distribution is complex but several studies show that a lower labor share is associated with higher inequality in personal incomes (as measured by the Gini coefficient), mainly because profits, rents and other income from capital are concentrated amongst the rich (Bengtsson and Waldenström, 2015, Daudey and García-Peñalosa, 2007, ILO, 2013, Rani and Furrer, 2016). This is also suggested by Figure 1.3 which shows that average labor shares and average Gini coefficients develop in opposite directions: Across country income groups, a decrease in the labor share since 1990 came along with an increase in personal income inequality. The labor share is therefore a highly informative macroeconomic variable to explore when analyzing the roots of personal inequality. As has been emphasized by Atkinson (2009), shifting the focus from the personal to the factor level can deliver a more integrated understanding of the determinants of inequality between individuals. It might not only be relevant how income is distributed but also how it was earned. By decomposing inequality into factor shares and their concentration, the underlying causes of income disparities can be more easily grasped. Eventually, the labor share plays a role in the discourse on inequality since factor shares also "address the concern of social justice with the fairness of different sources of income" (Atkinson, 2009, p. 5). For example, people might consider it an injustice when capital profits are increasing faster than wages (Glyn, 2009). This is also because employment not only has an income aspect but also a social function. Having a decent job can be a source of self-esteem and the esteem of others, a function which Sen (2000) terms "recognition aspect" (p.5). In that sense, income from work also differs from earnings that come from charity or social transfers (Ray, 1998).

Given that production factors, especially capital, are still very unequally distributed within societies, a decreasing labor share is a significant barrier in reducing **poverty**. As the poor are largely dependent on productive and remunerative jobs to generate income, the decoupling of wages from productivity has slowed down poverty alleviation. There is a large body of literature which shows that it is mainly labor market dynamics, i.e. more decent jobs and increasing wages, that lifts people out of poverty (see Besley and Cord, 2007, Melamed et al., 2011, WB, 2016d and others for country examples). Hence, poverty would have receded more quickly if productivity increases had translated to a greater extent into increases in labor income in the past. But on the contrary, the decoupling of wages from productivity has fostered the phenomenon of the working poor, a phenomenon which prevents people from climbing into the middle class (see table 1.1). Working poverty is the headcount of employed people whose incomes fall below the poverty line. Although the share of extreme working poor (incomes below 1.25 USD a day) has decreased from 45.1 to 14.4 % and the share of moderate working poor (incomes below 2 USD a day) from 68.6 to 32.2 % in total employment since 1991 in the developing world, the progress in the least developed countries has been limited (ILO, 2014a). In absolute numbers, extreme working poverty has increased from 133 to 138 million and moderate working poverty from 176 to 242 million in income economies between 1991 and 2013. As a result, 375 million employed people in the developing world still lived in extreme and 839 million in moderate poverty in 2013. This implies that about one third of employed people in developing countries are poor (despite working) and that about 90 % of poor people are working (Fields, 2011, ILO, 2014a, WB, 2016d). The challenge in developing countries is therefore not to reduce unemployment but to create decent, well-paid jobs. In fact, about two-thirds of workers in low income countries and about half of workers in middle income countries are working under vulnerable conditions, meaning that their work does not generate adequate earnings and formal arrangements and social security are likely to be missing.[5] The 8th SDG therefore calls to “promote sustained, inclusive and sustainable economic growth, full and productive employment and decent work for all” (UNSD, 2016) to increase the growth elasticity of poverty, i.e. the connection between the change in economic growth and poverty reduction. Target 8.2 of the goal further demands to “focus on high-value added and labor-intensive sectors” since those sectors are most likely to reach the poor. This relationship is also known in the literature as the “virtuous circle of links among growth, employment and poverty reduction” (Islam, 2006): The stronger the link between economic growth and the creation of decent employment, i.e. the higher the labor-intensity of growth, the more likely it is that growth will be pro-poor (ILO, 2013, Loayza and Raddatz, 2006, OECD, 2009). Goal 8 is thus directly linked to target 10.4 which calls for a higher labor share.

Additionally, a high labor share is favorable for a stable political and macroeconomic environment, which might further help to reduce poverty and inequality among a country’s society. First, and as has been mentioned above, the higher the labor share, the more likely it is that improved macroeconomic conditions also translate into higher household incomes and that gains from a globalized economy are fairly distributed. This, in turn, could maintain people’s support for open markets. If, on the other hand, inequality is high and the poor have little hope of future income improvements, this might not only lead to the rejection of economic integration but also to social and political unrest, threatening future economic growth (Berg and Ostry, 2011, IMF, 2017). Second, labor income has a higher marginal

[5]The ILO classifies own-account workers (typically subsistence farmers or street vendors) and unpaid family workers as vulnerable workers.

Table 1.1: **Working poverty, 1991-2013**

	Share of working poor in total employment in %							
	Extreme poverty (1.25 USD)				Moderate poverty (2 USD)			
	1991	2000	2007	2013	1991	2000	2007	2013
DCs	45.1	32.7	20.4	14.4	68.6	56.6	41.1	32.2
LICs	65.8	60.4	46.2	37.4	87.1	84.6	73.6	65.2
LMICs	45.7	37.5	27.3	19.4	74	68.2	57.3	48.2
UMICs	40.3	22.6	8.4	3.7	61.1	41.6	20.4	10.0
	Total working poor in millions							
	Extreme poverty (1.25 USD)				Moderate poverty (2 USD)			
	1991	2000	2007	2013	1991	2000	2007	2013
DCS	811	693	491	375	1234	1198	989	839
LICs	133	156	146	138	176	219	232	242
LMICs	293	292	245	190	475	530	514	471
UMICs	384	245	100	47	583	450	243	126

Note: Figures in PPP (purchasing power parity). DCs = Developing countries, LICs = Low income countries, LMICs = Lower middle-income countries, UMICs = Upper middle-income countries.
Source: ILO (2014a).

propensity to consume than capital income (ILO and WB, 2015, Onaran et al., 2011). A lower labor share therefore diminishes domestic demand, which leads to lower growth and an increased dependency on exports if investments do not rise by the same amount (ILO, 2013). Low labor incomes may further cause financial instabilities if capital incomes are invested in financial rather than productive assets (ILO and WB, 2015).

Finally, the labor share also touches the environmental dimension of sustainable development. Target 4 of the 8th SDG (decent work and economic growth) demands a lower domestic material consumption per GDP “to decouple economic growth from environmental degradation” (UNSD, 2016).[6] Economic output can be produced in a capital- or labor-intensive manner, depending on the composition of economic sectors and the degree in how far capital and labor can replace each other within a sector. A labor-intensive production has the advantage that it is on average much less pollution-, energy- and material-intensive than a capital-intensive production, as several (ecological) economists, such as Antweiler et al. (2001), Cole (2003, 2004), Cole and Elliott (2005), Zhang (2016), argue. This is because (physical) capital is by definition composed of, produced by and operated by material resources, as well as by sources of energy, which, in turn, are produced by the support of material resources (Daly and Farley, 2011). Labor-augmenting technological change might

[6]Additionally, target 9.2 calls for a lower “CO_2 emission per unit of value added”.

therefore help to decrease dependence on **material resources** while at the same time stabilizing or even increasing the incomes of the working poor. In how far this is possible depends on the elasticity of substitution between production factors: The higher the elasticity of substitution, i.e. the easier labor can replace physical capital and material resources, the more likely it is that there are positive employment and labor share effects (Bovenberg, 1999, Bovenberg and van der Ploeg, 1996). On the downside, a higher labor share and the associated higher propensity to consume is likely to increase overall **carbon emissions**. As argued by Ravallion et al. (2000) and others, lower incomes also tend to have a higher marginal propensity to emit, creating a conflict between redistribution of incomes and climate change mitigation. Indeed, higher income inequality (and thus lower labor shares) has been found to be associated with lower carbon emissions, at least in poor countries (Grunewald et al., 2017, Holtz-Eakin and Selden, 1995). The aggregated effect of changes in the labor share – from the production as well as consumption side – on the environmental system is therefore very complex and not clear.

On the whole, to achieve the ambitious set of sustainable development goals, it will be key to designing policies that consider and minimize trade-offs between the various goals of economic efficiency, social equity and environmental conservation (Barbier and Burgess, 2017, WB, 2016d). Given its diversified impacts on the social, economic and environmental system, the labor share is an integral part of this challenging task.

1.1.4 What is the role of labor in sustainable agriculture?

1.1.4.1 Sustainability in the agricultural sector

The agricultural sector is home to the majority of the poor, generates substantial economic output and at the same time is largely responsible for the over-use of the planet's resources. Hence, it deserves particular attention. In fact, almost two-thirds of the working poor are employed in the agricultural sector and about half of agricultural laborers are poor (Castañeda et al., 2016). In 2015, the sector represented about one-third of GDP in low income countries (WB, 2016a). Moreover, it is a major emitter of greenhouse gases, accounts for 70 % of global water uses and threatens biodiversity due to deforestation and its extensive use of fertilizer, herbicides and pesticides (Sachs, 2015).

Within this context, the agricultural sector has significant transformation potential for low and middle income countries towards sustainable development (SDSN, 2013). The 2nd SDG therefore explicitly requests to "promote sustainable agriculture" (UNSD, 2016). Sustainable agriculture describes a form of agriculture that ensures a profitable and stable production of crops (and livestock) while at the same time preserving environmental resources and ensuring a fair share of benefits (Zhen et al., 2005). The farming sector is also a sector with one of the highest labor shares in the developing world. This is because most of the agricultural activity is pursued by smallholder farmers who employ few capital assets and mainly work manually (Inklaar and Timmer, 2013). Hence, the debate on sustainable agriculture also needs to address the role of labor for transformation.

1.1.4.2 Small-scale versus large-scale farming

Several studies show that increasing agricultural incomes of small-scale farmers significantly reduces poverty (Besley and Cord, 2007, WB, 2008). This is not only due to the fact that many farmers are poor but also due to the high labor-intensity of smallholder farming, which creates employment opportunities in poor rural areas (Loayza and Raddatz, 2006, Wiggins et al., 2010). At the same time, there is a trend towards large-scale farming, which relies more on machinery and chemical inputs, and is hence relatively capital-intensive (Wiggins et al., 2010).[7] This dynamic, which is mainly driven by the increased commercialization of agriculture, as well as large investments in agricultural land, has considerable economic, distributional and ecological implications. The substitution of labor with capital on large-scale farms implies a considerable change in the production technology. On the one hand, the increased industrialization implies higher negative external effects on the environment, primarily due to the application of fossil-fuel intensive as well as monocultural practices and the associated greenhouse gas emissions, loss of biodiversity and degradation of natural resources (Robertson et al., 2000, Tilman et al., 2002). On the other hand, technological change may increase overall revenues. The empirical literature discusses whether there are economies or diseconomies of scale regarding agricultural production by comparing the production per land unit of smallholders and large-scale farms – with mixed results. Many studies find smallholders to be more productive per land unit, which is mainly attributed to their more effective use of labor (Binswanger et al., 1995, Klasen et al., 2016, Lipton, 2005, Wiggins et al., 2010). Other research emphasizes that larger farms perform better as they can exploit economies of scale regarding marketing, wholesale trading and storage and since they can make more effective use of innovations (Collier and Dercon, 2014, Deininger and Byerlee, 2011). In case there are economies of scale, the shift to large-scale farming increases agricultural incomes, potentially also for the poor. But at the same

[7] As any other sector, agricultural output can be produced capital- or labor-intensively, depending on the factor-intensity of the produced crop and on the specific elasticity of substitution, for example between labor-intensive manual weeding and the capital-intensive use of herbicides.

time, it raises the capital share and probably also increases inequality as income is transferred from labor to the owners of agricultural capital. Nolte and Ostermeier (2017) show that large-scale farms crowd out smallholders, which has negative employment effects since small farms apply more labor per land unit than larger farms.[8]

1.1.4.3 Cash crop farming as a sustainable development path for smallholders?

The persistence of poverty amongst smallholder farmers and severe environmental degradation underscores the importance of the transformation of the agriculture sector, with various transition paths having been discussed (Collier and Dercon, 2014, Tilman et al., 2002). To approach agricultural sustainability, the goals of social inclusion, economic prosperity and ecological stability have to be promoted at the same time, which requires a balance in trade-offs between them.

The literature perceives the transition from purely or semi-subsistence farming to the cultivation of cash crops[9] as a potential route for agricultural growth and poverty reduction amongst small-scale farmers by increasing incomes as well as employment (Klasen et al., 2013, WB, 2008). Many smallholder farmers are poor because they engage in unprofitable subsistence farming rather than commercial agriculture as large-scale farms do. This is mainly because smallholders face substantial input and output market failures (Hettig and Sipangule, 2016). For smallholder farmers to escape poverty, it is essential that they diversify their farming activities and include crops for sale on (global) markets into their portfolio, such as cocoa, vanilla or cotton. However, a successful integration into global crop markets depends crucially on the ability of farmers to cope with the risks associated with cash crop production. Cash crop farming may increase incomes but at the same time creates dependencies as farmers directly depend on market prices and their variability, which may reduce their food security (Achterbosch et al., 2014, Barbier, 1989, Rist et al., 2010, Steffan-Dewenter et al., 2007, Sunderlin et al., 2001, Wood et al., 2013). Furthermore, monocultural cash crop production increases the sensitivity to ecological risks, such as soil degradation or harvest failures due to weather shocks or pests and diseases (Steffan-Dewenter et al., 2007).

The ecological impact of cash crop farming does not fundamentally differ from that of food crop production (Barbier, 1989). The environmental sustainability of the farming sector rather depends on the crop management practices that the farmer employs. Cash crop farming can potentially implement sustainable intensification practices and thus promote

[8] The precise employment effects, however, depend on the factor intensity of crop production and whether large-scale farms establish contract-farming schemes (Nolte and Ostermeier, 2017).

[9] Cash crops are food and non-food commodities that are primarily produced for sale on agricultural markets. Food (or subsistence) crops, by contrast, are mainly produced for domestic consumption (Barbier, 1989).

the movement towards sustainable agriculture (Achterbosch et al., 2014). Simple intensification practices aim to increasing production output, and thus income, primarily through higher yields rather than extending farmland. This has positive ecological impacts if it reduces the pressure to clear further forest, wet- or grassland for agriculture. However, an intensive management of cash crops often involves a considerable use of chemical inputs, such as fertilizers and pesticides, which, in turn, threatens environmental stability. In this context, a sustainable intensification of agriculture intends to increase yields while at the same time minimizing greenhouse gas emissions and the depletion of soil, biodiversity and the ecosystem (Beddington et al., 2011, Garnett et al., 2013, SDSN, 2013). This cultivation strategy thus also takes the environmental costs of fossil fuel-intensive practices and the degradation of natural resources into account in order to achieve an efficient management of natural resources (Bowman and Zilberman, 2013, Tilman et al., 2002). Sustainable agricultural intensification involves, for example, intercropping or micro-dosing of fertilizers (Achterbosch et al., 2014). As such cultivation strategies tend to be labor-intensive and smallholders are relatively labor abundant, there is the possibility that small-scale cash crop agriculture may alleviate poverty and create employment and at the same time support ecological sustainability in the farming sector (Achterbosch et al., 2014, Silici et al., 2015, UNCTAD, 2015). This potential, however, depends crucially on the farmers' risk and crop management skills.

1.2 Current state of research

The concept of sustainable development is broad and complex and its empirical assessment therefore highly challenging. The 2030 Agenda for Sustainable Development is an attempt by the international community to grasp and promote this vision. To this end, 17 goals, 169 targets and 230 indicators have been established, one of the latter being the labor's share in income.

While the relevance of the labor share for sustainable development and especially for a fair and equitable society is straightforward, its assessment is less clear.[10] In the context of the developing world, measuring the labor share is an extremely arduous endeavor. The functional labor distribution is well documented in high income economies but the situation is quite different for low and middle income countries. Mainly two reasons hamper the measurement of factor incomes in the context of the developing world: First, national accounting

[10]This discrepancy between relevance and measurement is not only an open issue of the labor share but also of many other SDG indicators.

data in the majority of poor countries is limited, incomplete and often also unreliable (UN, 2012). Especially in Sub-Saharan Africa, country statistics are marked by data gaps and inconsistencies (Jerven, 2012). This is not only due to the under-funding and insufficient resources with which statistical offices in poor countries are confronted. Another cause is the labor market structure of low and middle income countries, which also leads to the second reason: In contrast to high income countries, most of the workers in the developing world are not in wage employment but are self-employed. They are own-account workers or unpaid family workers, typically subsistence farmers or micro and small entrepreneurs, such as street vendors, whose activities are often located in the informal sector. This means that the majority of the labor force not only earns income from labor – as wage employees do – but also from capital assets, such as land or investment in equipment and machines. This creates a significant complication in measuring factor income shares in the developing world. To determine the labor income of the self-employed and to be able to compute the labor share, the labor component of the self-employed income needs to be filtered out in a first step. This, however, requires making assumptions about the capital-labor mix of self-employed activities as the production process usually remains unobserved. This task is further complicated by the fact that many self-employed activities take place in the informal sector.

On these grounds, findings on the magnitude and development of the labor share in poor countries are limited. Most existing data sets that allow us to compute the labor share only provide data for high income and some middle income countries. The most important data source in that context is the United Nations' System of National Accounts (UN SNA). These accounts allow to compute the share of employees' wages in national output for the majority of developing countries. However, due to the reasons mentioned above, a systematic recording of the self-employment sector is missing and the labor share in national income that covers the entire labor force cannot easily be determined. But given that a large portiont of workers in the developing world are self-employed, it is of crucial importance to account for the labor incomes of the self-employed as well. Otherwise, the measurement of the labor share underestimates the actual share of labor incomes in total output. Furthermore – and fundamental for dynamic analyses – a partial labor share, the so-called unadjusted labor share, does not permit meaningful conclusions about the evolution of the labor share over time. In the course of development, self-employed individuals typically leave subsistence agriculture to work in the wage-employment sector. As a consequence, their labor incomes suddenly appear in wage statistics, raising the labor share, even though their labor incomes might not have substantially changed (or only very little). Further effort is therefore needed to measure the all-encompassing labor share, the so-called adjusted labor share.

The empirical literature on the labor share thus is confronted with major measurement difficulties. The majority of the studies are restricted to high income economies, where data quality and coverage is high and labor income from wage and self-employment observable. For instance, Piketty's (2014) highly illuminating results on factor income distribution are bound to OECD countries and a few major emerging economies where a well-documented tax base is available that can be used as a data source. There are some studies with global coverage, such as Diwan (2001), Harrison (2005), Karabarbounis and Neiman (2014), Maarek and Decreuse (2015), Rodriguez and Jayadev (2010) and Stockhammer (2013). These studies, however, remain either limited to the corporate or manufacturing sector (such as Karabarbounis and Neiman, 2014 or Maarek and Decreuse, 2015) and thus turn a blind eye to small private businesses, which make up a significant portion of the workforce in developing countries, or they base their assessment on the unadjusted labor share (such as Harrison, 2005, Jayadev, 2007, Stockhammer, 2013). Using the unadjusted labor share may yield inconclusive results as the labor share is biased downwards and its time trend upwards, since it is does not control for shifts between different sectors. When they employ the adjusted labor share in robustness checks, this sharply reduces the sample size, mainly to high income countries. Notwithstanding these restraints, these studies yield valuable results. They all suggest a decline of the unadjusted, as well as corporate, labor share across the globe since 1990, confirming the findings of OECD studies and extending the results to developing economies. The finding that the share of employees' wages in national income has declined not only in high income countries, but also in the developing world, is remarkable. As a substantial share of the workforce switched from self- to wage-employment over the same period and the wage-employment sector became increasingly important in developing countries, ceteris paribus, the opposite was expected. But while national income has been rising, the proportion of the economic pie going to all wage laborers has become smaller, even though the number of laborers has increased in absolute terms. Overall productivity has thus decoupled from wages in the last decades and income generation has increasingly shifted from labor to capital. This is even more surprising in light of the fact that the last three decades were marked by increasing global trade. As mentioned above, standard models predict that trade benefits the abundant production factor in a country, which is labor in the case of developing countries. These findings also run counter to conventional growth and development theories, most prominently Solow's model, which relies on constant factor shares. Kanbur and Stiglitz (2015) therefore call for "new theories", which can explain the increasing share of capital and the associated upsurge of income inequality. In light of these observations, literature has concentrated on the analysis of the driving forces behind the labor share decline in the late 2000s. Trade, as well as financial globalization, have been identified as significant drivers of the downward trend, which is mainly explained by the changing bargaining positions of capital and labor (Harrison, 2005, Jayadev, 2007, Maarek and Decreuse, 2015, Stockhammer, 2013). As capital becomes relatively mobile in the course of globalization and can offer a credible threat of relocating abroad, domestic labor now directly competes with labor abroad (Rodrik, 1997). This weakens the bargaining position of labor vis-à-vis capital, exerts a downward pressure on wages and eventually results in a decreasing labor share. Consistent with this view is the claim that the elasticity of substitution between capital and labor moves beyond one that enables capital to be more easily substituted for labor in the production process. In that regard, Karabarbounis and Neiman (2014) find technological change to have significantly contributed to the decline in the labor share by pushing down the relative price of capital. They estimate the substitution elasticity between capital and labor to be greater than unity in the long-term, allowing capital to smoothly replace labor and eventually leading to decreasing labor shares as the relative cost of capital falls less than the absolute volume of investments increases.

As mentioned above, these important findings remain either limited to the corporate or manufacturing sector or rely on the unadjusted labor share. Given that the labor market in developing countries is characterized by segregation into different sectors and substantial movements between them, labor share analyses that cover the whole economy might contribute important findings that the existing literature cannot capture. For example, deregulation of markets may not only directly impact sectoral labor shares but also induce labor force dynamics between different sectors that should be integrated into the assessment as well. Currently, research fails to provide satisfactory evidence on the economy-wide labor share and its determinants in the developing world which is a clear gap in the economic literature. Such insights are, however, crucial to designing and evaluating policies that affect the entire labor market. Only if it is understood how the labor share evolves and what its drivers are, can policy makers set bounds to declining trends of the labor share and the concomitant detrimental effects for income equality and poverty alleviation.

A second focus of this thesis is placed on the transformation of the agricultural sector towards sustainable development, and the role of labor- and capital-intensive strategies in facilitating this transformation. This thesis assesses one potential route of agricultural transformation, namely the transition of smallholder farmers from pure or semi-subsistence agriculture to commercial farming. The potential of cash crop agriculture in reducing poverty among smallholders and at the same time limiting environmental damage depends significantly on the cultivation strategy of the farmer. If smallholders manage their farms inefficiently and lack agronomic skills, this potential may not be fully harnessed. First, farm management skills have been found to be a central factor for maintaining and increasing yields, and thus reducing poverty (Mueller et al., 2012, Neumann et al., 2010, Tittonell and Giller, 2013, Tittonell et al., 2007). Second, the appropriate management of chemical inputs, such as fertilizers and pesticides, helps to maintain environmental stability. Especially in the long run, improper management of inputs may not only cause depletion of soils but can put the farmer's yield at additional risk, as intensified monocropping is more prone to pests and diseases (Steffan-Dewenter et al., 2007). As a result, yield performance has been found to vary substantially between cash crop farmers, which is – besides input and output market failures – mainly attributed to varying management practices (Euler et al., 2016, Mueller et al., 2012, Neumann et al., 2010, Tittonell and Giller, 2013, Tittonell et al., 2007, UNCTAD, 2015). Determining yield gaps – the difference between potential and actual yield – and understanding the underlying management practices is therefore crucial in reducing poverty and identifying sustainable management strategies (Ittersum et al., 2013, SDSN, 2013). As farm management practices are likely to vary in their degree of economic (as well as ecological) sustainability, long-term insights into the link between yields and cultivation strategies are of key importance in this regard. But while the short-term benefits of cash crop farming for smallholders are well-documented in the literature (Carletto et al., 2009, Klasen et al., 2013, Tittonell et al., 2007), long-term evidence is scarce. This is mainly because such assessments require long-term panel data, which are – as already mentioned above – hardly available for the (semi-)informal agricultural sector. But insights into whether cash crop farming can also reduce poverty amongst smallholders sustainably and which cultivation strategy can close yield gaps in the long run could contribute to the development of sustainable farming and thus poverty reduction strategies.

1.3 Contribution to the literature

This dissertation contributes to the debate on sustainable development and the associated role of labor in two ways:

Firstly, it focuses on the labor income share, which is a fundamental ingredient for poverty-reducing and equitable development. By addressing the enormous difficulties associated with its measurement, this thesis intends to overcome the gap between the socio-economic relevance of the labor share and its empirical assessment. For this purpose, it develops a new macro-level data set on the labor share, covering about 100 low and middle income countries from 1990 to 2011, that is backed up with micro-economic evidence and addresses the specific challenges associated with its measurement in developing countries (chapter 2). Furthermore, this dissertation reviews existing labor share data sets and discusses their strength and weaknesses to give guidance on deciding for the most appropriate measure and on necessary future steps in data collection (chapter 3). It also contributes to the debate and literature on the development of the labor share and its macro-economic determinants. It shows that there is a need to distinguish between types of capital when assessing the impact of financial globalization on the labor share and provides evidence that de facto foreign investment cannot explain the decline of the labor share in developing countries whereas data suggests that trade is a substantial driver of the observed downturn (chapter 4).

Secondly, this dissertation addresses the transformation of the agricultural sector towards sustainable development and assesses the transition of smallholder farmers to cash-crop agriculture as one potential path of development. Relying on a unique panel data set that has a time horizon of more than ten years, it contributes to the literature by showing that cash-crop farming has the potential to reduce poverty amongst smallholders in both the short and long term but that this potential can only fully be harnessed when a farmer applies proper labor- and capital-intensive management practices (chapter 5).

Brief summaries of these contributions, their research questions, methodological approaches and main results, are summarized below.

All chapters take a long-term view by using panel data. This means that phenomena are not observed at one point in time but over a period of several years or even decades, which allows to draw conclusions about long-term effects. Panel data is rare in developing countries but the use of it brings important econometric benefits: They allow to control for (unobserved) household and country fixed effects, endogeneity and initial conditions and further enable the estimation of dynamic models and to account for the between and within variation of variables.

The second chapter, entitled *Measuring the Labor Income Share of Developing Countries – Lessons from Social Accounting Matrices*, is dedicated to the measurement of the labor income share in developing countries. When this dissertation was initiated, no data on factor income distribution was available that includes a broad range of low and middle income countries, captures entire economies and further adjusts for self-employment. This is largely the result of the poor availability and reliability of national account data in developing countries as well as the fact that the self-employed, whose labor income is hard to capture, account for a significant portion of the workforce and often work in the informal sector. This chapter addresses these challenges and computes a panel data set on the labor share that allows the following chapters to assess the magnitudes and trends, as well as the determinants, of the labor share. To deal with measurement difficulties, social accounting matrices (SAMs) were consulted in addition to the UN SNA, to construct a labor share macro-level data set that is backed up with micro-economic evidence. First, SAMs are used as case studies to open the “black box” of national accounts and obtain knowledge on self-employment in developing countries to formulate assumptions that are necessary to compute labor share data at the macro-level. Second, a pool of SAMs serves as a benchmark to check the reliability of the estimates obtained from national account data. The final data set that adjusts for the labor income of the self-employed provides estimates for about 100 developing countries from 1990 to 2011. The labor share is found to be, on average, close to one half (47 %) and thus less than the standard ’two-thirds’ in the economic literature. The data further suggests that the findings of declining labor shares in previous studies also applies to the specific sample of low and middle income countries since the early 1990s. This corresponds to Piketty’s (2014) hypothesis of wealth accumulation proceeding faster than economic growth: Also in the developing world, income generation seems to be shifting more and more from labor to capital, implying nothing else than a shrinking labor share.

The third chapter, entitled *The Labor Income Share in Developing Countries: A Review and Analysis of International Panel Data*, directly builds on chapter 2 and reviews the above mentioned data set and other international panel data sets on the labor income share in low and middle income countries. In addition to data sets that are either limited in country or sector coverage or do not adjust for self-employed labor income, this review also includes the Penn World Tables (PWT) labor share data set, which was published in 2013. This data set builds on the UN SNA as well and provides adjusted labor share estimates for a broad range of developing and advanced countries. This chapter has a two-fold objective. Firstly, it provides an overview of different measurement approaches and data sources. Given that labor income of the self-employed is not directly observed, computing adjusted labor share data requires making assumptions. Although different data sets aim to measure the same thing (the labor share), estimates are very heterogeneous, which is attributed to the differing underlying assumptions. Various data sets relying on different assumptions are compared and their strengths and weaknesses discussed. Secondly, the chapter presents descriptive statistics on the labor income share and extracts results that hold true independent of the data set used. Unlike the standard suggestions in the literature and in line with the findings of the estimates developed in chapter 2, there is evidence that the labor share is neither constant nor of a magnitude of two-thirds. Across the board, the labor income share has been declining in the developing world since 1990, indicating that labor income has been lagging behind overall productivity increases for the last two decades, and is found to be one-half in size at most. There is evidence that the labor share of the self-employed, as well as that of wage employees, contributes to the decline. The share of self-employed in the workforce decreased over time, and correspondingly, also the labor share of the self-employment sector has decreased. This decline, however, has not been compensated by an increase in the labor share of the wage employment sector, although wage employees make up a growing proportion of the labor force in these countries. The negative trend of the aggregate labor share has been especially endured by low-skilled workers, whereas high-skilled workers have managed to increase their labor income share in national value added. Also the manufacturing sector has experienced a shrinking labor share since 2000. Decomposing by sector further suggests that not only have changes within sectors driven these findings, but also shifts away from labor-intensive agriculture towards more capital-intensive sectors. Finally, there is evidence that the growing gap between a country's wage rates and productivity (and not changes in employment) is driving these results.

The fourth chapter turns to the analysis of the determinants of the labor share. An alarming result of the first two chapters is the substantial downturn of the labor share in the developing world since the early 1990s. The fourth chapter, entitled *Financial Globalization and the Labor Share in Developing Countries: The Type of Capital Matters*, therefore assesses the drivers of this trend. More specifically, it investigates how de facto financial globalization has influenced the labor share in developing countries. As has been reviewed above, previous research has found that international capital mobility can partly explain the decline in the labor share in developing countries. This chapter adds to this strand of literature and further contributes to the research that emphasizes the differences between types of international capital flows, their determinants, and effects (e.g. Daude and Fratzscher, 2008). It is argued that there is a need to distinguish between different types of capital – foreign direct and portfolio investments – when analyzing the influence of financial globalization on the labor share. This is because different forms of foreign investment have different fixed costs and impacts on the host countries' production process and vary concerning their bargaining power vis-à-vis labor. 'Capital' has mostly been considered to be a pretty homogeneous concept in this specific context. Although this aggregate view is sometimes helpful, assuming an aggregate elasticity of substitution between capital and labor can be misleading in cases where different modes of production are associated with specific capital flows, as is the issue here. To empirically asses these relationships, the analysis relies on the labor share data set constructed in chapter 2 as well as the recently published PWT labor share data. It therefore covers the entire economy and accounts for the problem of labor income for the self-employed. The econometric analysis of the impact of foreign direct investment versus portfolio investment, in a sample of about 40 developing and transition countries after 1992, supports the claim of heterogeneous effects of capital inflows. Using different panel data techniques to address potential endogeneity problems, it is found that foreign direct investment has a positive effect on the labor share in developing countries, while the impact of portfolio investment is significantly smaller, and potentially negative. As the increase of foreign portfolio investments was rather modest compared to foreign direct investment in the observed time period, the analysis concludes that de facto financial globalization by itself cannot explain the decline of the labor share in developing countries over the last decades. Instead, results suggest that trade might be a potential candidate.

The fifth chapter with the title *Cash Crops as a Sustainable Pathway out of Poverty? Panel Data Evidence on Heterogeneity from Cocoa Farmers in Sulawesi, Indonesia* has a different focus. It contributes to the sustainable development debate by assessing whether cash crop cultivation sustainably reduces poverty amongst smallholders and exploring which role various labor- and capital-intensive management practices play for the welfare outcomes of cash crop farmers. The diversification into cash crops has a great potential for reducing poverty in the developing world that may not be fully harnessed because many smallholders are inefficient producers. Since cash crop agriculture may experience boom and bust cycles, caused by volatile world market prices, local weather shocks and pests, welfare effects are likely to differ significantly between farmers. Furthermore, income gains may only be static and it is not certain whether the poverty and vulnerability of smallholder households are reduced sustainably, particularly when farmers lack proper farm management skills. To examine the long-term poverty impacts of cash crop agriculture, the analysis draws on a unique panel data set of smallholder farmers in Central Sulawesi, Indonesia, covering the years 2000, 2006, and 2013. The analysis shows that – over the analyzed time horizon of more than ten years – cocoa cultivation is associated with a strong and sustainable reduction in poverty. Cocoa farmers fare better than non-cocoa farmers and welfare gains can mainly be attributed to increasing cocoa yields. Yet, yield gaps remain large, are increasingly heterogeneous and a significant share of cocoa farmers remain poor. This variability in yields can be traced back to farm management practices that include both the application of chemical inputs (especially fertilizer) and labor-intensive practices (especially removing infested cocoa pods and the pruning of trees), with the latter found to be crucial for pest control. Linking these findings to poverty transitions, the analysis shows that better intensification and maintenance practices facilitate the transition out of poverty and shields against income losses. Training smallholders in cash crop management not only has the potential to close yield gaps and improve the livelihoods of smallholder farmers but also to maintain environmental stability by improving the application of synthetic inputs and taking the pressure off forests.

Chapter 2

Measuring the Labor Income Share of Developing Countries: Lessons from Social Accounting Matrices

Abstract

This paper addresses the challenges associated with 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. I consult social accounting matrices as additional source of information to construct a labor share data set that is backed up with micro-economic evidence. The final data set covers about 100 developing countries from 1990 to 2011. The data suggests that the finding of declining labor shares of previous studies also applies to the specific sample of low and middle income countries. Furthermore, I find the labor share in developing countries to be about one-half in size and thus less than the standard 'two-thirds' in economic literature.

2.1 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, 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.

The measurement of the labor share, however, is notoriously difficult for 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 (ILO, 2015, WB, 2013).[1] An additional difficulty arises from the fact that self-

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

employment in developing 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 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 (Günther 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 thus 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 (macro-level) national accounts have data gaps regarding the self-employment sector and may suffer from measurement errors, I additionally consult micro-level data to increase the reliability of labor share data constructed at the aggregate level. For this purpose, I draw upon social accounting matrices (SAMs). SAMs are micro-founded presentations of national accounts in matrix form which integrate information from various data sources besides national accounts such as household and labor force surveys. 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 and to obtain knowledge on self-employment labor income in developing countries. These insights are used to formulate assumptions necessary to compute labor share data at the macro-level. 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 reliability of estimates obtained from national account data. By this means, the information content of micro- and macro-level data can be exploited in a meaningful manner.

The final data set covers about 100 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 seems to apply to the specific sample of low and middle income countries as the data suggests that labor's relative income in developing countries has been declining by on average 10 % points since the early 1990s. This holds true for most of the developing regions and seems to be independent of a country's development stage. Furthermore, I find the labor share in developing countries to be about one-half in size and thus lower than in high income countries.

The paper is organized as follows. Section 2.2 presents the concept of the labor share and elaborates on its measurement from national accounts. Existing data sets are reviewed in section 2.3. Section 2.4 discusses the challenges associated with measuring the labor share of developing countries from national accounts. Section 2.5 performs three case studies using SAMs to extract information about the self-employed and their labor income. Findings are used to formulate assumptions and construct labor share data from national accounts in the following step (section 2.6). Section 2.7 validates the data by comparing it to a pool of 51 SAMs and section 2.8 presents some properties of the data set. Section 2.9 concludes.

2.2 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:

$$\mathrm{Y} = \frac{\mathrm{w}}{\mathrm{P}} \times \mathrm{L} + \frac{\mathrm{i}}{\mathrm{P}} \times \mathrm{K}, \tag{2.1}$$

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

$$LS = \frac{w \times L}{P \times Y}. \tag{2.2}$$

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):

$$LS_n = \frac{CoE}{GDP}. \tag{2.3}$$

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 Gollin (2002) and Krueger (1998), 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,

[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 might therefore imply different data.

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, 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:

$$LS_{G1} = \frac{CoE + MI}{GDP}, \tag{2.4}$$

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:

$$LS_{G2} = \frac{CoE}{GDP - MI}. \tag{2.5}$$

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:

$$LS_{G3} = \frac{CoE}{GDP} \times \frac{TE}{E} = \frac{\frac{CoE}{E}}{\frac{GDP}{TE}}, \tag{2.6}$$

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 %. 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.

2.3 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, 2007, Ellis and Smith, 2007, Elsby and Sahin, 2013, Guscina, 2006, Hutchinson and Persyn, 2012, IMF, 2007, Jaumotte and Tytell, 2007, OECD, 2012, Slaughter, 2001, and others) , 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 more 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 Karabar-

[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.

bounis and Neiman (2014), they mainly base their analysis on the naïve labor share. As data is 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 (such as Maarek and Decreuse, 2015, Ortega and Rodriguez, 2001 use the UNIDO INDSTAT data set which, 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 proxy for MI, Inklaar and Timmer (2013) 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 relies in almost equal shares on LS_{G2} – assuming that self-employed mixed income has the same labor share as employees – and, where not available, on LS_{G1} – classifying all self-employed income (proxied by agricultural value added) as labor income. In the few remaining cases, they hold on to the naïve share when it exceeds 70 % 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 thus 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 % and 46 % 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 a set of assumptions, databases should verify their results, for example by checking them against country- or region-specific data. Furthermore, studies may not adequately account

[5] For example, when Rodriguez and Jayadev (2010) adjust their naïve labor share data set 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.

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 data set contributes to the literature in three respects: First, it draws upon additional information from SAMs to increase the reliability of macro-level data on the labor share. 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 is demanding in light of the increasing evidence of non-constant labor shares. 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.

2.4 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 (micro-level) 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, 2014b). 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 (Inklaar and Timmer, 2013). This proxy is plausible, yet it disregards capital, especially land, as agricultural production factor and leaves aside labor income from other forms of self-employment (ibid.). 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.

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.

2.5 Social Accounting Matrices

A SAM is a matrix representation of national accounts that displays flows of all transactions that take place in an economy. SAMs are constructed by matching and complementing national accounts, input-output tables, labor force surveys, household surveys et cetera. They thus bridge income data collected at the household level and macro-economic data which implies a higher reliability than national accounts. 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). As SAMs break down national accounts in greater detail, they also make the composition of labor visible. By this means, SAMs can be used to identify the sectors of the self-employed as well as the corresponding productivities and factor intensities. This information can be used as basis for estimating the labor income of the self-employed. Unfortunately, SAMs are 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.

In theory, a SAM always balances, but in the empirical practice it never does from the outset. This is because the data stems from different sources, national accounts are often inconsistent in developing countries and SAMs require to convert every item into money flows. For this reason, statistical methods are needed to adjust the unbalanced SAM. This is most frequently done with the cross-entropy approach which 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 can therefore 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 to include 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.

2.5.1 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 are therefore 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.

As can be seen in the SAM of Bolivia for 1997 (table 2.1), self-employed earning mixed income mostly work in the traditional agricultural sector, 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 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 %, in the agricultural sector 65 % and in the retail sector 58 % (Yusuf, 2006). At the same time, mining has with 15 % the lowest labor share (ibid.). A similar pictures emerges from the SAM of Zambia for 2001 (see figure 2.1). Furthermore, in a given sector, the self-employed seem to pursue a more labor-intensive strategy than

Table 2.1: **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

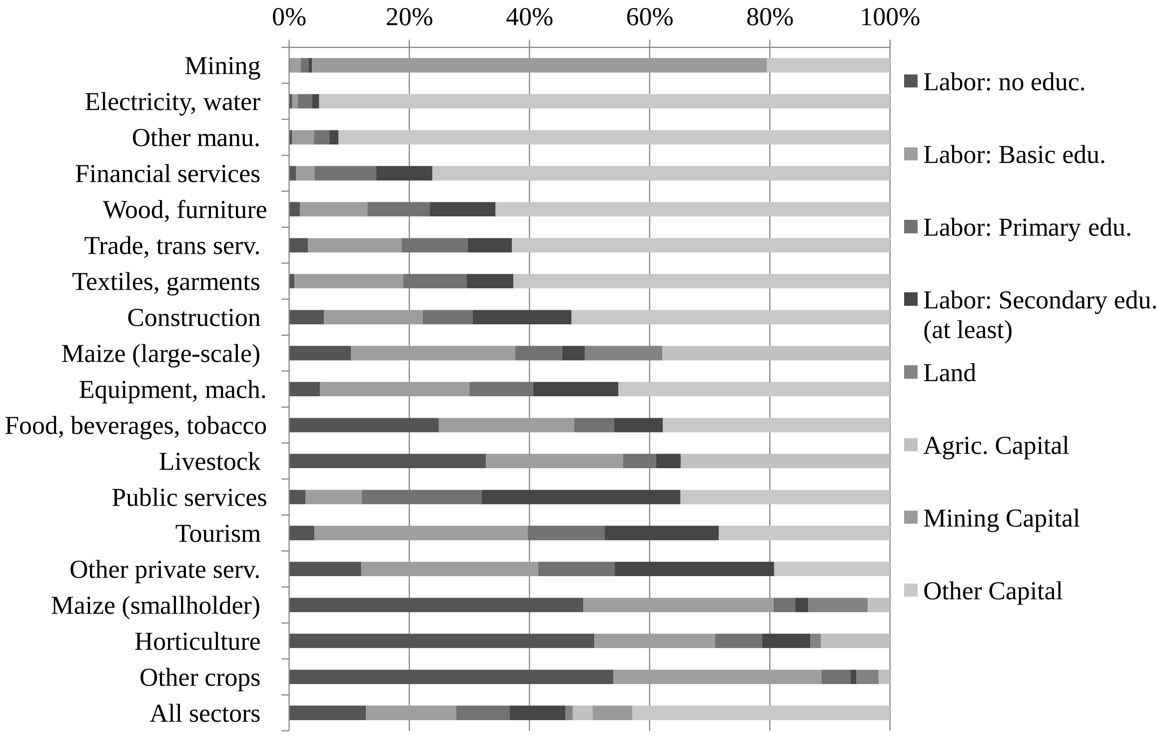
Source: Thiele and Piazolo (2002, p.6).

larger firms. The employment of agricultural capital and thus the capital share increases with farm size: In the case of maize agriculture, labor makes up 87 % of all factor inputs on small-scale farms but only 49.2 % on large-scale farms.[7] 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 2.1, 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).

Finally, the Bolivian SAM gives some indication on how the labor income of the self-employed compares to employees' wages. As can be seen in figure 2.2, 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

[7]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 (WB, 2013, Wiggins et al., 2010).

Figure 2.1: **Factor employment across sectors in Zambia, 2001**

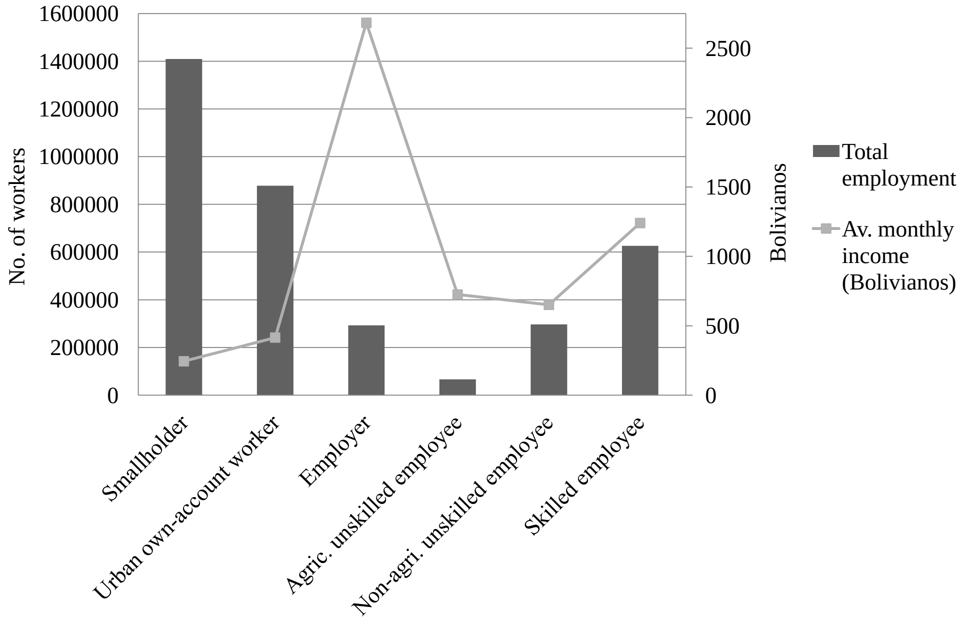


Source: Author's illustration based on Thurlow et al. (2004, Table 5.6).

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 is therefore 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 depends therefore crucially on the employment structure of an economy. Figure 2.3 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 vulnera-

Figure 2.2: **Employment and income by household group in Bolivia, 1997**



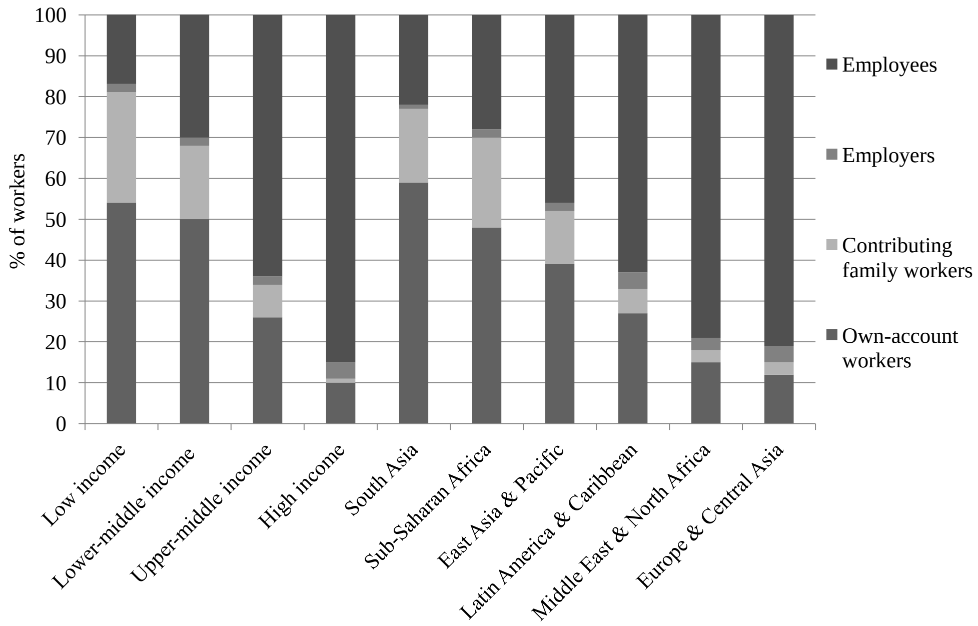
Source: Author's illustration based on Thiele and Piazolo (2002, table 8).

ble (self-)employment (i.e. own-account and contributing family workers) is about 80 % in low-income countries; here only 2 % 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 % of all employed, about 6 % 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). 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 and WB, 2013).

2.6 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,

Figure 2.3: **Status in employment across income groups and regions, 2010**



Note: Self-employment = Own-account workers + Contributing family workers + Employers; Vulnerable employment = Own-account workers + Contributing family workers.
Source: Author's illustration based on ILO (2017a).

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 2.3.[8] Data is retrieved from the most recent UN SNA series available.[9] 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 SAMs revealed that there is an (albeit small) non-

[8]Data on CoE is determined 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 Bühn, 2016, US Bureau of Economic Analysis, 2009).

[9]Within a series, 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.

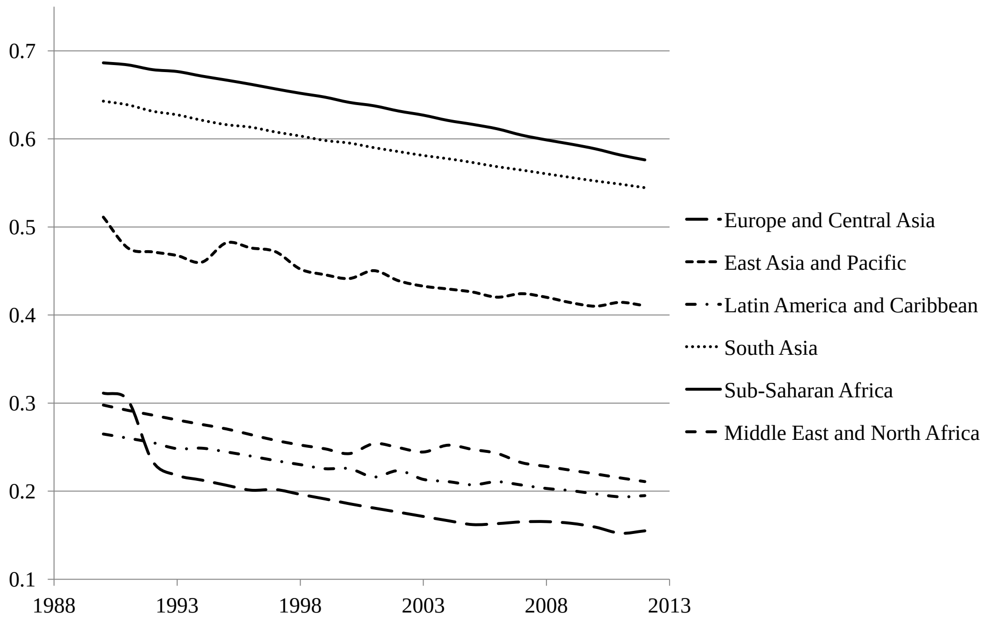
labor share in smallholder agriculture and that the higher the share of urban own-account workers and employers, the higher the capital share. The next option – *Gollin's second adjustment* – assumes self-employed income to contain the same mix of capital and labor income as the rest of the economy. 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 (equation 2.6). 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 to chose 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 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 2.4 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:

$$LS_{G3'} = \frac{CoE}{GDP} \times \frac{TE}{TE - AE}, \tag{2.7}$$

where agricultural employment (AE) serves as proxy for self-employment. The full

Figure 2.4: **Agricultural employment shares by region, 1990-2012**



Source: Author's illustration based on FAO (2012) and WB (2017).

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 % and average at 50 % or below. Furthermore, it ranges between Gollin's first and second adjustment for most countries which 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 % in China, 240 % in Bhutan or 318 % in the case of Burkina Faso). 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 91 %.[10] 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 rea-

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

sonably high (greater than 21 %) and an imputation of wages would overshoot (greater than 91 %). 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 (Johnson et al., 1997, Kaufmann and Kaliberda, 1996). 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: Very high adjusted labor shares (above 91 % or even above 100 %) go hand in hand with very low naïve labor shares (below 21 %), suggesting that the actual labor share lies somewhere in between.[11] 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 2.4, FAO, 2012, WB, 2013. For the low and lower middle income countries from these two regions, I therefore only impute a share of employees' wages:

$$LS_{G3''} = \frac{CoE}{GDP} \times \frac{TE}{TE - \frac{2}{3}AE}. \tag{2.8}$$

Following Bentolila and Saint-Paul (2003), the self-employed are assumed to earn on average two-thirds of employee income. Of course, this assumption is of arbitrary kind but the resulting adjusted labor shares appear reliable. They range between 11 and 77 % in Sub-Saharan Africa and 42 and 75 % in South Asia and, where available, move between Gollin's first and second adjustment or below.

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 2.2 summarizes the resulting labor share and its components. The final data set covers about 100 low and middle income countries from 1990 until 2011 (see appendix A for a list of countries included) for the final data set). It is an unbalanced panel with in total 1397 observations.[12] The labor share ranges from 6 to 92 % with a mean and a median of 47

[11] The most extreme example is Burkina Faso which has a mean naïve labor share of 21 % that wage imputation lifts up to 318 %.

[12] The PWT data set has more than 50 % more observations in its sample of low and middle income countries

Table 2.2: **The final labor share (in %) and its components**

Adjustment	Range	Mean	Median	Obs.	Comments
Final labor share	6.0-91.7	46.9	46.9	1397 (100 %)	Composition of the below adjustments
1. Step: Gollin's 3rd adjustment (with agri. employment as proxy for self-employment)					
a) $LS_{G3'}$	6.0-87.2	46.4	46.3	707 (50.6 %)	
b) $LS_{G3''}$	10.8-77.0	46.8	47.7	256 (18.3 %)	In low and lower middle inc. countries in SA and SSA
2. Step: Use naïve labor share in case it already covers self-employment					
LS_n	23.7-90.7	52.4	50.5	89 (6.4 %)	
3. Step: Framing the data with Gollin's 1st adjustment (upper bound) and 2nd adjustment (lower bound)					
a) LS_{G1}	26.2-64.5	48.6	52.6	54 (3.9 %)	
b) LS_{G2}	21.0-73.4	46.1	46.3	291 (20.8%)	

Source: Author's calculation based on UN SNA (2015), FAO (2012) and WB (2017).

%. While the PWT labor share is based in more or less equal parts on LS_{G1} (using agricultural value added as a proxy for MI) and LS_{G2}, my data relies in the majority of cases (70 %) 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 two-thirds 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 (Inklaar and Timmer, 2013). The summary statistics suggest that this is not the case given that in 20 % of cases LS_{G2} serves as a boundary.

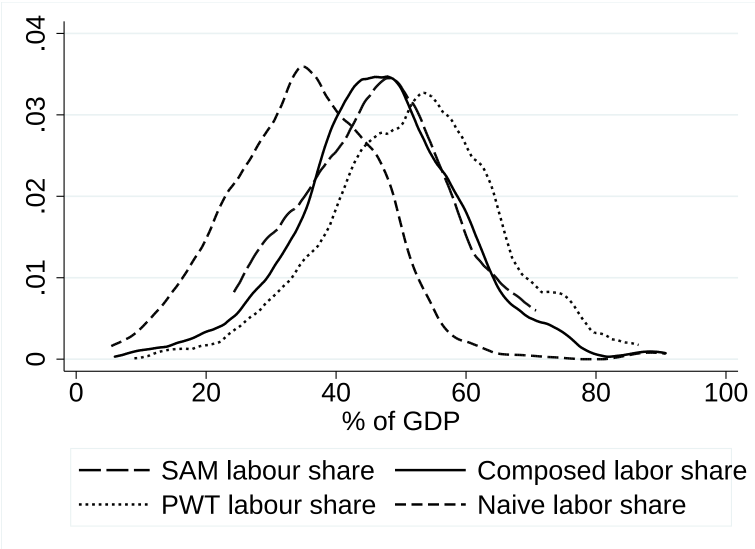
2.7 Validation of data

To check the reliability and validity of the macro-level estimates, they are checked against micro-level data 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

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.

Figure 2.5: **Distribution of labor share data**

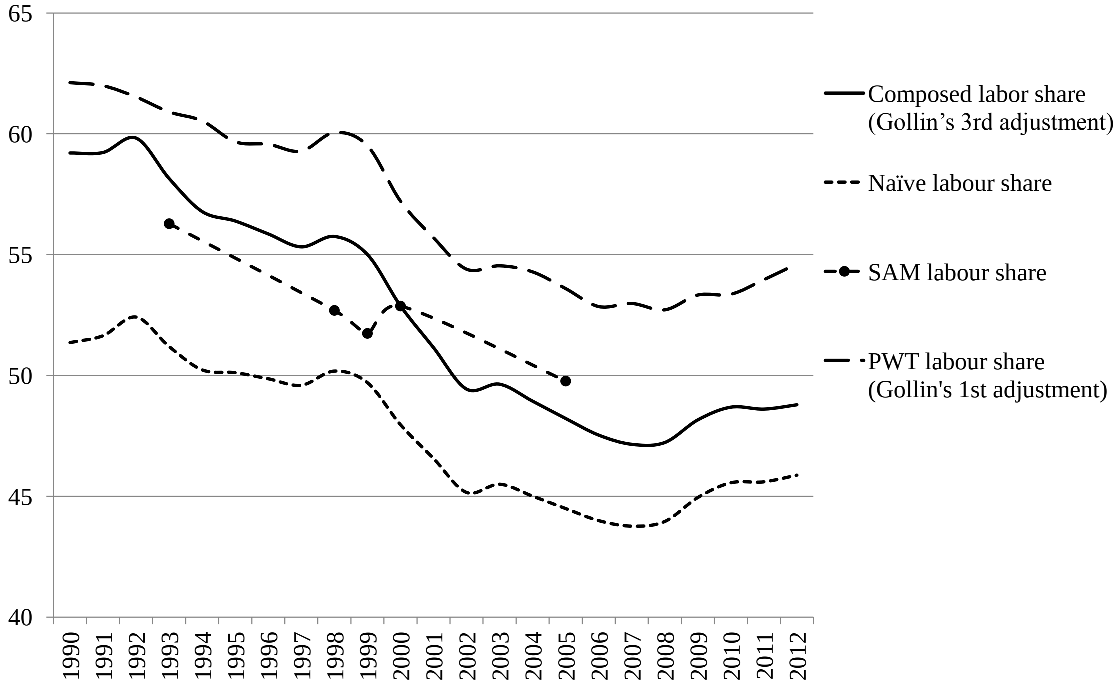


Note: Kernel density estimates.
Source: Author's illustration based on FAO (2012), IFPRI (2015), PWT (2013), UN DESA (2015), UN SNA (2015) and WB (2017).

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. For this purpose, figure 2.5 provides the probability density function for the SAM data pool obtained from Epachenikov kernel density estimates. The SAM labor share data ranges between 24 and 71 %, with a mean and a median of 46 %. These values are very close to the macro-level estimates from national accounts, giving support to the way of construction. Both estimates are close to a normal distribution. Figure 2.5 further shows the distribution of the naïve labor share and the PWT adjusted labor share. As expected, the distribution of the unadjusted labor share is slightly to the left of the adjusted estimates. With a mean of 52 %, the PWT estimates are relatively high which is mainly due to the reliance on Gollin's first and second adjustment. As argued in section 2.2 and 2.6, relying on these adjustments in the context of low and middle income countries runs risk to overestimate the labor share.

SAMs only offer limited possibility to check the validity of the macro-level 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

Figure 2.6: **Labor share of South Africa, 1990-2012**

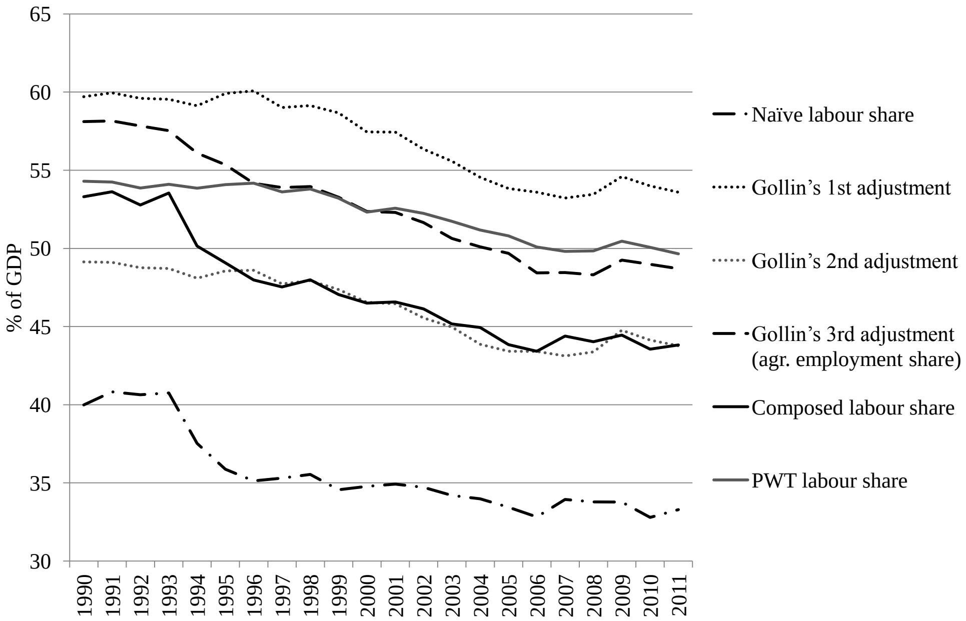


Note: PWT uses agricultural value added as a proxy for self-employed labor income, the composed labor share uses agricultural employment as a proxy for self-employment.
Source: Author’s illustration based on FAO (2012), IFPRI (2015), PWT (2013), UN DESA (2015), UN SNA (2015) and WB (2017).

estimates (see figure 2.6), the country’s labor share decreased by 7 % points between 1993 and 2005 (from 56.3 to 49.8 %). 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 macro-level labor share (see figure 2.7). 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

Figure 2.7: **Different labor share adjustments, 1990-2011**



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.
Source: Author's illustration based on FAO (2012), PWT (2013), UN SNA (2015) and WB (2017).

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 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's first and second adjustment and is therefore centered between these two measures, resulting in comparatively high labor shares.

2.8 Properties of the data set

2.8.1 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 2.7, 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 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. 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).

The significant downward trend is also seen when regressing the composed and the naïve labor share on time and the SNA system in a fixed and random effects model (see table 2.3). The composed labor share on average decreases by 0.5 and the naïve share by 0.25 % points per year over the observed period (i.e. in total by about 10.5 and by 5.25 % points respectively). The regression shows that the SNA series has a negative but insignificant influence on the resulting data.[15]

As shown in figure 2.8, the fall in the labor share has been present in all developing regions between 1990 and 2011. East Asia and the Pacific is the region which experienced the fastest decrease (on average by 14% points) during that period, followed by Latin America and the Caribbean (10 % points) and Eastern Europe and Central Asia (8 % points). A considerable decline also occurred in Sub-Saharan Africa (5 % points) and the Middle East and North Africa (4 % points). Only in South Asia (Sri Lanka, Bhutan and India), the labor share remained more or less on a constant level. The level of the labor shares varies between the regions. South Asia exhibits the highest labor shares (on average 70 %), which is, however, mainly due to the high reported naïve share of Bhutan (about 90 %). The labor shares are lowest in the Middle East and North Africa (about 40 %) which is expected as most of the oil-producing countries are located in this region. In the other regions, labor shares range between 40 and 60 %. The average level is therefore well below the standard of 'two-thirds' in all regions except for South Asia. This finding corresponds to recent economic studies

[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 during crises (ILO, 2013).

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

Table 2.3: **Regression of labor share on time trend and SNA system**

VARIABLE	Composed LS	Naïve LS
Fixed Effects Model		
Time trend	-0.514***	-0.250***
	[0.078]	[0.070]
SNA series	-2.596	-0.990
	[2.149]	[1.704]
Random Effects Model		
Time trend	-0.519***	-0.255***
	[0.076]	[0.069]
SNA series	-2.235	-0.730
	[2.061]	[1.665]
Observations	1397	1397
Number of countries	94	94
Av. observations per country	15	15

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, * p-value <0.1.
Source: Author's calculation based on FAO (2012), UN SNA (2015) and WB (2017).

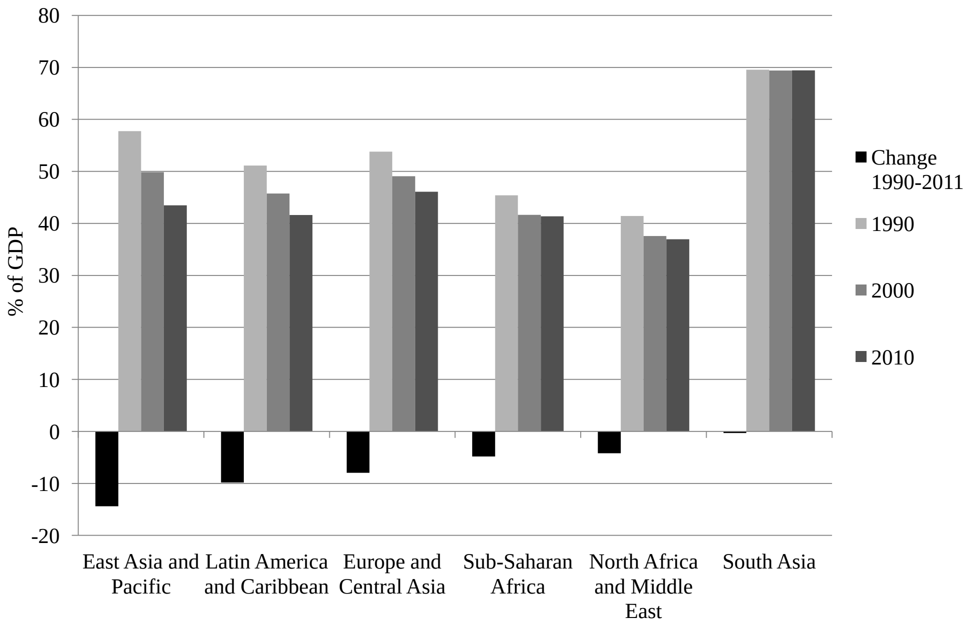
which argue that the labor income share in developing countries is significantly lower than that in high income economies and about one-half in size (for example, Chen et al., 2010, Imrohorolu and Üngör, 2016, Izyumov and Vahaly, 2015, Young and Lawson, 2014).

Finally, Figure 2.9 displays labor shares for different income groups (low, lower-middle and upper-middle income) according to the World Bank's country classification in 2000. The level of a country's labor share seems to be independent of a country's stage of development. Also the negative trend occurs across all income groups.

2.8.2 Unit roots

Descriptives on labor share data already provide some 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 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

Figure 2.8: **Average labor shares by region, 1990, 2000, 2010**



Note: Data is interpolated and kept constant beyond start and end points for this illustration to deal with unbalanced panel data.
Source: Author's illustration based on FAO (2012), PWT (2013), UN SNA (2015) and WB (2017).

roots, using a Fisher test statistic as presented in Maddala and Wu (1999):

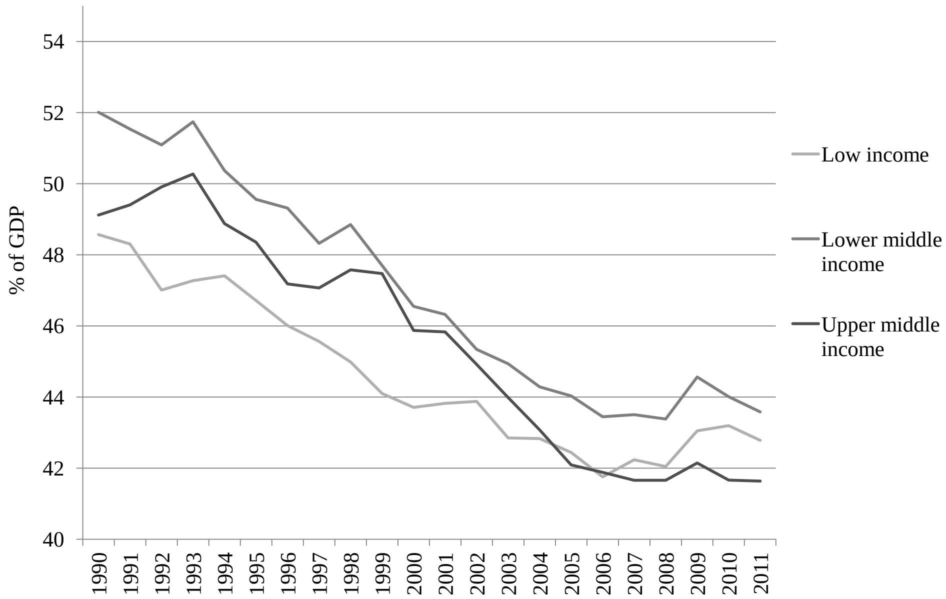
$$\lambda = -2\sum_{i=1}^{N} ln(\pi_i) \tag{2.9}$$

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 2.4 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 1 % level of statistical significance, thus providing

[16]The test is χ^2-distributed with 2N degrees of freedom.

Figure 2.9: **Labor shares by income classification, 1990-2011**



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.
Source: Author's illustration based on FAO (2012), PWT (2013), UN SNA (2015) and WB (2017).

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.

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

[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.

Table 2.4: **Augmented Dickey-Fuller tests of labor share data**

Lags	No Trend	With Trend	With Constant
1	χ^2(174)=271.5***	χ^2(174)=410.6***	χ^2(164)=476.7***
2	χ^2(170)=260.5***	χ^2(170)=281.6***	χ^2(154)=399.1***
3	χ^2(164)=370.7***	χ^2(164)=267.9***	χ^2(144)=375.8***

Note: Degrees of freedom in parentheses. *** p-value <0.01.
Source: Author's calculation.

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 micro-data 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 micro-economic data can only be a second best option. It is therefore 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 should therefore develop new economic models which move beyond the constancy of factor shares and assumption of 'two-thirds' (Kanbur and Stiglitz, 2015).

Chapter 3

The Labor Income Share in Developing Countries: A Review and Analysis of International Panel Data

Abstract

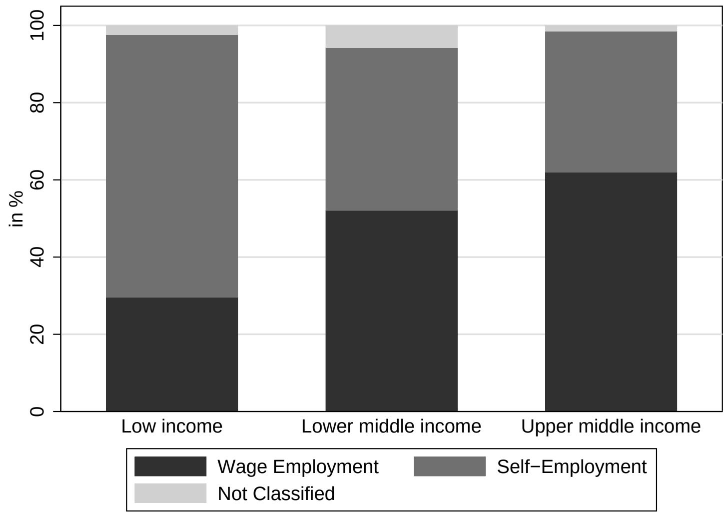
This paper reviews international panel data on the labor income share in low and middle income countries with two objectives. First, it provides an overview of different measurement approaches and data sources. Given that labor income of the self-employed – who account for a large portion of the workforce and often work in the informal sector – is not directly observed in these countries, computing the labor share requires several assumptions. Various data sets relying on different assumptions are compared and their strengths and weaknesses discussed. Second, the paper presents basic statistics on the labor income share and extracts results, which hold true independent of the data set used. Unlike standard propositions, there is evidence that the labor share is neither constant nor does it represent two-thirds of total output. The labor income share has been declining in the developing world since 1990, indicating that labor income has been lagging behind overall productivity increases for the last two decades, and is found to constitute half of total production output at most. There is evidence that not only has the labor share for the self employed declined, but also for wage employees, although they make up an increasing proportion of the labor force in these countries. The decline in the labor share can also be seen in the manufacturing sector since 2000 and has especially affected low-skilled workers, whereas high-skilled workers managed to increase their labor income share in national value added. Decomposing by sector further suggests that not only have sectoral changes driven these findings but also shifts away from labor-intensive agriculture towards more capital-intensive sectors. Finally, there is evidence that the increasing gap between a country's wage rates and productivity – and not changes in employment – is driving these results.

3.1 Motivation

The labor share measures the share of an economy's national income that stems from labor, in contrast to the income share earned by other factors of production, mainly capital. The labor share is of particular relevance for developing countries, especially in their effort to fight poverty and inequality. In the developing world, a bulk of the society only has its labor force to earn income and most low income households are poor because their work does not generate enough income. About one third of all employed persons in these countries are *working poor*, meaning that they live on less than 2 US-Dollar a day (ILO, 2014a). Hence, to ensure that an economy's income achievements are spread among its society and poverty is successfully addressed, it is essential that productivity gains also translate into higher wages. This is the case if the labor share is on a constant and sufficiently high level. However, there are increasing signs that labor has been losing ground against capital in the last decades, not only in high income countries but also in the developing world. This suggests that labor income has been lagging behind overall productivity increases and that welfare gains have not equally reached the recipients of capital as well as labor income. Furthermore, as capital income continues to be more concentrated than labor income and inclines to go to rich households, a declining labor share is likely to correspond to an increase in inequality between individuals.

These developments have led the United Nations to incorporate the labor share into the 2015 adopted Agenda for Sustainable Development within the scope of the Sustainable Development Goal (SDG) 10, which is to "reduce inequality within and among countries" (UNSD, 2016). Target 10.4 ("Adopt policies, especially fiscal, wage and social protection policies, and progressively achieve greater equality") urges for more policy action against national inequality and uses the labor share as an indicator. For example, policies involving setting a minimum wage or tax concessions for investment, directly influence the relationship between capital and labor and hence inequality. The labor share has been implemented to evaluate whether public policy is designed such that increased production leads to broad improvement in the living standards of a society, and not only of a small group of people earning capital income. To assess the achievement of this target – i.e. the development of the labor share over time –, data on an economy's labor income and total national income (measured, for example, by GDP) is needed. However, measuring labor income in the context of developing countries is an extremely difficult undertaking. A massive data problem arises from the fact that the majority of the working population in low and middle income countries works in the self-employed sector (in contrast to the wage employment sector). Although wage employment has been increasing over time, and in the course of economic development, self-employment still makes up about two-thirds of total employment in low income countries, about one half in lower middle income countries and about one third in upper middle income countries (see figure 3.1). The difficulty in measuring income stemming from self-employment is that their labor income is not directly observed.

Figure 3.1: **Employment structure by income group, 2013**



Source: ILO (2017b).

This is because the self-employed in low and middle income countries are usually own-account workers or contributing family members (for example subsistence farmers or street vendors) whose activities are located in the informal sector. As a consequence, their income usually does not appear in (national) statistics and needs to be estimated. Furthermore, even if data on self-employed income is available, it consists of income from labor as well as from capital and its labor share has to be first extracted. Since there is no comprehensive information of good quality available on the labor-capital mix of self-employed income, assumptions are required.

As a consequence, the United Nations, or more specifically the International Labor Organization (ILO) which is the custodian of this indicator within the scope of the SDGs, relies on the share of labor income of wage employees in GDP, leaving out the self-employed. This labor share is termed *unadjusted* or *naive* labor share in the literature and is meaningful in high income countries where about 15 % of the labor force is self-employed. However, in countries where a large share or even the majority of workers are self-employed, this will systematically “underestimate the proportion of GDP accrued to total employment” (UNSD, 2016). Furthermore, in a dynamic perspective, an increase in the unadjusted labor share – which is to be achieved under target 10.4 – might simply be the result of people entering wage employment. When the self-employed switch to wage employment – in developing countries, this typically is the movement away from subsistence agriculture to the corporate sector – their labor income for the first time appears in official statistics, raising the labor share, even though their labor income has not significantly changed. To avoid this, the ILO suggests estimating an *adjusted* labor share, which also includes the labor income of the self-employed (UNSD, 2016). As previously mentioned, emphasis is placed on the term 'estimate', since no adequate and broad data base on self-employed labor income exists.

While the labor share has been neglected by the economic discipline for some decades, the literature revived the analysis of the labor share in the early 2000s and also addressed the issue of self-employment in this context. However, the vast majority of researchers and international organizations have concentrated on high income and a few emerging economies where they encountered reliable and broad data. To date, only a few studies explicitly deal with the measurement of the labor share in low and middle income countries and address the issue of self-employment in these countries.

This paper reviews the various approaches used in the literature to measure the *adjusted* labor share (i.e. including self-employment) in the developing world. As the adjustment process relies on estimations, different data sets and studies using different assumptions (and data sources) yield varying results. This paper surveys the data and the underlying assumptions and discusses their strengths and weaknesses. In this way, this paper intends to give guidance when deciding on the most appropriate measure and on the necessary steps in future data collection. Furthermore, the data is merged to assess how far their empirical findings vary and if there is a general picture emerging from the data. The various data sources all show a significant decline in the labor share since the 1990s, when data for developing countries became available. Across the board, the labor share is one half in size at most. Moreover, all regions and country income groups experienced this downturn, although to varying degrees. The decline holds true for wage employees, as well as for the self-employed, and has also affected the manufacturing sector since 2000, which traditionally is a source of hope for productivity increases in conjunction with broad income effects. The fall in the labor share has especially affected low-skilled workers, while high-skill workers managed to increase their labor share. Decomposing by sector further suggests that not only changes within sectors have driven these findings but also shifts away from labor-intensive agriculture towards more capital-intensive sectors such as real estate. This development takes place during a phase of strong labor force growth, suggesting that the decline is a result of an increasing gap between productivity and wages (and not due to fewer people in employment).

This paper is organized as follows: Section 3.2 illustrates the concept of the labor share and presents different measurement approaches. Section 3.3 reviews existing data sets and their underlying assumptions. I then analyze the data and present basic statistics on the magnitude and trend of the labor share in section 3.4. Section 3.5 takes a look at the different components of the labor share and examines which parts drive the descriptive results at the aggregate level. Section 3.6 synthesizes the results and discusses implications for future measurement and analyses.

3.2 The labor share in theory and its practical measurement

The labor share is a measure of the income distribution between different factors of production, i.e. between labor on one hand and capital (including land) on the other. It reflects how much of a country's national income is earned by labor. It thereby differs from measures, such as the Gini coefficient, which display the income distribution between individuals. However, the personal income distribution can be directly determined from factor income shares once the owners of capital, land and labor are known (Ray, 1998).

Assuming that value added, or production output, is given by $Y = f(K,L)$, where K is capital (including land capital) and L labor (including human capital) used in production, the income distribution between production factors is given by:

$$\mathrm{Y} = \frac{\mathrm{w}}{\mathrm{P}} \times \mathrm{L} + \frac{\mathrm{i}}{\mathrm{P}} \times \mathrm{K}, \tag{3.1}$$

where w is the wage rate, i is the interest rate and P is the price level.

The labor share LS then can be expressed as:

$$LS = \frac{w \times L}{P \times Y} = \frac{w \times L}{w \times L + i \times K}. \tag{3.2}$$

As such, the concept of the labor share is similar to the measurement of the real unit labor cost (Marterbauer and Walterskirchen, 2003) and the wage-productivity ratio (ILO, 2013). It is the counterpart of the capital share in national income, which is inversely given by:

$$KS = \frac{i \times K}{P \times Y} = \frac{i \times K}{w \times L + i \times K}. \tag{3.3}$$

The standard approach to describe the relationship between the factors of production and their production output continues to be the Cobb-Douglas production function (Cobb and Douglas, 1928). This production function assumes the capital share to be constant over time and that wages move parallel to productivity. Changes in the labor share may only originate from shifts to sectors that use one of the production factors with relative intensity (for example through trade), non-neutral technological progress, or a deviation of a factor's remuneration from its marginal product caused by labor adjustment costs or bargaining between capital and labor (Bentolila and Saint-Paul, 2003). Early empirical estimations of the factor income distribution using the Cobb-Douglas production function found the labor share to range between 60 and 75 % in the United States and other high income countries (Douglas, 1967, 1976). This gave rise to the standard value of two-thirds for labor's share in production output. The same studies approved the long-term stability of factor shares, which also became one of the 'stylized facts' of economic growth put forward by Kaldor (1957).

In practice, the labor share is measured by drawing on national accounting data. In a first step, data on the total wage bill of employees, which is usually readily available as "compensation of employees" (CoE) in the primary distribution of income accounts, is divided by the total production output of a country (GDP):

$$LS_{unadj} = \frac{CoE}{GDP}. \tag{3.4}$$

This simple measure is referred to in the literature as the unadjusted labor share (LS_{unadj}) because it only takes wage employees into account and does not adjust for the labor income of the self-employed. Adjusting for self-employment is not straightforward because (1) the self-employed's income is often not directly observable and (2) the self-employed not only generate income from labor force participation but also from capital investments.

The first point is a serious data problem in developing countries. Self-employment is the standard in these countries (see Figure 3.1) but the activities of the self-employed are rarely recorded since most of them are located in the informal sector where incomes are difficult to capture. Self-employment in developing countries primarily refers to workers who are forced into self-employment, given that formal labor markets are relatively underdeveloped offering only limited job opportunities (Fields, 2014, WB, 2013) . People are own-account workers (typically subsistence farmers or street vendors) or unpaid family workers, mainly because they cannot find employment on the regular job market. People who are self-employed in developing countries are thus generally in a position of vulnerability.

Even if statistical offices are able to collect data on self-employed income, the second point causes a further problem since the data usually comes as 'mixed income', which contains - as the term already suggests - both capital and labor income. The labor component of the self-employed mixed income still has to be estimated, given that regular data surveys cannot easily capture the capital-labor-mix used in production.

Despite these obstacles, it is essential to adjust the labor share for self-employment. If the whole self-employment sector is left aside, the labor share would be underestimated and the capital share overestimated (Kravis, 1959, Krueger, 1998). This handling would implicitly assume that self-employed income only consists of capital income, since self-employed income is added to the denominator of equation 3.3 but not to its numerator. This procedure has even more severe impacts in a dynamic perspective as it does not adequately reflect structural changes in employment: Ceteris paribus, the movement of workers out of self-employment into wage employment would automatically raise the labor share, even though overall labor income has effectively not changed. This increase would simply be the result of fragmented data collection, which captures the income of wage employees but not of the self-employed. An informative measure of the labor share therefore needs to encompass the entire share of national income, which captures labor, regardless of whether it is earned by employees or the self-employed.

There are several suggestions on how to adjust the labor share for the income of the self-employed. Most prominently, Gollin (2002) has identified three potential approaches, relying on three different assumptions. His article soon became the standard reference.

His first two suggestions make use of the item 'mixed income'. By estimating the share of labor in mixed income and adding it to the unadjusted share, we can arrive at a sound measure of the labor share.

Gollin's first adjustment (G1) adds the entire amount of mixed income to the compensation of employees:

$$LS_{G1} = \frac{CoE + MI}{GDP}, \tag{3.5}$$

where MI is the mixed income of the self-employed. This procedure overestimates the labor share as it assumes self-employed income to only be generated from labor and ignores other factors of production, such as land in subsistence farming.

His second adjustment (G2) takes this into account and only adds a share of mixed income to the compensation of employees. It assumes mixed income to have the same labor share as the rest of the economy. It subtracts mixed income from total value added such that the share of compensation of employees in the wage employment sector applies to the whole economy:

$$LS_{G2} = \frac{CoE}{GDP - MI}. \tag{3.6}$$

This approach is more plausible but disregards the fact that capital and labor shares might vary substantially between the self-employment and wage employment sectors. In developing countries, self-employed enterprises are likely to be more labor-intensive than corporations as the self-employed have limited access to capital. This adjustment thus tends to underestimate the labor share in these countries.

A major drawback of these first two approaches in the context of the developing world is that only about one-third of low and middle income countries, which report compensation of employees, also provide data on self-employed mixed income.

Gollin's third adjustment (G3) places fewer demands on the data since it only requires information on the employment structure of a country. Like the second adjustment, it starts from a certain resemblance between the wage and self-employment sectors and assumes the average labor income of the self-employed and employees to be the same, i.e. their labor productivity to be identical. By using data on the employment structure, the average wage bill is imputed to the self-employed:

$$LS_{G3} = \frac{CoE}{GDP} \times \frac{TE}{E} = \frac{\frac{CoE}{E}}{\frac{GDP}{TE}}, \tag{3.7}$$

where TE is total employment, E employees and $TE = E + S$ with S denoting self-employment. While the unadjusted labor share reflects the share of the total wage bill of employees in GDP, the labor share computed using this third adjustment relates the wage per employee to the value added per employed person. It follows that the adjusted labor share rises (falls) if the wage per employee grows faster (slower) than the productivity per employed person. A drawback of this approach is that it does not consider that employees and the self-employed might work in different sectors and under different conditions – for example employing different skills – with the result that they achieve different levels of productivity. This adjustment might therefore underestimate the labor share in high income countries where the self-employed belong to the top income earners of the economy. On the other hand, it is likely to overestimate the labor income of the self-employed in low and middle income countries where they belong to the low-skilled, vulnerable sector. To account for these systematic differences between sectors and skills, an advanced version of this adjustment performs the wage imputation separately by sector and skill. This, however, requires high-quality data, which is very rare in the context of the developing world.

Neither of these adjustments generates completely satisfactory results; each measure has to rely on assumptions that might not always reflect the true situation of a country, yielding divergent estimates. Low and middle income countries further face a poor data situation which limits the computation of and choice between different measures. The next section collates and reviews available data and derived labor share measures.

3.3 Data review

A look into the literature reveals that most of the analyses are still restricted to advanced countries (Arpaia et al., 2009, Elsby and Sahin, 2013, Hutchinson and Persyn, 2012, Jaumotte and Tytell, 2007, Jayadev, 2007). There are only a few studies that analyze the labor share on a global scale (Bernanke and Gürkaynak, 2001, Diwan, 2001, Guerriero and Sen, 2012, Harrison, 2005, Karabarbounis and Neiman, 2014, Maarek and Decreuse, 2015, Ortega and Rodriguez, 2001, Rodriguez and Jayadev, 2010, Stockhammer, 2013). However, in recent years, there has been an increasing effort among researchers and international organizations to address the measurement of labor shares in low and middle income countries. Table 3.1 summarizes all currently available data sets, which (also) cover low and middle income countries since 1990, as only then did data became also available for the developing world.

The most important data source to compute the labor share on a global level is the United Nations System of National Accounts (UN SNA) . It standardizes national accounting and collects data from member countries to compile data on various national accounts, mainly on income and production accounts. It provides data on GDP for almost all countries around the world. Since 1990, it also records data on the compensation of employees for about two-thirds of low and middle income countries. The unadjusted labor share (denoted as SNA unadj.) can therefore easily be computed for 93 low and middle income countries, covering an average time span of 15.3 years per country and resulting in 1421 observations. Not only is it an unbalanced panel data set but it also does not include a systematic and consistent record of self-employed income. Only about one-third of developing countries, which report compensation of employees, also report mixed income on a regular basis to the UN SNA. Adjusting the labor share for self-employed income by making use of mixed income is therefore only possible against the backdrop of losing the bulk of observations, mainly the least developed countries (especially countries in South Asia, South-East Asia and Sub-Saharan Africa), which do not have the institutional capacity to collect the data. LS_{G1} and LS_{G2} can only be computed from UN SNA for 38 countries (denoted SNA G1 and SNA G2). The third adjustment alternative requires data on the employment structure of a country, just as it is available in the ILO's database KILM (Key Indicators of the Labour Market). Although less demanding, the data only covers a share of those countries that also reports on the compensation of employees. Computing LS_{G3} using KILM and UN SNA data (denoted SNA G3) gives estimates for 73 low and middle income countries. Due to data gaps in the employment structure data, it provides a total of 766 observations.

Accordingly, only consulting UN SNA and KILM as data sources is not satisfactory due to the data constraints. Further effort is needed to obtain a broad data set on the adjusted labor share for the developing world. This is possible either by consulting additional national or regional data sources to extend the coverage and fill the gaps of data from UN SNA and KILM. Another way would be to identify variables which can serve as proxy variables for self-employed income or the employment structure and are available on a broader scale.

Matthieu Charpe and his colleagues at ILO decided in favor of the first option. They compute LS_{unadj} and LS_{G3} from UN SNA and KILM and expand the database by adding data using OECD statistics (mainly for Mexico and middle income countries in Eastern Europe) and from China's and Brazil's statistical offices. The compiled data set (denoted ILO unadj./adj.) covers 73 countries, providing a total of 1044 estimates and was published within the scope of the World of Work (WOW) Reports .

Feenstra et al. (2015) and myself used the second method and searched for proxy variables to address the problem of limited data availability. Feenstra et al. (2015) chose value added in agriculture as a proxy for self-employed income, which is available in the World Input Output Database (WIOD). The rationale being that most of the self-employed in low and middle income countries (i.e. countries for which mixed income is not available in UN SNA) are active in the agricultural sector where the labor share is very high. They use this proxy to compute LS_{G1}, meaning that all agricultural value added is added to employee compensation. Through this method, they manage to compute adjusted labor shares for about 60 additional low and middle income countries. They build a data set which is compiled of different adjustment approaches. For each country and year, they employ the most appropriate of Gollin's adjustments, given the respective data availability and plausibility. The final data set comprises 93 low and middle income countries and is composed in almost equal parts of LS_{G1} (using agricultural value added as proxy) and LS_{G2} (using mixed income from UN SNA). In a few cases, they use LS_{unadj} or LS_{G3}, latter computed using KILM data. They increase the number of observations by interpolating missing data and computing constant labor shares at the start and end points. Their final data set – which is published in the Penn World Tables (PWT) and is here denoted as PWT – has 2298 observations.

In my paper (Trapp, 2015), I chose the share of agricultural employment in total employment (taken from FAOStat and WB World Development Indicators) as a proxy for the share of self-employment, given that most of the self-employed in developing countries are farmers and most agricultural workers are self-employed. I use this proxy to compute LS_{G3}. As this is likely to overestimate the labor share in the least developed countries, I only imputed two-thirds of the average wage sum of employees (and not the full wage sum) to the self-employed in the low and middle income countries of South Asia and Sub-Saharan Africa. Like the PWT data, my data set is a mix of different adjustment approaches that employs the most appropriate measure considering data availability and economic conditions. In the majority of cases (68 %), the data set employs LS_{G3}; LS_{G2} is used in 21 % of cases and the remainder is composed of LS_{G2} and LS_{unadj}. The final data set (denoted as Trapp) has 1421 observations for 93 countries. These are are fewer observations per country than in the PWT data, which is the result of skipping the step of inter- and extrapolation.

The Socio Economic Accounts (SEA) from the WIOD, as well as the INDSTAT database from UN's Industrial Development Organization (UNIDO), are two more available data sources. In contrast to the data sets presented above, they are not based on UN SNA. The WIOD project has extended the EU KLEMS (EU level analysis of capital, labor, energy, material and services) database to a few developing countries by drawing on data from several national statistics offices and constructing socio-economic accounts, which, among other things, contain information on employment, labor compensation and value added. Data is available aggregated as well as disaggregated by 35 sectors or skills (low-, medium- and high-skilled). Following Gollin's third approach, the labor income of the self-employed has been imputed from wage employees to the self-employed, in most cases by sector and if possible by additional characteristics. The WIOD SEA are only available for 16 low and middle income countries since 1995, resulting in 258 observations (denoted as WIOD unadj./adj.). The UNIDO INDSTAT database is a large industrial statistics database. Like the WIOD SEA, it too provides data on employment, labor compensation and value added on the aggregate level as well as disaggregated by 23 industries. Data is available for 96 low and middle income countries since the 1970s. It only covers the corporate manufacturing sector, implying that other sectors and self-employed activities are not considered. Nevertheless, it is included in this review (denoted as UNIDO), as it is often used in the literature and provides valuable information on the labor share in the manufacturing sector.

As can be seen in table 3.1, the data sets vary considerably in terms of coverage and adjustment approach. The advantage of computing LS_{G1} and LS_{G2} from UN SNA is that this approach makes use of directly observed mixed income. However, the data is only available for a few countries. LS_{G3} can be computed for more countries by drawing on additional employment data. In terms of coverage, the ILO data set by Charpe et al. (2014) is preferred over the computation that only relies on employment data from KILM. The G3 approach, however, has to rely on wage imputation, rather than on actual observations, which can be a problem if the underlying assumption is unwarranted. This seems to be the case with regard to some countries, as SNA G3 yields estimates of up to 658.4 % and the

ILO data of up to 231.7 %.

Employing a proxy variable to estimate the labor share – as in the PWT and Trapp data sets – are only a second best option. Both proxies (agricultural value added for self-employed income in the case of PWT data and the agricultural employment share for the self-employment share in my data set) are plausible but disregard self-employed activities out of the agricultural sector. This may result in labor share estimates being too low. On the other hand, agricultural value added, in addition to labor, also involves other production factors (especially land) (Inklaar and Timmer, 2013), while the agricultural employment share – in addition to self-employed people – also includes agricultural employees (such as day laborers). As a result, this might overstate the true labor share. In how far these two factors make up for each other differs from country by country and depends, amongst other things, on the sectoral structure of an economy. The more a country's economy corresponds to the classic notion of an agrarian society, the more appropriate are the proxies. Structural changes in the agricultural sector, especially an increase in industrialization, resulting in higher capital and lower labor shares, cannot be captured by the PWT proxy. My data set is more flexible in this regard as varying proportions of the average wage bill are imputed to the self-employed depending on the economic development of a country. But this is can also only be a simplification of the actual developments. In this regard, the WIOD data has the great advantage that they have been imputed by sector, and if possible, even by additional characteristics. They can therefore reflect the sectoral development of a country much better. On the downside, data is only available for a few low and middle income countries, mainly emerging economies in Eastern Europe.

Table 3.1: **Overview of labor share measures for low- and middle-income countries since 1990**

Data set	*Obs.*	*Years*	*Ctry.*	*Mean*	*Median*	*Min*	*Max*	*SD*	*Adj. approach*	*Data sources*	*Authors*
SNA unadj.	1421	15.3	93	35.3	35.5	5.4	90.7	11.8	unadj.	UN SNA	UN 2017
SNA G1	508	13.4	38	56.5	56.1	26.2	87	10.4	G1	UN SNA	UN 2017
SNA G2	508	13.4	38	45.6	46	21	73.4	8.5	G2	UN SNA	UN 2017
SNA G3	766	10.5	73	62	55.5	21.5	658.4	33.8	G3	UN SNA, KILM	UN 2017, ILO 2017
ILO unadj.	1044	14.3	73	39.6	39.9	3.4	93.8	14	unadj.	UN SNA, KILM, OECD, China NBS, SNA Brazil	Charpe 2011
ILO adj.	1044	14.3	73	56.9	56.2	3.4	231.7	25.1	G3	UN SNA, KILM, OECD, China NBS, SNA Brazil	Charpe et al. 2014
PWT	2298	24.7	93	52	52.6	9	86.6	13.1	G2 (47 %), G1[a] (47 %), G3 (3 %), unadj. (3 %)	UN SNA, WIOD	Feenstra et al. 2015
Trapp	1421	15.3	93	46.8	47	6	90.7	12.5	G3[b] full (50%), G3[b] 2/3 (18 %),G1 (4 %), G2 (21 %), unadj. (6 %)	UN SNA, FAOStat, WB WDI	Trapp 2015
WIOD unadj.	258	16.1	16	42.3	44.5	22.2	61.8	8.5	unadj.	WIOD SEA	Timmer et al. 2015
WIOD adj.	258	16.1	16	53.2	53.4	31.5	104.5	11.3	G3	WIOD SEA	Timmer et al. 2015
UNIDO	1072	11.2	96	29.9	28.3	1.7	140.9	14	corp. manuf. sector	INDSTAT2	UNIDO 2015

[a]agricultural value added used as a proxy for mixed income [b]agricultural employment share used as a proxy for the self-employment share

The measurement of the labor share in low and middle income countries is clearly subject to a quantity-quality trade-off: The broader the coverage, the more it has to rely on assumptions and the more uncertain are the resulting estimates. In the end, all measures have to rely on assumptions to obtain a measure of the labor share for the whole economy, since the labor income of the self-employed is not directly observed. A data set on the labor share should therefore be judged according to its underlying assumptions, i.e. in how far they correspond to the economic reality of a country. Another important point is data coverage and quality. Especially in developing countries, where the scope, detail and quality of the data is not always reliable and requires scrutiny (Jerven, 2012). In light of these circumstances, the data set by PWT and myself are preferred options because they have a broad coverage and at the same time choose the most appropriate adjustment approach on a case-by-case basis. Since data availability and economic conditions vary from country to country, it is not advisable to rely on one single adjustment approach. For example, some countries (such as Bhutan) report an unadjusted labor share of more than 70 % and hence seem to already have covered the income of the self-employed in the item compensation of employees – although this runs counter to international accounting standards. Any further adjustment in these cases overestimates the labor share. Equally, computing LS_{G3} (which most data sets do) gives reasonable estimates in some cases; however, in other cases, it gives unrealistically high results of up to 658.4 % (see SNA G3 in table 3.1). A one-size-fits-all approach is therefore not useful.

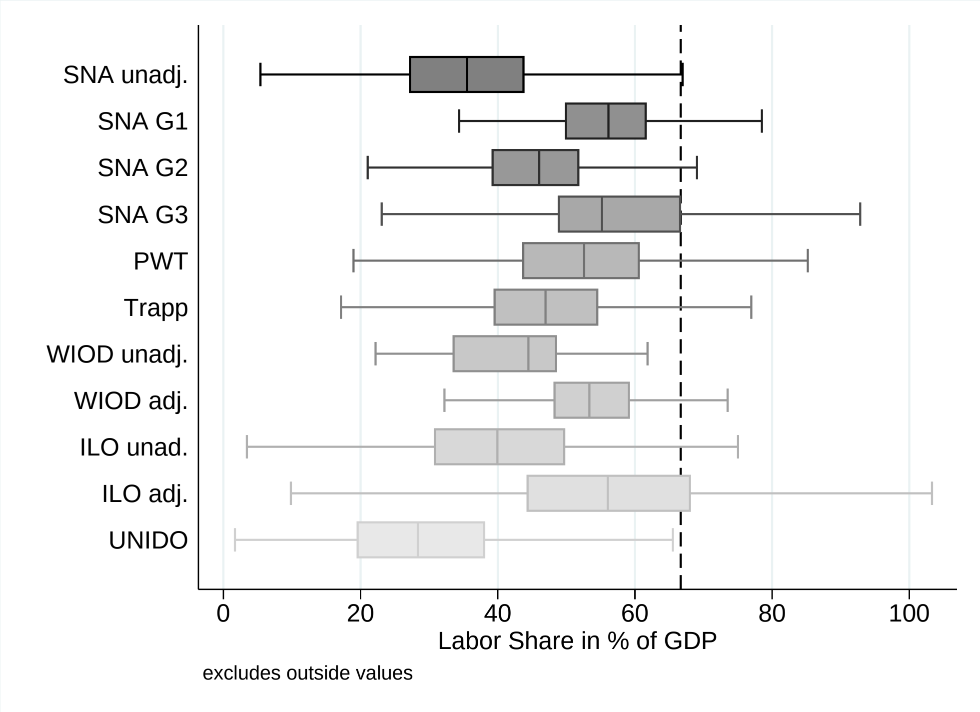
The PWT data employs the labor share that is based on the most plausible and available data: LS_{G2} is the first choice and used if mixed income is available. If it is not available, the lower of LS_{G1} (proxied by agricultural value added) or LS_{G3} is used, given the risk of overestimation in these two approaches in the context of developing countries. No further adjustment is made when the unadjusted labor share exceeds 70 %. My data follows a slightly different approach, as it takes the income group and region into account and computes two different versions of LS_{G3}. As explained above, varying fractions of the average wage sum of employees are imputed to the self-employed depending on region and income status. The resulting estimates are framed with LS_{G1} as the upper bound and LS_{G2} as the lower bound (if mixed income is available) and the labor share is left unadjusted in case it is already reasonably high (greater than 21 %) and an adjustment would overestimate the labor share (greater than 91 %). Furthermore, my data set corrects for a considerable plunge in the labor share estimates of post-Soviet states in the early 1990s since this is not only the result of the heavy economic transformation at that time but also due to changes in the acquisition of data (suddenly, an informal and unobserved economy evolved). Another advantage of my data set is that the final estimates are checked against micro estimates from social accounting matrices, which is recommended for data sets based in large part on assumptions.

As a result of varying coverage (of countries and time periods) and varied adjustment approaches involving different assumptions, the estimates of unadjusted and adjusted labor shares differ considerably between the data sets. Before discussing the level and trend of the estimates in the next section, the correlation between the estimates is investigated. Table 3.2 shows the pairwise correlations between the adjusted and unadjusted labor share measures. As expected, the unadjusted measures (SNA unadj., ILO unadj. and WIOD unadj.) are highly correlated. When it comes to the adjusted estimates, however, the correlations are only low or moderate. Although all figures intend to measure the same thing, there are major differences between them. This is mainly the result of the different assumptions lying behind the measurement approaches. The data set SNA G3, for example, has the highest correlation with the adjusted labor share measures from the ILO and WIOD, which too rely on Gollin's third adjustment. The correlations between the data sets SNA G1 and SNA G2, as well as the PWT, Trapp and WIOD data, are moderate (correlation coefficients between 0.49 and 0.96). SNA G3 and the adjusted labor share from the ILO, however, are hardly correlated with the other estimates, which is probably the result of the uncontrolled imputation of wages which yields estimates far beyond 100 %. The PWT measure has the highest correlation with SNA G1 and SNA G2, as it is mainly composed of these two approaches. The Trapp data set exhibits the highest correlation with SNA G2, because 21 % of the data set is composed of this measure and the imputation procedure results in labor share estimates of similar magnitude. The UNIDO estimates only loosely correlate with the other measures, as they only refer to a small share of the whole workforce and economy. It has the highest correlations with the unadjusted labor shares (SNA unadj., ILO unadj. and WIOD unadj.).

Table 3.2: **Correlation matrix of labor share estimates**

	SNA unadj.	SNA G1	SNA G2	SNA G3	ILO unadj.	ILO adj.	PWT	Trapp	WIOD unadj.	WIOD adj.	UNIDO
SNA unadj.	1 n=1421										
SNA G1	-0.03 n=508	1 n=508									
SNA G2	0.7 n=508	0.67 n=508	1 n=508								
SNA G3	0.12 n=766	0.29 n=339	0.24 n=339	1 n=766							
ILO unadj.	0.76 n=1036	-0.08 n=401	0.57 n=401	-0.04 n=582	1 n=1044						
ILO adj.	0.37 n=1036	-0.03 n=401	0.36 n=401	0.40 n=582	0.48 n=1044	1 n=1044					
PWT	0.58 n=1357	0.60 n=508	0.87 n=508	0.16 n=748	0.53 n=995	0.35 n=995	1 n=2298				
Trapp	0.72 n=1421	0.62 n=508	0.96 n=508	0.33 n=766	0.56 n=1036	0.43 n=1036	0.57 n=1357	1 n=1421			
WIOD unadj.	0.85 n=220	0.16 n=149	0.56 n=149	-0.01 n=180	0.29 n=198	0.35 n=198	0.57 n=258	0.53 n=220	1 n=258		
WIOD adj.	0.45 n=220	0.53 n=149	0.68 n=149	0.21 n=180	0.46 n=198	0.41 n=198	0.49 n=258	0.54 n=220	0.62 n=258	1 n=258	
UNIDO	0.41 n=706	0.08 n=274	0.34 n=274	-0.10 n=469	0.45 n=600	0.17 n=600	0.24 n=886	0.18 n=706	0.47 n=211	0.28 n=211	1 n=1072

Figure 3.2: **Box plots of labor shares, 1990-2011**



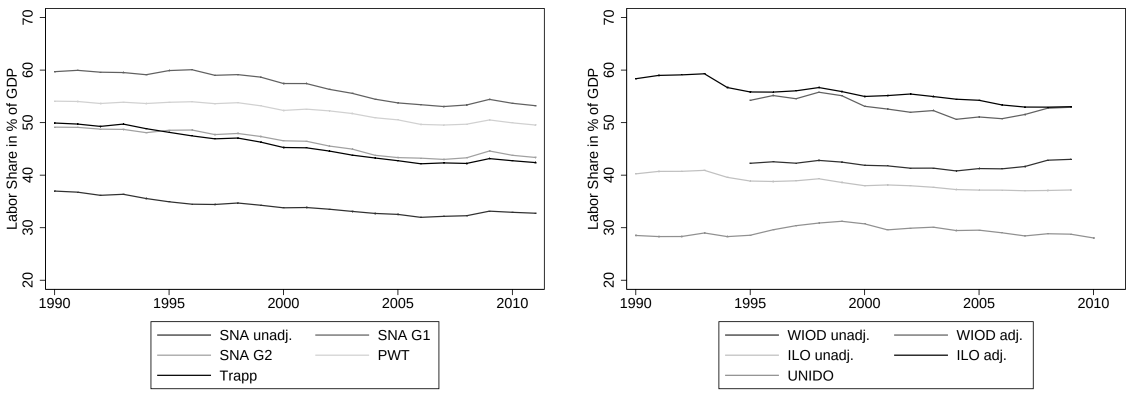
3.4 Level and trends

3.4.1 Overall findings

This section displays descriptive statistics on the different labor share measures (1) to investigate the level and trend of the labor share in developing countries and (2) to assess the differences and common grounds in the results of these estimates. Despite the divergent measurement approaches and data sources: Is there a general picture emerging from the data?

Figure 3.2 provides a box plot of the labor share measures. The median of the unadjusted labor share measures range between 35.3 and 44.5 % and that of the adjusted measures between 46 and 56.2 %. This not only shows the variance in the different estimates but also the importance of adjusting the wage share for the income of the self-employed. If the labor share is not adjusted in the context of developing countries, it would be understated by about 10 to 20 % points. A reference line for the standard value of two-thirds used in the economic literature is also drawn into figure 3.2. None of the measures comes close to this standard value. As argued by some researchers before, labor shares in developing countries do not necessarily converge to the level of two-thirds prevailing in advanced countries but

Figure 3.3: **Mean labor shares, 1990-2011**



Note: Data is interpolated and kept constant beyond start and end points for this illustration to deal with unbalanced panel data sets.

remain about 15 % lower and range around one-half (Chen et al., 2010, Imrohorolu and Üngör, 2016, Izyumov and Vahaly, 2015, Ortega and Rodriguez, 2001, Young and Lawson, 2014).

As expected, measures based on G1 and G3, which are likely to overestimate the labor share in developing countries, yield the highest values. SNA G2, which might underestimate the labor share in the context of developing countries, yields the lowest estimates of adjusted labor shares. The UNIDO estimates, which indicate the labor share in the manufacturing sector, are the lowest: It has a median of 29.9 %. The other estimates are in between. As can be seen in Table 3.1, the mean is always very close to the median. An exception is the case of SNA G3, where the mean is much higher due to the outliers at the right tail of the distribution. The range of the distribution is especially high in the case of SNA G3 (21.5 to 658.4 %) but also in the case of ILO unadj. (3.4 to 93.8 %), ILO adj. (3.4 to 231.7 %) and UNIDO (1.7 to 140.9 %) (note that Figure 3.1 does not display outliers which lie beyond the whiskers). Statistically, labor share values can exceed 100 % but values far beyond that limit do not appear realistic. In further analyses, I will therefore leave the measure of SNA G3 aside and focus on the other G3 alternatives such as the ILO data.

Figure 3.3 shows the unweighted averages of the estimates over time and allows us to visually asses trends in the labor share. The left-hand panel shows that SNA unadj., SNA G1, SNA G2, PWT and Trapp more or less run parallel to each other. Also the ILO labor shares (see right-hand panel) follow a similar pattern, resulting from the fact that they all build upon the same data source: UN SNA. The differences lie in the level: SNA

G1 runs about 20 % points and SNA G2 about 10 % points above SNA unadj. The PWT estimates range between SNA G1 and SNA G2, while the Trapp estimates are centered between SNA unadj. (no self-employed income) and SNA G1 (total mixed income is added to the compensation of employees) and are close to SNA G2. By contrast, the UNIDO and WIOD estimates – which are based on other data sources – follow a different pattern. However, on average, the WIOD and ILO estimates of adjusted labor shares, both relying on G3, and SNA G1, move on the same level.

Interestingly and despite the differences in levels, all measures exhibit a negative trend: The labor share seems to be stable in the early 1990s but starts to decrease in the second half of the decade. It slightly recovers during the Financial Crisis of 2007-08 but falls back to the initial level afterwards. This trend is robust in all estimates. This strongly suggests that declining labor shares are not only an issue in advanced countries but also in the developing world. Only the UNIDO estimates follow a different pattern and show a slight increase in the 1990s with a slight peak at the end of the 1990s but they have decreased since then. The industrial sector has a special role in terms of economic development as, according to conventional wisdom, this has been the sector where value added is growing, wages are high and the living standards of a whole society are increased through spill-over effects. Against this background, it is surprising to see that the labor share in the industrial sector is on a constantly low level and even decreasing since 2000.

To more reliably check whether the estimates follow a time trend, they are regressed on years in a fixed and random effects model (see Table 3.3).[1] The regression results confirm a downward trend in the labor share in low and middle income countries since 1990, independent of the form of measurement. An exception to this general picture is only the unadjusted labor share from WIOD and the UNIDO estimates. According to the SNA G1, SNA G2 and Trapp estimates, the adjusted labor share decreased sharply over the observed period, on average by about 0.55 % points per year and in total by about 10 % points. The estimates from PWT, ILO and WIOD on adjusted labor shares exhibit a more moderate decline but still suggest a decrease of about 0.25 % points per year and in total by about 5 % points. It is remarkable that also the unadjusted measures (SNA and ILO unadj.), which only record compensation of wage employees, show a downward trend in the last three decades, although the wage employment sector has developed during that time.

[1]Both specifications are displayed as the Hausman test fails to reject the null hypothesis of exogeneity of the explanatory variables with the time and country fixed effects at the 1 % level of significance.

Table 3.3: **Time trends in labor shares**

VARIABLES	(1) SNA unadj.	(2) SNA G1	(3) SNA G2	(4) PWT	(5) Trapp	(6) ILO unadj.	(7) ILO adj.	(8) WIOD unadj.	(9) WIOD adj.	(10) UNIDO
Fixed effects										
Year	-0.274***	-0.548***	-0.528***	-0.246***	-0.568***	-0.294***	-0.383***	-0.002	-0.244***	-0.057
	[0.021]	[0.039]	[0.038]	[0.012]	[0.026]	[0.030]	[0.062]	[0.035]	[0.078]	[0.051]
Constant	38.345***	63.079***	51.934***	54.842***	53.119***	42.331***	60.438***	42.297***	56.258***	30.366***
	[0.259]	[0.498]	[0.488]	[0.172]	[0.316]	[0.307]	[0.634]	[0.471]	[1.050]	[0.541]
Random effects										
Year	-0.274***	-0.545***	-0.522***	-0.246***	-0.565***	-0.292***	-0.380***	-0.002	-0.241***	-0.057
	[0.021]	[0.039]	[0.038]	[0.012]	[0.026]	[0.030]	[0.062]	[0.035]	[0.079]	[0.050]
Constant	37.074***	62.681***	51.857***	54.679***	51.829***	41.463***	59.732***	42.053***	55.936***	30.284***
	[1.297]	[1.754]	[1.372]	[1.281]	[1.270]	[1.628]	[3.025]	[2.001]	[2.473]	[1.294]
Obs.	1,421	508	507	2,298	1,421	1,044	1,044	258	258	1,072
Countries	93	38	38	93	93	73	73	16	16	96

Standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1

To conclude, there is evidence that the stylized fact of constant factor shares does not hold but that the factor labor is losing ground against the factor capital in the developing world. When the labor share is decreasing although the economy continues to grow – which is the case in most countries –, this means that an economy's productivity is growing faster than labor income and that welfare gains are not fully translated into higher wages. While wages increase, productivity is increasing much faster and capital is able to disproportionately increase its revenues. The literature discusses various reasons of these observed dynamics. Especially technological change towards capital and high-skilled labor, weakening of labor market institutions and increased international financialization and competition are suspected to decrease the labor share. It is remarkable that the latter is considered to have a negative effect also on the labor share of developing countries as classical trade theory (mainly Heckscher-Ohlin model and Stolper-Samuelson theorem) predicts the labor share of these countries to rise with trade: Poor countries are relatively labor-abundant and hence trade will boost the demand for labor-intensive goods. This, in turn, is predicted to translate into higher wages and a higher labor share and should especially lift the labor share in the wage employment sector, expecting that trade promotes its development.

3.4.2 By region and income group

This subsection examines whether the above findings only apply on average or if the detected low magnitude and decline of the labor share is present across all regions and income groups.

As can be seen in figure 3.4, the average level of the labor share varies to some degree between the regions. Europe and Central Asia exhibit slightly higher labor shares than the other regions (adjusted labor shares between 49.7 and 62.7 %). Except for the labor share in the manufacturing sector (as measured by UNIDO), also South Asia has comparatively high labor shares, even when Bhutan is dropped from the sample (adjusted labor shares between 52.7 and 64.9 %). The labor share estimates are lowest in the region of Middle East and North Africa (adjusted labor shares between 34.1 and 50.6 %), which is expected as many oil-producing countries are located in that region. In the case of Sub-Saharan Africa and South Asia, there is a major difference between the unadjusted and adjusted shares, a consequence of the large self-employment sector. The labor shares in the regions of East Asia and Pacific, as well as Latin America and the Caribbean, are in the mid-range. Except for the measures, which are likely to overestimate the labor share (SNA G1 and ILO adj.), the adjusted labor share never reaches the standard value of two-thirds.

The downward trend in the labor share is present in all regions. There are considerable differences in the magnitude, but the negative trend prevails on all continents and is visible for all measures (unadjusted and adjusted) of the labor share. Also the labor share in the manufacturing sector (UNIDO) is decreasing in four out of the six regions. Only the WIOD adj. measures suggest a moderately positive trend in Latin America and the Caribbean and Middle East and North Africa. The overall picture, however, is that all regions have experienced a non-negligible decline in the labor share since 1990. The decline is more pronounced in East Asia and Pacific, South Asia and Europe and Central Asia and rather moderate in the Middle East and North Africa.

Figure 3.5 differentiates between country income groups according to the classification by the World Bank as of 2000. The picture is quite uniform across income groups: The adjusted labor share remains at a very low level (roughly around 50 %) and has been declining considerably since 1990. There are hardly any differences between the income groups despite the fact that the higher the income group, the higher the unadjusted shares and the lower the gap between the adjusted and unadjusted measures. This corresponds to figure 3.1 which illustrates that the wage employment sector is increasing with average incomes. Apart from this, there seems to be no relation between a country's stage of development and its labor share. It is especially worrying that even the labor share in low income countries decreased in the last decades. The hope that increasing globalization and economic growth promotes factor labor in the poor countries seems not to have materialized and may have run counter the fight against poverty in these countries.

3.5 The components of the labor share

Why do we see these low levels of and decline in the labor share? This section takes a look at the components of the labor share to investigate the driving forces behind these findings. For this, recapitulate equation 3.3 and that the labor share is the proportion of a country's economic pie that goes to workers in the form of labor compensation. The slice of labor compensation, in turn, is the product of labor income per worker (or working hour) and worker (or working hour, respectively). Workers can be further subdivided into wage laborers and self-employed, or classified by skill. The total economic pie can also be viewed as the sum of several sectoral outputs.

3.5.1 Labor force, income and productivity

First, I assess whether the decreasing labor share is the result of an increasing gap between labor income and total output (also termed the wage-productivity gap), or just the result of a decreasing number of workers. When GDP is constant, the labor share can decrease either as a result of falling labor incomes or as a result of a shrinking labor force (or a combination thereof). Most developing economies, however, have been growing during the last few decades (ILO, 2010). The question therefore is how far output increases have also translated into higher labor incomes: Do we observe a decline in the labor share because every worker gets a smaller share of overall output, or because there are fewer workers?

As can be seen in figure 3.6, total employment has increased in all regions over the period examined: Between 1991 and 2012, it almost doubled in Sub-Saharan Africa and the Arab States, it increased by around 50 % in Asia and the Pacific, Latin America and the Caribbean and South Asia and rose by about 11 % in Europa and Central Asia. At the same time, total employment is increasingly composed of wage employment. The share of self-employment is falling but remains on a very high level in all regions except for the Arab states and Europe and Central Asia. Similarly, the WIOD data suggests that the total working hours increased by 20.5 % between 1995 and 2009 and the UNIDO data suggest that the number of employees in the manufacturing sector increased by 29.8 % between 1990 and 2010.

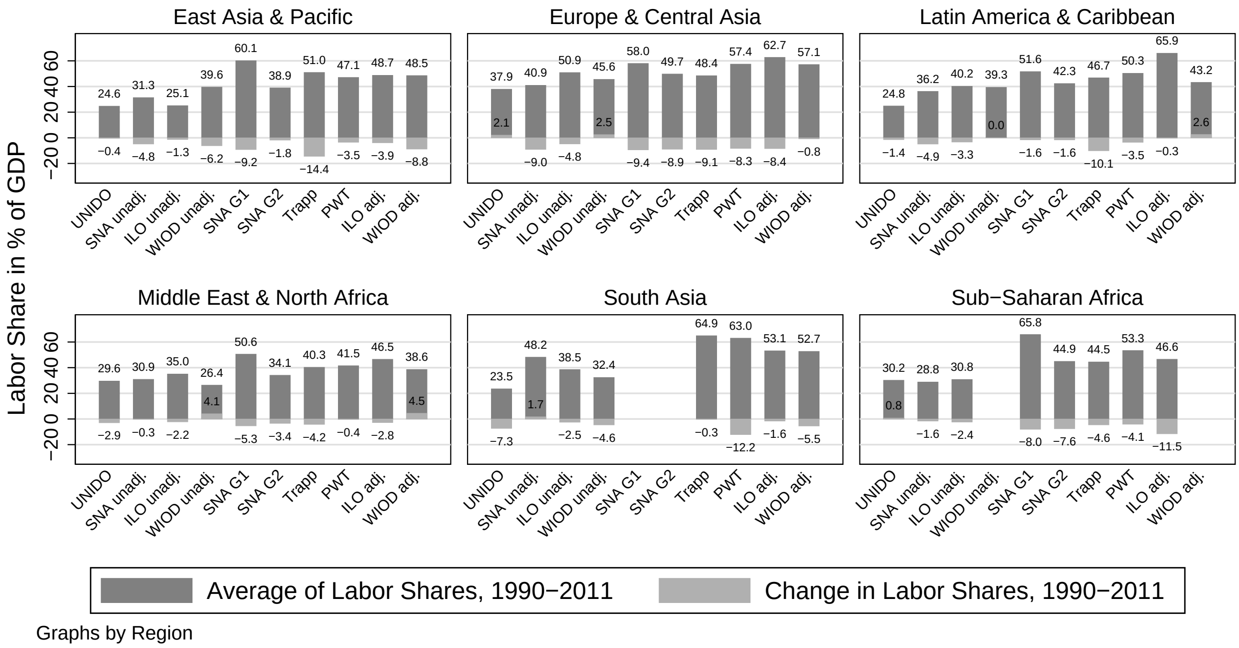
As such, there is evidence that the decline in the adjusted labor share is not driven by a shrinking labor force. Also the decline in the unadjusted labor share cannot be explained with a smaller wage employment sector. In a growing economy, where the labor force is increasing ($\triangle L > 0$) and labor income per worker is constant ($\triangle w = 0$), capital income growth ($\triangle i \times K$) has to exceed the growth rate of the labor force ($\triangle i \times K > \triangle L$) in order for a decline in the labor share to be observed (see Equation 3.3). This implies that the ratio between wages and total output ($w/w \times L + i \times K$) has to decrease by a larger percentage than the labor force is increasing. The gap between labor income *per worker* and productivity (wage-productivity gap) must have widened considerably over the examined period. If labor income per worker is increasing as well ($\triangle w, \triangle L > 0$) – which is the case in most countries (ILO, 2017b) – capital income has to grow even faster to exceed the growth rate of total labor income ($\triangle w \times L$). The employment statistics therefore suggest that the slice going to labor is not only decreasing but also that the slice going to each worker is decreasing as well.

Table 3.4 regresses the labor force participation rate (LFPR) on the labor share to assess the relation between the relative size of employment and the factor income distribution.

The labor force participation rate is the share of the population which is active in the labor market, either by having a job or searching for one.[2] It is therefore an indicator of the relative labor supply in a country and should be positively associated with the labor share. Interestingly, while a higher LFPR in the upper middle income countries is indeed positively correlated with the labor share, the opposite seems to be the case in low and lower middle income countries. This correlation does not necessarily imply causation and further effort is needed to check whether there is also causation in place. However, I would like to mention the model of a dual sector economy by Lewis (1954) in this context as it might provide a causal explanation for this finding. In this model, a poor economy is divided into a low-productive subsistence sector and a high-productive industrial sector. As the latter is more productive, it can pay higher wages and people prefer to transition there and leave the subsistence sector. However, in the beginning, the industrial sector is relatively small and does not offer enough jobs to employ everyone. To attract workers, the industrial sector thus does not have to pay wages equal to productivity but just sufficiently higher wages than those in the subsistence sector. The model predicts that the higher the labor force participation rate, i.e. the higher the labor supply, the more downward pressure is placed on wages in the industrial sector. As a result of these dynamics, the gap between wages and productivity increases and the labor share decreases (Gollin, 2014). In the course of development, the industrial sector develops and absorbs an increasingly higher share of the workforce such that the pressure on wages decreases. Eventually, wages are paid according to productivity and the labor share decline comes to a halt. If labor becomes scarce, an increasing labor supply may even increase the labor share. Column (10) regresses the LFPR on the UNIDO labor share data and therefore exclusively refers to the industrial sector. There seems to be no correlation in low income countries but a significantly negative correlation between the LFPR and the industrial labor share in lower and upper middle income countries. This is not expected by Lewis' model and additional forces seem to be at work that increase the gap between productivity and labor income, as mentioned in section 3.4.

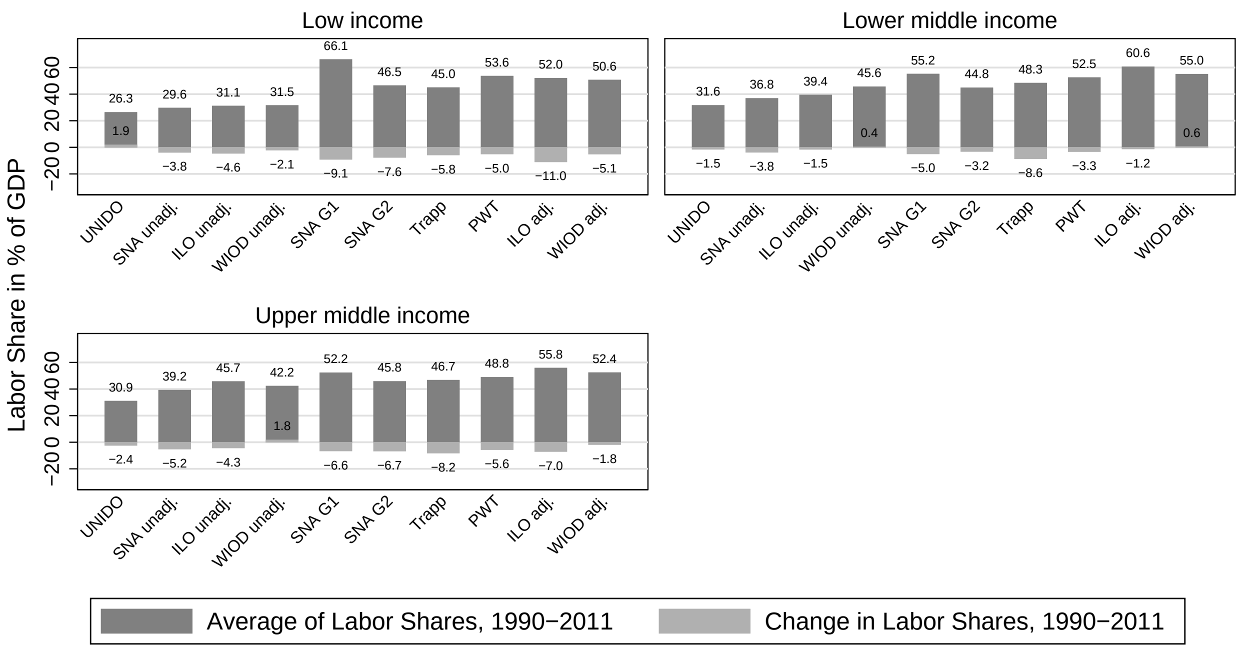
[2]The LFPR is usually higher in poorer countries, as people spend fewer time in education. In this sample, it is 71.6 % in the low income and 64 % in the middle income countries (ILO 2017).

Figure 3.4: **Mean and change in labor shares by region, 1990-2011**



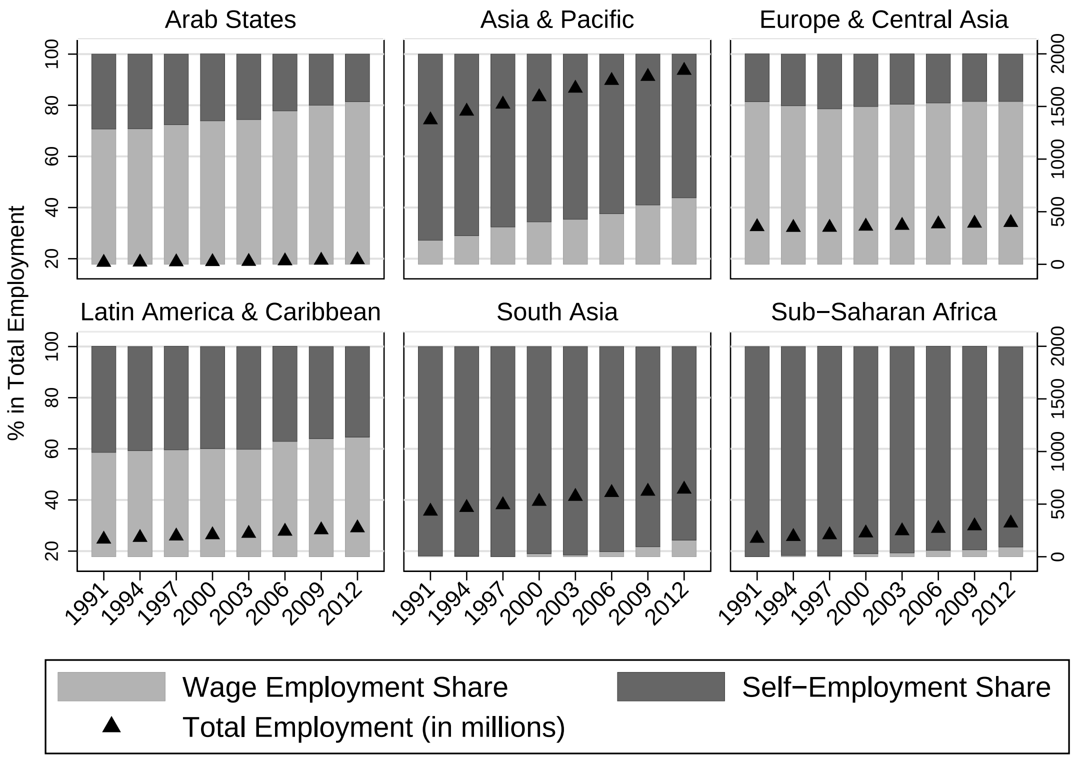
Note: Exceptions of the given time range are WIOD unadj./adj.(1995-2009), ILO unadj./adj. (1990-2008) and UNIDO (1990-2010).

Figure 3.5: **Mean and change in labor shares by income group, 1990-2011**



Note: Exceptions of the given time range are WIOD unadj./adj.(1995-2009), ILO unadj./adj. (1990-2008) and UNIDO (1990-2010). Income group as of 2000.

Figure 3.6: **Employment trends by region, 1991-2012**



Source: ILO (2017b).

Table 3.4: **Regression with labor force participation rate**

VARIABLES	(1) SNA unadj.	(2) ILO unadj.	(3) WIOD unadj.	(4) SNA G1	(5) SNA G2	(6) PWT	(7) Trapp	(8) WIOD adj.	(9) ILO adj.	(10) UNIDO
Low Income Countries										
LFPR	-0.096	-0.421***	0.221	0.068	-0.204	0.200***	-0.351*	0.347	-1.302***	0.220
	[0.128]	[0.106]	[0.268]	[0.216]	[0.278]	[0.072]	[0.181]	[0.347]	[0.345]	[0.309]
Year	-0.126**	-0.051	-0.300***	-0.925***	-1.045***	-0.244***	-0.592***	-0.356***	-0.603***	0.130
	[0.057]	[0.056]	[0.058]	[0.098]	[0.126]	[0.026]	[0.081]	[0.076]	[0.182]	[0.121]
Constant	36.184***	57.152***	23.481	76.316***	72.403***	43.134***	76.355***	32.668	140.229***	9.738
	[9.102]	[7.354]	[17.873]	[14.720]	[18.960]	[5.126]	[12.872]	[23.106]	[24.013]	[22.558]
Obs.	338	220	20	79	79	662	338	20	220	268
Countries	34	21	3	8	8	39	34	3	21	38
Lower Middle Income Countries										
LFPR	-0.130*	-0.232**	0.111	0.099	0.148	-0.321***	-0.258***	-0.284	0.120	-0.762***
	[0.071]	[0.095]	[0.186]	[0.198]	[0.179]	[0.050]	[0.082]	[0.271]	[0.176]	[0.173]
Year	-0.377***	-0.363***	-0.129	-0.587***	-0.452***	-0.172***	-0.703***	-0.315*	-0.234**	0.188*
	[0.039]	[0.056]	[0.113]	[0.103]	[0.093]	[0.022]	[0.044]	[0.165]	[0.104]	[0.099]
Constant	48.688***	58.011***	35.088**	55.964***	40.201***	74.345***	71.922***	75.532***	57.134***	75.541***
	[4.566]	[6.020]	[13.585]	[12.548]	[11.348]	[3.192]	[5.221]	[19.770]	[11.180]	[10.757]
Obs.	636	488	81	182	181	902	636	81	488	445
Countries	64	56	13	26	26	72	64	13	56	58
Upper Middle income countries										
LFPR	-0.073	0.019	0.506***	0.445***	0.603***	-0.035	-0.022	1.504***	-0.072	-0.660***
	[0.092]	[0.116]	[0.177]	[0.169]	[0.175]	[0.067]	[0.114]	[0.494]	[0.171]	[0.229]
Year	-0.271***	-0.380***	0.016	-0.467***	-0.500***	-0.304***	-0.428***	-0.408**	-0.504***	-0.336***
	[0.031]	[0.043]	[0.060]	[0.052]	[0.054]	[0.022]	[0.039]	[0.168]	[0.064]	[0.077]
Constant	47.042***	48.610***	9.104	28.375**	11.381	55.269***	52.417***	-41.244	65.201***	78.369***
	[5.935]	[7.469]	[11.679]	[11.137]	[11.563]	[4.324]	[7.355]	[32.534]	[11.018]	[14.779]
Obs.	413	312	129	229	229	652	413	129	312	322
Countries	45	32	13	24	24	52	45	13	32	38

LFPR = Labor Force Participation Rate, Standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1

Source: ILO 2017

3.5.2 Wage and self-employment sector

Also decomposing the aggregate labor share into that of wage employees and self-employed can provide insights into structural developments of the labor market and associated changes in the labor income share.

In the course of development, people switch from self- to wage employment (see figure 3.1). Ceteris paribus, the unadjusted labor share (which measures the share of wage employee compensation in GDP) should increase and the share of self-employed labor income in GDP decrease as a result of the shifting labor force. Section 3.4 has shown that the aggregate labor share decreased over time and already gave some indication that this is also the result of a decline in the labor share of the wage employment sector. Figure 3.7 decomposes the aggregate labor share into that of the wage and self-employment sector and shows their average developments over time. There is evidence that the decline in the aggregate labor share is the consequence of a fall in the labor share across both sectors. The share of self-employed in the workforce decreased over time, and correspondingly, also the labor share of the self-employment sector decreased, given that fewer workers earn self-employed labor income. The various data sources indicate that the labor share of the self-employed workers have especially decreased since the mid-1990s. 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; on average, it even decreased. This negative trend is most pronounced in the UN SNA data but the decline is also found in the ILO data while the WIOD data indicates a labor share of the wage employment sector on a more or less constant level. These findings are not expected when workers are paid according to their productivity. Productivity increases in the wage employment sector must have therefore outpaced wages by far. Again, Lewis' two-sector model offers an interpretation of these findings, given that the subsistence sector described above primarily refers to self-employment and the industrial sector to wage employment.

The WIOD data, which only covers middle income countries, allows us to separately assess the labor income of wage employees and self-employed as well as the number of working hours. As can be seen in figure 3.8, the labor share of the wage employment sector increased slightly by 0.8 % points between 1995 and 2009, while the labor share of the self-employed sector decreased by 2.1 % points. Total labor income of wage employees could keep pace with the overall value added, resulting in a more or less unchanged labor share. The labor share of the self-employed, however, decreased because total value added increased faster (by 903.5 % over the entire period) than total self-employed labor income (which increased only by 807.5 %). The average labor income, i.e. the slice in the economic pie per worker, increased for wage employees as well as for self-employed, but the whole economic pie grew much faster than total labor income, such that capital could increase its share and the adjusted labor share fell by 1.3 % points.

Although wage employment has increased over time, an average of about 40 % of people in this sample of low and middle income countries still work in the self-employment sector. With values around 10 to 20 % (depending on the calculation of self-employed labor income), the labor share of the self-employment sector is very low. In comparison, the labor share of wage employment is two to three-times higher (on average between 20 and 45 %, depending on country coverage and data source). The slice for each self-employed person in the economic pie is much smaller than the slice of wage employees. This difference cannot be explained by the size of the labor force and is mainly driven by the productivity gap between the two sectors. This productivity gap is mainly the result of different skill contents of the respective workforce, as well as the economic sector in which employees and self-employed typically work. A large portion of the self-employed work in the low-productive agricultural sector, whereas employees typically work in the more productive industrial sector, as also suggested by Lewis' (1954) dual sector model. This finding further corresponds to studies that estimate this so-called 'agricultural productivity gap' and predict workers outside agriculture to be two to four times more productive than workers inside agriculture (see for example, Gollin, 2014, McCullough, 2017).

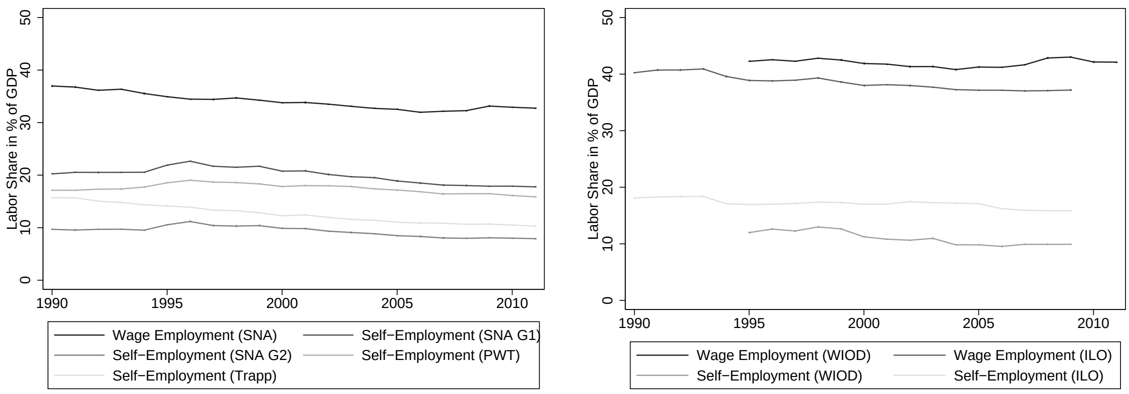
Hence, the overall low level of the aggregate labor share is primarily the result of the low labor share of the self-employment sector and corresponds to the finding that the agricultural sector absorbs a large share of the (self-employed) workforce but contributes comparatively little to national GDP. A second reason is the wage-productivity gap in the wage employment sector.

3.5.3 Decomposing by sector and skill

The magnitude and development of labor shares vary considerably between sectors and workers of different skills. Unfortunately, SNA data on compensation of employees and mixed income is usually only available on the aggregate level but the WIOD data allows us to decompose by sector and skill. This is only possible, however, for middle income countries.

Standard economic propositions suggest that the globalization process especially favors the low-skilled workers of developing countries because they are the relatively abundant

Figure 3.7: **Mean labor shares of the wage and self-employment sector, 1990-2011**

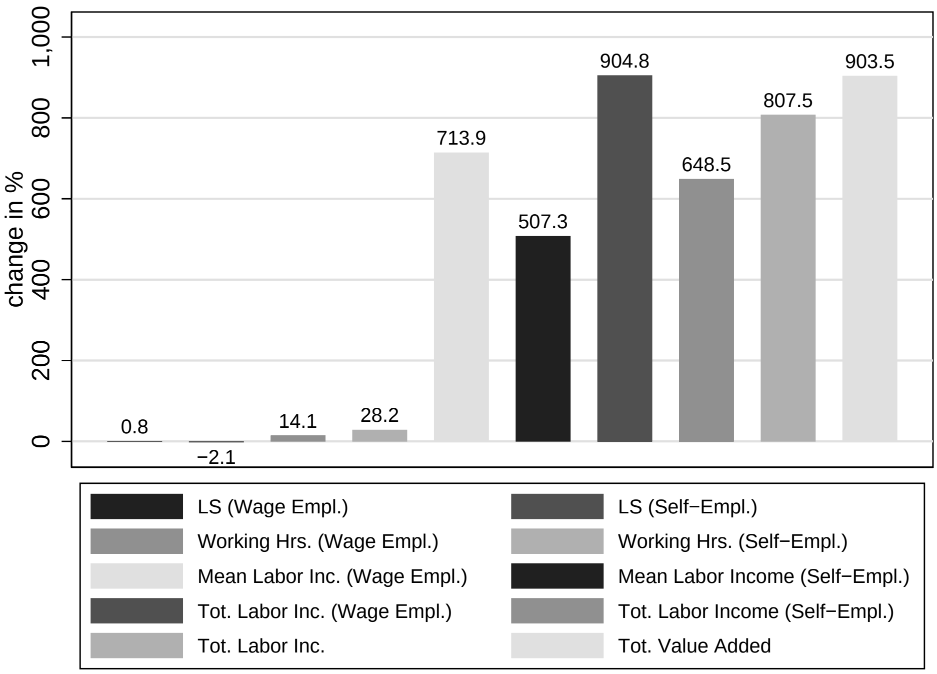


Note: Data is interpolated and kept constant beyond start and end points for this illustration to deal with unbalanced panel data sets.

production factor. Figure 3.9 decomposes the labor share by skill and reflects the contrary. Although the low-skilled make up almost two-thirds of the labor force, they only earn about one third of all labor incomes and about 16.5 % of national income in 1995. Until 2009, their portion in total labor and national income has further declined to 12.2 % and 23 %, respectively, while their number of working hours remained more or less unchanged. The finding for high-skilled workers is exactly the opposite: In 1995, only a very small share of the workforce was high-skilled (6.6 %), but their share in the overall labor share was disproportionately high with 23.4 % and they further increased their share in labor income to 33 % and 17.3 % (from 12.7 %) in national income over time. Their representation in the workforce has also slightly increased to 10 %. The findings for the middle-skilled workers are somewhere in between: They are the second largest group in the workforce and their working hours increase over time, while their share in overall labor and national income remains more or less on the same level during the observed period. The gap between overall productivity and the average labor income of the middle-skilled thus has widened over time.

This indicates that the low levels in aggregate labor share are primarily driven by the low labor incomes of the low-skilled workers, which is in line with the findings for the self-employment sector above as it typically accommodates the low-skilled. Also the decline in the labor share was entirely at their expense. The literature discusses various reasons for these trends, such as technological change, which is biased towards high-skilled activities (Dabla-Norris, 2015, Goldberg and Pavcnik, 2007). These dynamics have direct implications for the income inequality in developing countries: As the decline in the labor share

Figure 3.8: **Percentage change of labor share components, 1995-2009**

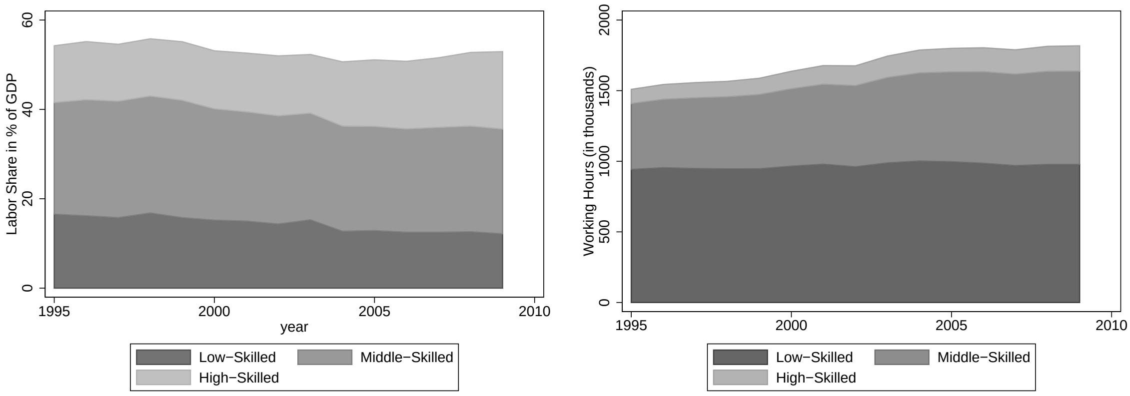


Source: WIOD (2013).

affected the low-skilled and hence the bottom of the income distribution, it is likely that inequality *within* the labor share, i.e. within workers of different skills, has increased. By contrast, high-skilled laborers – who earn the highest incomes – could further increase their income shares but still only make up a small proportion of the total work force (see also Francese and Mulas-Granados, 2015).

Finally, I decompose by economic sector. This gives a mixed picture of the labor share (see figure 3.10): The labor share is highest in the sectors of agriculture and transport (over 80 %), followed by the textile and leather industry as well as public administration, education, health and social work with labor shares of around 70 %. The labor share is lowest in the real estate business (13 %). Most of the industries, however, exhibit a labor share of around 50 %. The low level of the aggregate labor share hence results from the generally rather low labor shares of 50 % of most sectors but also from the fact that sectors with high labor shares only play a limited role in terms of value added. For example, the value added share of labor-intensive agriculture is only 8.3 %, on average, whereas the value added share of the capital-intensive real estate sector amounts to 7.7 %, on average. About half of the industries experienced a decline in their labor share (especially the sectors mining and quar-

Figure 3.9: **Mean labor shares and working hours by skill, 1995-2009**



Note: Data is interpolated and kept constant beyond start and end points for this illustration to deal with unbalanced panel data sets.
Source: WIOD Data.

rying as well as postal services and telecommunications) between 1995 and 2009, whereas the other half shows constant or increasing labor shares. A similar picture emerges when only looking at the different branches of manufacturing. Overall, there is no clear trend within sectors regarding factor shares that could explain the decline of the aggregate labor share. However, on average, there is a tendency that sectors with low labor shares increased their share in total value added (mainly stemming from renting of machines and equipment and postal services and telecommunication), while sectors with high labor shares (especially agriculture but also transport) became less important in terms of value added shares (see figure 3.11). It appears that there has been a shift away from the agricultural sector towards capital-intensive sectors such as real estate and the renting of machines and equipment. The observed decline in the overall labor share therefore seems to result from a shift away from sectors with high labor shares towards sectors with higher capital shares, rather than changes within industries.

3.6 Synthesis of results and recommendations for data collection

Future research on the labor share of the developing world will stand and fall with the available data base. Reviewing data on the labor share in low and middle income countries has shown that the currently available data is not sufficient. To date, there is a clear gap between the generally growing interest in the labor share and its insufficient practical measurement so that research findings on the development of the labor share in the developing world remain incomplete. This paper intends to contribute to the economic literature by collating and reviewing available labor share measures. The major problem of measuring the labor share of the developing world is that information about the self-employed in developing countries, their earnings and labor intensities, are mostly missing but they make up a large share of the workforce in these countries; in the low income countries they are even the majority. As a consequence of these data constraints, it is necessary to formulate assumptions about the self-employed labor income to compute a labor share which covers all workers, i.e. wage employees as well as the self-employed. This can only be a second-best solution and data review has shown that there is no perfect methodology to adjust the labor share for the self-employed. Different data sets rely on different assumptions when computing the labor share which results in a considerable disparity between the estimates. The best approach seems to be to employ a mix of assumptions, in consideration for the data availability and the economic condition of each country, which the PWT and Trapp data sets do. A one-size-fits-all approach does not seem appropriate. The WIOD data relies on more advanced and detailed methods, which can more reliably estimate the labor share, especially in a dynamic perspective. However, this requires high-quality data, which is only provided by a handful of middle income countries. When measuring the labor share, one must deal with a quantity-quality trade-off of international income data.

An important policy recommendation is therefore to improve the collection of data on the labor income share, especially regarding the self-employed sector. This could be done in the course of the SDGs (of which the labor share is one indicator) and their assessment by 2030. To improve the coverage and quality of the data, it will certainly be necessary to increase funding for the equipment and staff of national statistics offices. A very basic first step could be to collect comprehensive data on the proportion of the self-employed in the labor force and their division into own-account workers, contributing family members and employers. This would allow one to apply different assumptions for each group to arrive at a more precise labor share. In parallel, the recording of mixed income should be extended to all developing countries to receive an assessment of the real (in contrast to assumed) earnings of the self-employed. Additionally, data on skills and the sectoral distribution of self-employed would help to improve the estimation of labor-intensities of the self-employed. With this data, one could account for skill and sector composition effects and further assess inequalities within the labor share. So far, such detailed data is only available in WIOD for 16 middle-income countries between 1995 and 2009.

Notwithstanding these restraints, the available data sets provide valuable insights into the capital-labor ratio in the developing world over the past decades. Contrary to the standard proposition of a constant labor share of two-thirds, I find the labor share to range between 46 and 56 % in developing countries, depending on the data set. The low level of the labor share in developing countries mainly stems from low productivity in the self-employment sector but also from the considerable gap between labor income and productivity in the wage employment sector. Additionally, there is evidence that the production factor of labor has been losing further ground against capital since the early 1990s. The downward trend is observed across data sets, regions and income groups, although its magnitude varies with the underlying data set. Given that the labor force has been growing over the observed period, the decline is the result of an increasing gap between labor incomes and overall productivity. Productivity gains, which have been achieved in most countries in the last three decades, did not translate into broad wage increases suggesting that the potential of increasing the living standard of the poor has not been fully exploited. This is especially worrying as capital is usually much more concentrated than labor and tends to flow to the top income earners. Furthermore, it appears that the downturn has been especially to the detriment of low-skilled workers, who are located at the bottom of the income distribution. One reason for the decline is found to be the shift from labor-intensive sectors (such as agriculture) to more capital-intensive sectors (such as real estate). This negative trend not only occurs amongst the self-employed but also in the wage employment sector, which is astonishing in light of the fact that wage employment has grown in importance over the period of observation. The dual sector model by Lewis offers a first explanation for this but future research should focus on the potential reasons behind the declining labor share in the specific sample of low and middle income countries. The downturn takes place during times of increased globalization and evolving financialization, suggesting a link between these phenomena. It is therefore proposed to investigate these relationships and explore whether there is not only a correlation but also causation in place. In general, new theories of income distribution are needed, which take leave of the two-third standard and stylized fact of constant labor shares over time (Kanbur and Stiglitz, 2015).

Figure 3.10: **Mean and change in labor shares by sector, 1995-2009**

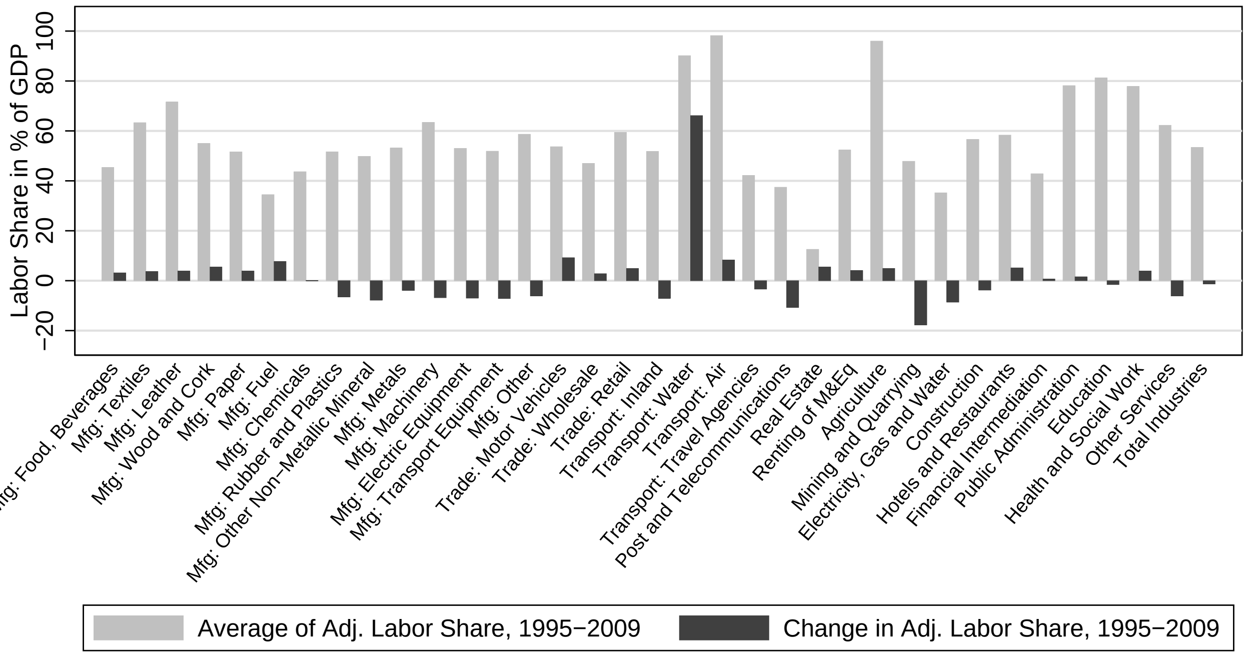
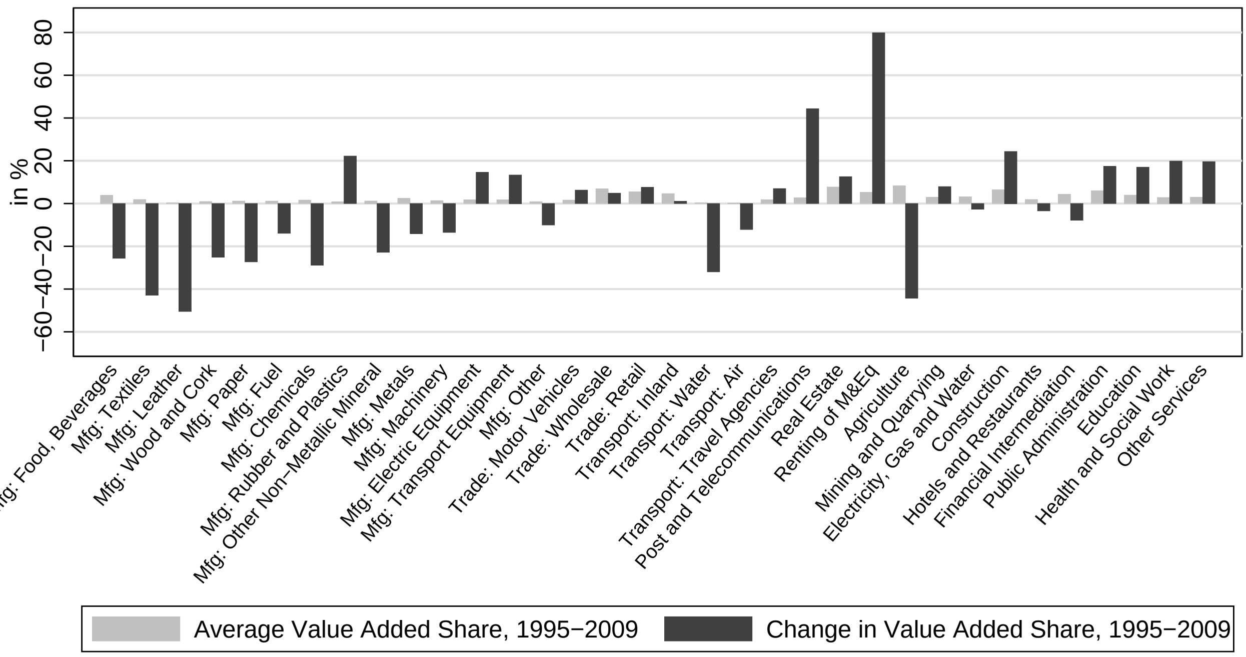


Figure 3.11: **Mean and change in value added by sector, 1995-2009**



Source: WIOD (2013).

Chapter 4

Financial Globalization and the Labor Share in Developing Countries: The Type of Capital Matters

Abstract

In this paper, we investigate how de facto financial globalization has influenced the labor share in developing countries. Our main argument is the need to distinguish between different types of capital in this context, as different forms of foreign investment have different fixed costs and impacts on the host countries' production process and vary concerning their bargaining power vis-à-vis labor. Assuming an aggregate elasticity of substitution between capital and labor would thus be misleading. Our econometric analysis of the impact of foreign direct vs. portfolio investment in a sample of about 40 developing and transition countries after 1992 supports this claim. Using different panel data techniques to address potential endogeneity problems, we find that FDI has a positive effect on the labor share in developing countries, while the impact of portfolio investment is significantly smaller, and potentially negative. Our results also highlight that de facto foreign investment cannot explain the decline of the labor share in developing countries over the investigated period.

4.1 Introduction

The post-1990 wave of globalization generated a vivid dispute about its distributional consequences amongst researchers, policymakers, and the public. The 'anti-globalization' movement of the late 1990s and the current backlash against globalization in the US and Europe, a broad literature on distributional effects of globalization in developing and advanced economies (see e.g. Bourguignon, 2015, Goldberg and Pavcnik, 2007, Slaughter, 2001) and the recent debate around Piketty (2014) demonstrate the wide interest in this issue.

International capital flows have been a characteristic feature of this globalization process and their effects on developing countries and distributional aspects have attracted the attention of previous research, as we review in more detail below. 'Capital' has mostly been considered as a pretty homogeneous concept in this specific context.[1] This aggregate view

[1] An example is the debate between and about the elasticity of substition between capital and labor. have recently emphasized the difference between wealth and capital in this context, an argument loosely related to our argument of heterogeneous types of (foreign) capital. For completeness, we mention that a strand in the

is sometimes helpful, as it keeps the exposition clear. However, it can be misleading in cases where very different modes of production are associated with specific capital flows.

The effect of foreign investment on developing countries' functional income distribution is such a case. While certain types of these investments (most notably portfolio investment) might represent capital in a general sense, foreign direct investment is further associated with transferring certain production technologies, management techniques, and other features that by themselves will alter factor demand and associated income shares in host developing countries.[2] This leads us to the hypothesis that foreign portfolio investment (FPI) will have a different impact on developing countries' labor share than foreign direct investment (FDI). Taking a first descriptive glance at the data that we are going to present and analyze in this paper supports the reasonability of this hypothesis: Figure 4.1 shows the unconditional correlations between mean annual changes of foreign investment and of the labor share (taken from PWT) in our sample of developing and transition countries after 1992 for FDI (left panel) and FPI (right panel). Without claiming any causation at that stage, three observations are worth noticing: First, there have been substantial changes in the labor share over the last two decades in several developing countries, mostly to the downside.[3] Second, de facto financial globalization is an unlikely candidate to explain the main part of this dynamics. This can be inferred from the low correlation, especially for portfolio investment (suggesting that other factors have been more relevant) and from the fact that the more relevant correlation between FDI and the labor share seems to be positive (suggesting that it cannot explain the declining labor share). This is not to say that foreign capital is unlikely to matter. On the contrary, FDI might have been an important force moderating the decline in the labor share. Additionally, figure 4.1 does not preclude the possibility that partial effects of foreign portfolio investment are potentially large. And third, correlations with the labor share seem to be quite different for FDI and portfolio investment: by and large, the correlation of FDI with the labor share seems to be positive while, if anything, it is rather negative for portfolio investment, although the latter does not seem to explain much cross-country difference and is much more susceptible to the potential outlier of Panama in this unconditional, descriptive setting.

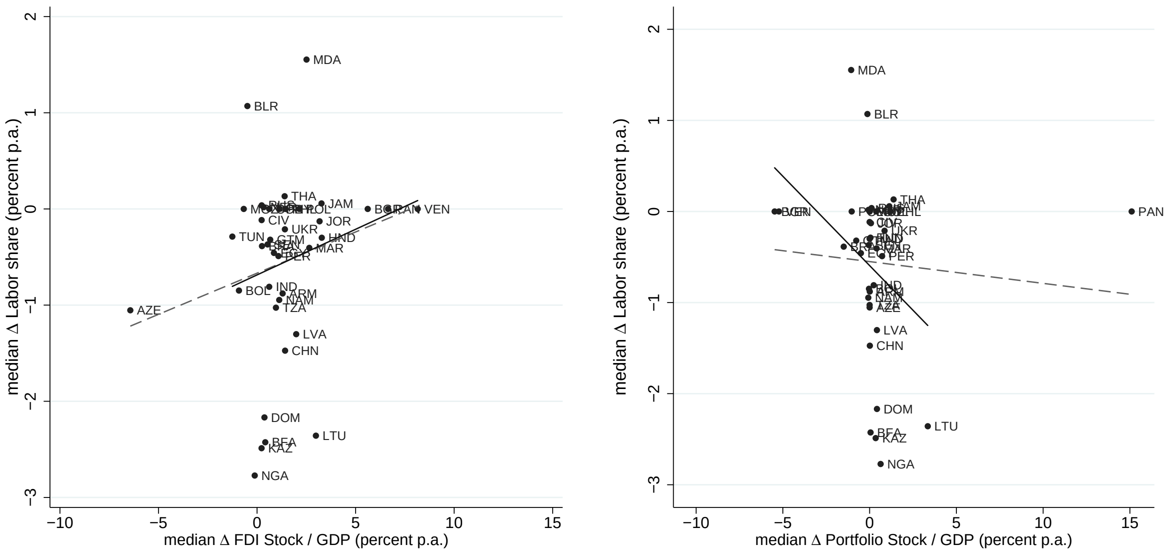
In this paper, we empirically elaborate on the impact of those two key types of foreign

literature has focused specifically on the social effects of FDI but – to our knowledge – has not paid attention to its differing impact compared to other capital flows.

[2]While this is generally true for advanced host economies as well, the technology distance and its associated effects are expected to be larger for developing countries (see the knowledge-capital model of FDI, e.g. Markusen et al., 1996, for the impact of skill and related factor differences on FDI).

[3]The only countries with notable increases, Bulgaria and Moldova, are economies recovering from the post-transition shock.

Figure 4.1: **Correlations between foreign investment and the labor income share**



Note: Dashed lines include the potential outliers Azerbaijan and Panama, respectively, solid lines do not.
Source: See C.1 in appendix C.

investment on the labor share in developing countries and substantiate their heterogeneous effects. Our empirical analysis relies on the recently published PWT labor share data and additionally on a new data set on labor shares in approximately 40 developing and transition countries that we constructed in the context of this study. To estimate the impact of foreign investment, we rely on several panel data techniques, including a distributed lag first-difference model and a novel IV identification strategy that explores the interaction of global financial conditions and distance from the world's financial centers and is based on the more general idea of Nunn and Qian (2014). While this provides us with an identification strategy that credibly meets the exogeneity and exclusion restriction despite controlling for unobserved cross-country heterogeneity, we have to rely on weak instrument techniques to draw conservative inference.

Across the board, our results confirm the different impact of FDI compared to FPI. More precisely, we find a positive impact of FDI on developing countries' labor share, while the impact of FPI tends to be negative but is often not statistically different from 0. This general result is robust to various estimation techniques and data set variations. Quantitatively, our results over the period 1992 to 2009 show that an increase of the FDI stock (as a percentage of GDP) by 10 % points increases the labor share by about 2 %. An increase of FPI of the same size would result in a decline of the labor share by a similar magnitude (but less statistical reliability). Economically, this is a relevant magnitude, leading us to the conclusion that foreign capital matters for developing countries' labor share. Furthermore, we find some evidence that this effect depends on a country's capital-to-labor ratio. However, despite the economically significant effects of foreign capital on developing countries' labor share, other factors were more important for it's dynamics: as the increase of FPI was rather modest compared to FDI, one can conclude that de facto financial globalization by itself cannot explain the decline of the labor share in developing countries over the last decades. Our results suggest that especially trade might be a potential candidate.

Our results provide a number of broader relevant insights and contributions. First and foremost, we contribute to a larger debate and literature on the overall distributional consequences of globalization in developing countries (e.g. Dollar and Kraay, 2004, Prasad et al., 2003, Verhoogen, 2008), showing that the popular view that increasing capital mobility came at the expense of labor income in these countries is generally not defensible, at least for de facto capital mobility. This has several policy implications for developing countries integrating into the world economy. Second, and relatedly, we add to a more focused debate about global developments of the labor share and its macroeconomic determinants and consequences (e.g. Harrison, 2005, Hutchinson and Persyn, 2012, Karabarbounis and Neiman, 2014).[4] Third, we add to a literature that emphasizes the differences between types of international capital flows, their determinants, and effects (e.g. Daude and Fratzscher, 2008). This also relates to the debate about the elasticity of substitution between capital and labor and raises the question to what extent an abstract notion of 'capital' will provide us deep insights into distributional effects on the global level. Last not least, we provide some methodological innovations by proposing a new identification strategy for the effects of foreign investment in developing countries and providing a new data set on labor shares in developing countries that covers the whole economy (as opposed to only the manufacturing sector) and uses country-specific information to correct for self-employment.

Our paper is structured as follows: Section 4.2 provides the economic motivation for our analysis and reviews the relevant literature related to our study. We present the data and estimation methodology in section 4.3 and the empirical results in section 4.4. Section 4.5 demonstrates the robustness of our results and provides some additional findings. Section 4.6 concludes.

[4]Maarek and Decreuse (2015) provide an analysis focusing exclusively on FDI and its effect on developing countries' labor share. We discuss our relation to this study in subsection 4.2.3. For studies focusing on OECD countries, see Bentolila and Saint-Paul (2003), Guscina (2006), Hutchinson and Persyn (2012), Jaumotte and Tytell (2007), Richardson and Khripounova (1998).

4.2 Theoretical motivation and related literature

In this section we discuss why it is important to distinguish foreign direct investment (FDI) from foreign portfolio investment (FPI) in assessing the impact of capital flows on developing countries' labor share. We start with a standard neoclassical argument why 'capital' in the common sense will have largely neutral effects on developing countries' labor share. However, we also point out that this argument rests on the assumed elasticity of substitution between capital and labor being close to 1. We provide some arguments why this elasticity might tend to be above 1 for FPI (mostly based on bargaining power considerations), while it is most likely to be lower than 1 for FDI, as the latter requires complementary domestic factor inputs (especially skilled labor) and does not enjoy the same bargaining power as FPI due to fixed costs and hold up problems in complex production networks. This leads us to our hypothesis that FDI and FPI will exercise different impacts on developing countries' labor shares.

4.2.1 A standard neoclassical interpretation

By definition, the labor share LS is the part of national income Y that is not acquired by capital ($LS := Y - \alpha Y$), which allows us to focus on our research question from the viewpoint of capital K. Following Piketty (2014), and based on Harrod and Domar, the capital share of income, α, will in the long run be determined by the return on capital, r, and the capital-to-income ratio:

$$\alpha = r \times K/Y, \tag{4.1}$$

with the latter adjusting in the long run to the ratio of the savings rate, s, to the growth rate, g.

From a standard neoclassical viewpoint with perfect competition, factor remuneration by its marginal product, and a Cobb-Douglas elasticity of substitution between capital and labor equal 1, one would expect a broadly neutral effect of capital flows on the labor share in the host economy: on the one hand, openness would reduce the return on capital in developing countries ($r \downarrow$) while increasing the return on the more abundant factor labor (i.e. wages). This is the rationale of standard trade models based on the factor-proportion approach (Heckscher-Ohlin-Stolper-Samuelson) and can be extended to financial globalization to the extent capital mobility acts as a substitute for trade (Ethier and Svensson, 1986, Mundell, 1957). On the other hand, however, the positive impact on wages and the decline in the return on capital would be 1:1 outweighed in the capital share as the K/L ratio would increase by the same amount, due to the elasticity of 1; in terms of equation (4.1): $r \downarrow = K/Y \uparrow \rightarrow \alpha = \alpha'$, which is also the rationale of the long-assumed stability of the labor share in neoclassical economics.

4.2.2 Moving beyond a substitution elasticity of 1

Recent contributions such as Karabarbounis and Neiman (2014) and Piketty (2014, p. 220) challenged this unity-elasticity arguing for an elasticity greater than 1, kicking off a fierce debate on that matter (see e.g. Kanbur and Stiglitz, 2015, Rognlie, 2015, Summers, 2014). A substitution elasticity above one means that there are many different uses of capital in the long run and that the marginal productivity of capital (and labor) is the more independent of the available quantity of capital and labor the higher the elasticity. Intuitively, fixed capital could then smoothly replace workers in the production process.

The view of an elasticity greater than one is also consistent with the view that the increased mobility of capital due to globalization increased its bargaining power vis-à-vis labor, whose de-facto mobility remained virtually unaltered (e.g. Harrison, 2005, Jayadev, 2007, Rodrik, 1997). According to this argument, threatening to offshore jobs, either by outsourcing or FDI, puts tight discipline on workers' wage claims.[5] As Arseneau and Leduc (2011) show, equilibrium effects of such outside options for entrepreneurs can be substantial in size.[6]

On the other hand, one may argue that human capital has become an ever increasing input factor in modern production that cannot easily be substituted away by physical capital and give more power to skilled laborers, resulting in a decline in the substitution elasticity.

After all, different forces influence the elasticity of substitution and their relative importance can differ over time, between countries, and between different types of capital. In the following subsection, we discuss the main considerations influencing the elasticities for two main types of investment in developing countries: FPI and FDI. How large and relevant these factors are in practice remains an empirical question, thus motivating our empirical analysis of the impact of foreign investment on the labor share in developing countries.

[5] Outsourcing/offshoring and investing abroad differ from each other in the aspect that the latter constitutes ownership while the former establishes an arms-length relationship.

[6] Similarly, since attracting foreign investment – especially FDI – has become a policy goal in itself in many developing countries, labor relations may have been characterized by wage restraints in an act of anticipatory obedience.

4.2.3 Factors that affect the substitution elasticity of foreign investment in developing countries

Foreign investment in developing countries mostly comes in the form of FDI, which is broadly speaking investment by multinational firms. FPI has historically been less relevant (see Figure 4.2) but is recently gaining importance in many developing, especially emerging economies. These foreign capital flows are distinguished by the fact that FDI implies some degree of control or influence in the host firm (see IMF, 2009, §§6.8-6.24).[7] One feature of this influence often is the direct takeover of management. FDI of multinational firms thus often has considerable influence on the production process in the host firm and economy, while FPI should rather be interpreted as providing additional capital to domestic (host) firms. In our view, this constitutes a major difference between the two forms of foreign investment that is likely to result in different returns to capital (r) and substitution elasticities and, ultimately, different impacts on developing countries' labor share.

Let us start with the claim that globalization has improved the bargaining power of capital vis-à-vis labor, which is likely to exercise a negative impact on the labor share (and a positive impact on the substitution elasticity). The associated threat to withdraw capital is less credible when that capital is fixed, or capital relocation is costly.

For FPI – which, by definition, only constitutes a very small share of the host firm's capital structure – withdrawal of capital is relatively easy, especially in developed and liquid capital markets. For example, it should not be difficult to sell a 0.2 % share of a company on the stock exchange, so that this threat is largely credible.[8] On the other hand, selling a share of over 10 % (and often much more), as it would be the case for foreign direct investors, is less of an option in most cases as it would require considerably more time. Besides from difficulties of placing such a large share in the host financial market, divestment might be costly because the host firm is often integrated in a multinational production network (e.g. Alfaro and Chen, 2014, Badinger and Egger, 2010, Blonigen et al., 2007, Yeaple, 2003). Detaching a single plant from this network might thus disrupt the whole multinational production process and create severe holdup problems.[9] There is a large literature theoretically investigating and empirically confirming these higher fixed setup costs

[7]Statistically, the distinction consists of FDI needing an ownership share of at least 10 % in the foreign affiliate.

[8]FPI can also come in the form of debt flows. In this case, foreign investors might care less about host firm developments because their capital is preferential to equity. However, it might still be possible to sell the debt in local financial markets.

[9]Furthermore, multinationals often transfer technology to host firms. In case they sell their stake, the technology is appropriated by the host firm or another investor, so the foreign direct investor has a higher incentive to maintain ownership and control.

of FDI and associated higher sensitivity to uncertainty, informational frictions, and risk.[10] These considerations lead us to the hypothesis that FPI is in a stronger bargaining position vis-à-vis developing country laborers than FDI and will thus tend to have a more negative effect on labor shares.

Our other key argument relates to the influence FPI and FDI have on the production process and associated substitution elasticities between capital and labor. As FPI takes smaller stakes in host firms, it can be seen as 'investment at the margin' that will potentially be used to conduct pending firm investments in fixed capital. In that sense, it helps substituting capital for labor, pushing the elasticity of substitution upward. FDI to developing countries, on the other hand, often revolutionizes the whole production process and produces at higher segments of the value chain (Harding and Javorcik, 2012). This often requires relatively high-skilled workers so that capital and labor complement each other considerably more than for FPI, thus potentially lowering the substitution elasticity. Furthermore, finding workers with required levels of human capital can often be difficult in developing countries and as multinationals also fear transfer of their technology through labor market churning (Görg and Strobl, 2005), they often pay higher wages (see e.g. Hijzen et al., 2013, Lipsey, 2002) which constitutes a further argument against FDI lowering the labor share in developing countries.

A related rationale is also explored by Maarek and Decreuse (2015) who argue (based on a search-theoretical model with firm heterogeneity and labor market frictions) that in a developing country with few foreign firms, FDI would lower the labor share via technology effects but as the proportion of foreign enterprises passes a certain threshold, FDI starts exercising a positive impact on the labor share because of competition for laborers between firms. They find some evidence of the associated U-shaped pattern in 98 developing countries over the period 1980 to 2000, although the large majority of countries lies in the part where a negative relationship is present since the estimated threshold of over 150 % (of FDI stock to GDP) is very high. While related to our paper, their study differs from ours in several aspects. First, we focus on different types of foreign investment in a broader perspective, instead of only looking at FDI. Second, we use country-wide labor shares instead of only focusing on manufacturing labor shares. While Maarek and Decreuse (2015) argue that FDI in developing countries is most relevant in the manufacturing sector, it is also well-known that FDI induces considerable vertical spillovers (e.g. Havranek and Irsova,

[10] Examples include Albuquerque (2003), Daude and Fratzscher (2008), Davies and Kristjánsdóttir (2010), Hashimoto and Wacker (2016), Javorcik and Wei (2009), Kesternich and Schnitzer (2010), Razin et al. (1998), van Nieuwerburgh and Veldkamp (2009), Wei (2000). See also Helpman et al. (2004) for fixed costs of horizontal FDI.

2011). Furthermore, although labor markets in developing countries are far from perfect, it is unlikely that wage developments in the manufacturing sector have no effects on wages in services, agriculture, and primaries. In that sense, our approach is more appropriate to capture general equilibrium effects.[11]

4.2.4 Empirical implication and hypothesis

Our discussion highlights that there are several reasons to assume that FDI and FPI have different elasticities of substitution between capital and labor, bargaining positions, and hence also different effects on the labor share in developing countries. Which factors prevail and whether they are large enough to produce a substitution elasticity significantly different from 1 and associated effects on the labor share remains an empirical question motivating our analysis. From the above discussion, it seems reasonable to assume that FPI might see a substitution elasticity close to 1 and have no strong effect on the labor share, although the discussed bargaining and substitution effects might tend to exercise a negative impact on the labor share. Whether the effect of FDI on developing countries' labor share is positive or not remains to be seen but from the above discussion we have strong reasons to assume that the impact, denoted β, will be more positive (less negative) for FDI than for FPI. Our most important hypothesis can thus formally be denoted as testing $H_0 : \beta_{FDI} = \beta_{FPI}$ vs. the alternative $H_1 : \beta_{FDI} \neq \beta_{FPI}$ (see subsection 4.3.2.1).

4.3 Data, inference, and identification

In this section, we first describe our data set – most notably which measures we use for the labor share and how we obtain foreign investment data – and show simple correlations in the data, including fixed effect (FE) and random effects (RE) regressions. We then present our econometric model, including the relevant testing hypothesis and identification strategy.

4.3.1 Data

We focus on the labor share as our dependent variable because of its macroeconomic and political economy relevance (see Atkinson, 2009, Karabarbounis and Neiman, 2014) and because most standard trade and open economy models suggest distributional effects of

[11]Moreover, the key point of a U-shaped relationship in the Maarek and Decreuse (2015) paper is suspicious of suffering from a spurious regression problem of interaction terms in fixed effect models. This might also explain why their quadratic term is unidentified in the IV regressions.

openness for production *factors*. Accordingly, we look at the functional income distribution which is distinct from (but related to) other studies that look at the personal income distribution or poverty effects of globalization (e.g. Arestis and Caner, 2010, Dollar and Kraay, 2004).[12]

4.3.1.1 Labor share

Simply speaking, the labor share is the fraction of an economy's income that accrues to labor (as opposed to capital). Recently, Inklaar and Timmer (2013) provided estimates of the labor share for up to 127 countries in the Penn World Tables (PWT) 8.0, which we take as the dependent variable for our baseline estimates.

A relevant contribution of our study, which initiated before the PWT 8.0 data were released, is that we develop an alternative measure for the labor share in developing countries. Trapp (2015) provides a detailed discussion of our method and the differences to the PWT data but the key difference concerns the adjustment for labor income of the self-employed.[13] Our approach mainly relies on Gollin's (2002) third suggestion which assumes that the self-employed earn the same wage as employees and corrects for the fact that this tends to overestimate the labor share in the more backward economies (where many of the self-employed engage in low-productive subsistence farming).[14] By contrast, the PWT data in almost equal parts are based on Gollin's second suggestion, which assumes that the labor share of self-employed income is the same as for the rest of the economy, and Gollin's first adjustment, which adds self-employed income (proxied by total agricultural value added) to the labor income of employees.[15] Furthermore, our data use more micro-founded informa-

[12] However, the functional income distribution generally allows making a link between personal income distribution on the micro level and a macroeconomic national accounts perspective (Checchi and Garcia-Penalosa, 2010, Daudey and García-Peñalosa, 2007, Glyn, 2009, Ray, 1998). This is particularly true in developing countries where most people (especially poor households) only have their labor to earn a living and do not have relevant capital income, so the labor share directly relates to the personal income distribution (Ray, 1998, p. 171).

[13] One may argue that correcting for self-employment is not important altogether, as the self-employed are usually not working for foreign companies. This neglects that especially FDI can set in motion social mobility towards the formal sector which increases labor compensation and thus the (unadjusted) labor share, even though labor income has effectively changed little.

[14] As data on the share of self-employment in total employment is rare, we use the agricultural employment share as a proxy. Where data on self-employed income is available, the first and second adjustment suggestions of Gollin (2002) serves as upper and lower bounds, respectively. No further adjustment is undertaken in countries that seemingly already accounted for self-employed labor income.

[15] In the PWT data, no further adjustment is undertaken in countries where the naive labor share exceeds 0.7. Gollin's third adjustment using the self-employment share in total employment is used when employment data are available and the resulting labor share is lower than that resulting from Gollin's first adjustment using agricultural value added as a proxy.

tion (e.g. from Social Accounting Matrices) about trends in self-employment in developing countries to substantiate the assumptions made. We thus think our data provide a more accurate measure of the labor share for the specific sample of our study because it incorporates more country-specific information about self-employment and does not build on as many assumptions as the PWT (interpolation, constant labor shares at start and end points). However, to refuse any concerns our labor share measure was constructed in a way to support our hypothesis, we rely on the PWT data for our baseline estimates and use the measure of Trapp (2015) only to check for robustness.

Compared to previous studies about the effect of globalization in developing countries, it is finally worth highlighting that both our labor share measures adjust for the problem of labor income of the self-employed (as opposed to Diwan, 2001, Harrison, 2005, Jayadev, 2007, Karabarbounis and Neiman, 2014) and cover the whole economy, instead of only relying on the manufacturing or corporate sector (such as Karabarbounis and Neiman, 2014, Maarek and Decreuse, 2015, respectively).

The measures for the labor share in our relevant sample range from 21.2 % in Azerbaijan (2008) to 78.1 % in Armenia (1998) for the PWT series, and from 18.7 % in Azerbaijan (2008) to 64.3 % in Bolivia (2000) for our newly constructed measure. For the econometric estimation, we log-transform the data. To avoid potential spurious regression problems to inference that can also arise in standard panel data models if series are integrated of order one (Kao, 1999), we test for unit roots using Fisher-type panel data tests based on Phillips and Perron and augmented Dickey-Fuller tests, including also drifts and trends up to three lags. Of the 15 different tests conducted, 14 (13, 12) allow to reject the null hypothesis of a unit root in our newly constructed log labor share on the 10 (5, 1) % level of statistical significance, while the same is only true for 5 (5, 5) of the PWT data.[16] Because this casts some doubt on the PWT series, we emphasize that our key results are also robust for our newly constructed labor share data which are less suspicious to suffer from unit-root-induced inference issues. Results are available upon request.

4.3.1.2 Foreign investment

Our main explanatory variables of interest are foreign direct investment (FDI) and foreign portfolio investment (FPI), both measured in stocks (taken from the International Investment Position, IIP, of the IMF's International Financial Statistics, IFS) relative to GDP (as reported by the UN SNA) in order to arrive at a good measure of the relative importance

[16] This might partly be due to the PWT method of filling missing values with interpolation and keeping labor shares constant.

of foreign investment in the host economy (see IMF, 2009, and Wacker, 2013, for more information on these measures). Along the lines of our discussion in section 4.2.3, the key distinction between these two types of foreign investment in the IIP is their degree of ownership which is reflected in different equity stakes in the host enterprises.

Note that this is a *de facto* measure of capital stocks or financial globalization (cf. Edinson et al., 2002). De jure measures, which are based on legal restrictions on international capital flows, may have some advantages but they do not always indicate the actual degree of investors presence in the country (see e.g. Kose et al., 2009b, who use an equivalent benchmark measure for de facto financial openness). For example, many countries in Sub-Saharan Africa have loosened their capital controls but are only experiencing small inflows of foreign investment. Furthermore, actual legislation does not tell much about the investment that has accumulated in the past and hence currently exercises economic effects in the sense of section 4.2.3 in the host economy, which is captured more appropriately by our stock measures. Finally, we are mainly interested in the heterogeneous effects of different types of capital flows which would be hard to compile from de jure data.

The according measures for FDI and FPI in our sample range from 0 (Côte d'Ivoire, 1994-1997) to 132.3 % (Azerbaijan, 2004) and from -0.04 (Tanzania, 2008) to 65.2 % of GDP (Jordan, 2005), respectively.

4.3.1.3 Control variables

To obtain the ceteris paribus effect of FDI and FPI stocks on the labor share, we control for a set of variables that have been found to influence the labor share in previous research and which are also likely to correlate with capital stocks, so that parameter estimates would be biased when omitting these variables. In the baseline regressions, we limit the control variables to those we consider most relevant and which still allow us to rely on a comprehensive sample. In section 4.5, we will demonstrate that our results are also robust to the inclusion of additional control variables.

To accommodate the possibility that the labor share is systematically different at higher development levels, we control for *GDP p.c.*, transformed into logs. Note that most of our panel estimations remove unobserved cross-country heterogeneity, so this variable will to some extent also capture cyclical effects. As an even more cyclical variable that is easily available, we control for the *inflation rate* which might influence the labor share in the short run since wages react to price fluctuations with some delay, as pointed out by Marterbauer and Walterskirchen (2003). To control for the fact that countries that produce more capital intensive should earn more interests and experience therefore a lower labor share, we include the *capital-to-labor (K/L) ratio* (with labor taken from WDI and capital stocks estimated from PWT 7.0 with the perpetual inventory method).

Furthermore, we control for *government consumption/GDP*, taken from PWT 7.0, since Harrison (2005) and Jayadev (2007) find that government inference positively influences the labor share. The reason is that governments in general pursue redistribution policies in favor of labor. Government policies, however, change with the opening up of capital markets and the resulting 'discipline effect' (Prasad et al., 2003, p. 2), leaving it a priori unclear whether government consumption correlates positively or negatively with the labor share. National governments in open economies may be prompted to adopt policies that disproportionally serve the interests of capital (Stiglitz, 2000).

Another standard control variable, especially with regard to developing countries, is *institutional quality*. We therefore experiment with a composite risk rating and an index for financial risk from the International Country Risk Guide (ICRG), where higher values indicate lower risk. The baseline results will focus on the composite risk rating.

Furthermore, *trade/GDP* is a control variable of particular interest to us because standard models predict that trade increases the labor share of developing countries. Our arguments instead suggest that trade may negatively influence the labor share because the bargaining power of labor can be weakened with increased international competition as labor at home indirectly competes with labor abroad (cf. Dube and Reddy, 2014, Ortega and Rodriguez, 2001). In any case, it is important to control for trade in our setting, as it might not only influence the labor share but also be correlated with foreign investment.

Finally, to control for the important effect of education, we use an *education* index compiled by the United Nations Development Program (UNDP) as our last baseline control variable. It combines mean years of schooling with expected years of schooling and has the advantage of wide availability. Again, this is a potentially important control variable in our setting, as a more educated labor force may acquire a higher labor share while at the same time influencing foreign investment (as e.g. the knowledge-capital model for FDI points out; cf. Blonigen et al., 2003).

As a mere statistical control, we further include an (unreported) dummy variable SNA which indicates if a country's system of national accounts follows the 1993 convention (or the 1968 convention otherwise).

In section 4.5, we demonstrate the robustness of our results to including additional/alternative control variables that we do not include in the baseline regression (mostly due to data availability and according sampling issues). Including gross fixed *capital formation* (GFCF/GDP) helps taking into account different aggregate production technologies. For a similar reason, we also control for *labor productivity*, defined as GDP per worker from PWT 7.0, although it is highly correlated with GDP. Furthermore, we control for *crisis* periods, identified by swift changes in the nominal exchange rate, which also tend to depress the labor share (cf. Arseneau and Leduc, 2011, Diwan, 2001, Harrison, 2005, Jayadev, 2007, Onaran, 2009). Theoretical considerations further suggest to also control for the *real interest rate* (WDI) because the government may be encouraged to pursue a high interest rate policy once the capital markets have been liberalized in order to attract foreign investors. This, however, can depress domestic investment and may have a negative effect on the labor share. We also consider the PPP-implied *exchange rate* (IMF WEO) because appreciations may adversely affect employment in the export sector and thus the labor share and because the exchange rate can also be considered as a proxy for the fixed costs for capital of relocating abroad (Harrison, 2005), with an appreciation decreasing the costs of relocating.[17] Finally, we also test for robustness to including an *employment vulnerability* measure: the fraction of paid family workers and own-account workers (as a percentage of total employment, from WDI).

4.3.1.4 Descriptive statistics and correlations

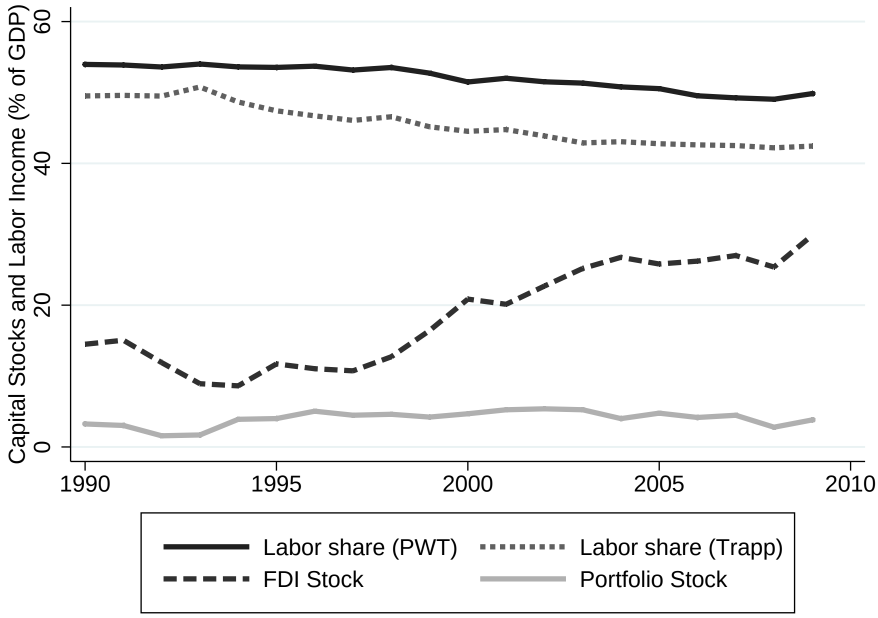
Table C.1 in appendix C provides summary statistics of each variable used (based on the sample for our baseline model (2) in table 4.1). The same appendix also provides a list of included countries.

Figure 4.2 shows the developments of our key variables of interest over time. As one can see, the labor share shows a significant downturn since the early 1990s, a trend which prevails in most developing regions. Regressing the log labor share on time (using fixed effects and limited to observations in the baseline sample) shows a negative trend of -0.008*** and -0.009** for the PWT and our newly constructed series, respectively. The figure further shows that FDI plays a much more important role than FPI in developing countries and saw a much more dynamic development through the sample period.

Table C.2 in appendix C provides pairwise variable correlations. Three observations seem worth highlighting. First, pairwise correlations in our baseline variables seem small, so multicollinearity is unlikely to be an issue. Second, the low correlation between our two labor share measures is remarkable and possibly highlights the degree to which the different adjustment methods suggested by Gollin (2002) might matter. Third, for both labor share measures, the (unconditional) correlation with portfolio stocks is more negative than with FDI stocks.

[17] Since we note price notation, an appreciation of the currency is associated with a decrease in the exchange rate.

Figure 4.2: **Labor shares and capital stocks in developing countries**



Source: See C.1 in appendix C.

Conditional correlations can be inferred from table 4.1 that provides simple panel data results from fixed effect (FE) and random effect (RE) estimation. For both estimation techniques, correlations of the labor share with FDI stocks are positive, while those with portfolio stocks are negative. While they are individually insignificantly different from 0 without controlling for other factors, their difference is statistically significant once one controls for other macroeconomic variables (at the 5 % level, at least), as indicated by the test statistic in the last line (and discussed in more detail in subsection 4.3.2.1). With those baseline controls, the positive correlation of the labor share with FDI itself also turns statistically significant, while the negative correlation with the portfolio stock is only significant in the FE estimation.

4.3.2 Econometric model and inference

While those first results are already indicative of our key hypothesis, they are potentially prone to several sources of endogeneity bias. We thus move to a more causal identification concerning the effect of foreign capital investments on the labor share in developing countries. As in the simple FE and RE results above, we start by modeling our labor share

Table 4.1: **Panel correlations (FE and RE)**

VARIABLES	(1) $\ln(LS_{PWT})$	(2) $\ln(LS_{PWT})$	(3) $\ln(LS_{PWT})$	(4) $\ln(LS_{PWT})$
FDI stock/GDP	0.00167	0.00178***	0.00148	0.00170**
	[0.00122]	[0.000419]	[0.00106]	[0.000789]
Portfolio stock/GDP	-0.00145	-0.00234***	-0.00166	-0.00177
	[0.00146]	[0.000789]	[0.00126]	[0.00112]
ln(GDP p.c.)		-0.359***		-0.280***
		[0.0465]		[0.0687]
ln(Inflation)		0.000225		-0.000633
(-1)		[0.00504]		[0.00524]
Risk		0.00174		0.00104
		[0.00130]		[0.00168]
ln(Government share)		-0.0655***		-0.0490
		[0.0173]		[0.0329]
Education index		0.887***		1.210***
		[0.268]		[0.191]
K/L		-3.03e-06***		-7.30e-07
		[9.58e-07]		[1.15e-06]
Trade		-0.00153***		-0.00127**
		[0.000391]		[0.000580]
Observations	433	309	433	309
Number of countries	51	38	51	38
R-squared (within)	0.27	0.57	0.27	0.55
Estimation	FE	FE	RE	RE
test statistic	1.84	16.55***	2.55	5.79**

Cluster-robust standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1
time dummies, constant and SNA not reported

variable, ln(*LS*), as a log-linear function of the foreign capital stock variables (FDI, FPI) conditional on a set of control variables, Ψ (some of which are log-transformed as well):

$$\ln(LS)_{it} = \beta_{FDI}\frac{FDI_{it}}{GDP_{it}} + \beta_{FPI}\frac{FPI_{it}}{GDP_{it}} + \Psi_{it}\theta + u_{it}, \tag{4.2}$$

where $u_{it} := \alpha_i + \gamma_t + \varepsilon_{it}$ with α_i being country dummy variables, γ_t representing year dummy variables[18] and ε_{it} is an error term with $\mathbb{E}(\varepsilon_{it}) = 0$ and existing second moment. As

[18] Note that the included time dummies also nest a time trend, even with a structural break and that they also account for any 'global' factors and shocks (such as oil prices).

discussed below, this model is estimated in first differences and using instrumental variable techniques, respectively.[19] With respect to statistical inference, all estimated standard errors of these models are robust to any pattern of heteroskedasticity and autocorrelation within countries.

4.3.2.1 Inference and null hypothesis

At this point, it is important to stress that our main argument (see subsection 4.2.3) and related null hypothesis is not about a parameter being statistically indifferent from zero, as in most empirical studies. As discussed in subsection 4.2.1, a parameter estimate of zero would even be a resonable a priori expectation under most conventional neoclassical assumptions. It would not be conflicting with our hypothesis when both forms of foreign investment have an impact on the labor share that is statistically not different from zero, as our main hypothesis is that $\beta_{FDI} > \beta_{FPI}$.

We therefore test for equality of parameters in our null hypothesis

$$H_0 : \beta_{FDI} = \beta_{FPI} \tag{4.3}$$

against the alternative

$$H_1 : \beta_{FDI} \neq \beta_{FPI}. \tag{4.4}$$

Although we assume $\beta_{FDI} > \beta_{FPI}$, we still test against a two-sided alternative given the absence of a formal model deriving this (alternative) hypothesis. Our inference is therefore rather conservative. Under the null hypothesis and conventional least squares estimation (especially first differences and FE), the according test statistic $t := \frac{\hat{\beta}_{FDI} - \hat{\beta}_{FPI}}{\hat{se}(\hat{\beta}_{FDI})}$ follows a t-distribution with $k-1$ degrees of freedom, where k is the number of estimated parameters.[20]

When using instrumental variable methods, we have to rely on other test statistics that are robust to weak instruments. In that case, the distribution of the IV estimator and according test statistics are not well-approximated by standard asymptotic limits. Therefore, we rely on the conditional likelihood ratio (CLR) test proposed by Moreira (2003) and on the Anderson and Rubin (1949) AR test, both of which are robust to weak instruments and can also be inverted to produce a confidence region for our parameters of interest. This allows a visual inspection to infer where the true parameter is likely to lie. Moreover, the AR test

[19] For the RE model presented above, it is assumed that $\alpha_i \overset{!}{=} \alpha \ \forall \ i$ and parameters are estimated via generalized least squares in this case.

[20] In case of GLS estimation in the RE model presented above, the distribution follows a χ^2 distribution with one d.o.f., i.e. the distribution of a simple normal deviate squared.

includes a test for the exogeneity condition $\mathbb{E}(Zu) = 0$. That is, the null is also rejected if exogeneity is not supported by the correlation of residuals with the instrument(s). Conversely, the CLR test assumes the exogeneity condition to be satisfied. While it has more power than the AR test, it can only accommodate a single endogenous regressor.

4.3.2.2 Identification

Against the background of our relevant hypothesis, a discussion of potential problems that may cause a bias to our parameters of interest, β_{FDI} and β_{FPI}, seems at order. It is important to stress that, given our hypothesis, the relevant problem we should be concerned about is a potential endogeneity problem that causes an upward bias in β_{FDI} relative to β_{FPI}. Conversely, anything that will bias β_{FDI} and β_{FPI} upward (or downward) at the same order is unfortunate for the precision of our point estimates (which we still care about) but does not affect inference concerning our relevant null hypothesis.

In our view, there is only one relevant economic problem that might cause such a bias, which is reverse causality from wages (which proxy for workers' skill) to types of foreign investment. It is widely accepted that multinational firms tend to pay higher wages and hire more skilled workers (e.g. Hijzen et al., 2013). To the extent that wages reflect skills, a higher labor share might attract mulitinationals' FDI, which is also less sensitive to a higher wage bill than FPI, and bias our estimated effect for the causal effect of FDI on the labor share upward relative to the effect of FPI.

Our distributed lag first-difference strategy takes care of this (and any other potential) source of reverse causality. The model can be written as

$$\Delta \ln(LS)_{it} = \beta^{FD}_{FDI} \Delta\Big(\frac{FDI_{i,t-1}}{GDP_{i,t-1}}\Big) + \beta^{FD}_{FPI} \Delta\Big(\frac{FPI_{i,t-1}}{GDP_{i,t-1}}\Big) + \Delta\Psi_{it}\theta^{FD} + \gamma^{FD}_{t} + \varepsilon^{FD}_{it}, \tag{4.5}$$

where Δ is the first-difference operator, i.e. $\Delta x_t = x_t - x_{t-1}$ (and $\Delta\Psi$ might also include lagged differences). Note that this transformation cancels out the (time-invariant) country fixed effects while still accounting for unobserved cross-country heterogeneity.

To see why this approach resolves reverse causality issues, first note that the model relates innovations in the labor share in year t to changes in foreign capital stocks in $t-1$. Hence, reverse causality could only be an issue if foreign investors in t (differently) react to changes in wages or, precisely, the labor share in $t+1$. This is very unlikely, especially since we look at capital stocks, not flows, which to a large extent reflect past investment (and its revaluations).[21] An issue could only arise with high persistence of the (first differenced) series, i.e. if wage (or labor share) developments in $t+1$ are largely echoing those in t. However, this is not the case as the correlations between current and lagged first differences of our labor share measures are only 0.05 (for the PWT series) and -0.07 (for our newly constructed series), and in neither case significant at the 10 % level. Furthermore, first-order autoregressions of these (differenced) series produce an (insignificant) AR(1) parameter estimate of 0.003 and -0.021, respectively, indicating that persistence in differences of the labor share is not an issue.

However, the skeptical reader might come up with other sources for an endogeneity bias. Therefore, we propose a novel strategy to identify the effect of international capital flows using instrumental variables based on global financial conditions that credibly meet the exogeneity and exclusion restrictions, though suffer from a weak-instruments problem, for which we account in our inference techniques. In our view, this identification approach is an innovation to the literature that has to date failed to provide a time-varying instrument for international capital that is not only credibly exogenous but also convincingly meets the exclusion restriction.

Our instrumental variable identification strategy is based on the well-established fact that capital flows to emerging and developing countries can at least partially be driven by push factors in industrialized economies, most notably monetary and financial conditions (e.g. Dabla-Norris et al., 2010, di Giovanni, 2005, Fernandez-Arias, 1996, Fratzscher, 2011, Reinhart et al., 1993, Rey, 2013). To gauge those financial conditions, we use the US financial conditions index (FCI) developed by Wacker et al. (2014). This measure is credibly exogenous as US financial conditions and monetary policy are not influenced by events in developing countries in general and the labor share in particular. Furthermore, it meets the exclusion restriction as the FCI is constructed to be conditional on the US business cycle, i.e. it captures developments in financial conditions that are exogenous to most important real developments. This avoids that latter aspects in the FCI exercise a relevant impact on developing countries' labor share through other channels than foreign investment, especially since we control for time dummies in the second stage regression. While the US are by far the most important foreign investor in developing countries, we certainly also want to gauge financial conditions in Japan and the European Union (EU) to improve identification in the first-stage regression. Unfortunately, elaborated FCIs with the required time range are not available for these economies, so we construct proxy measures that are basically an average

[21] Note in this context that capital flows are *not* simply the first difference of capital stocks. See Wacker (2016).

of equity prices, bond interest rates and the spread between long term and short term bond rates.[22] These measures should matter for capital flows to developing countries as they are crucial for the (re-)financing conditions of most relevant investors. The wave of capital flows to emerging economies in the aftermath of the US Fed easing after the financial crisis and its reversal amid the 'Taper tandrum' are obvious examples. To make these ('global') measures country-specific, we interact them with the distance of the capital of the respective host country to Washington D.C., Brussels, and Tokyo, respectively, using CEPII's GeoDist database (Mayer and Zignago, 2011). Economically, this captures the idea that US financial conditions might matter more for geographically close countries (e.g. in Latin America) than for Eastern European economies, where EU financial conditions might matter more. Statistically, our identification strategy essentially builds on the idea of Nunn and Qian (2014) that only the interaction term of both variables needs to be exogenous (conditional on the baseline controls). To see a discussion of the correlation between our newly proposed instruments and foreign investment, including first-stage regression results, see appendix C.

4.4 Estimation results

In this section, we report our baseline results of the first-difference and the IV model. In the following section 4.5, we provide some residual diagnostics and show that our results are robust to alternative sets of control variables and to the changes in the sample that they induce. In addition, we provide results from using an alternative measure for the labor share as the dependent variable and on the marginal effect of foreign investment in dependence of the domestic capital stock.

4.4.1 First-difference results

Table 4.2 starts with the first-difference results. The unconditional model in column (1) already confirms our basic intuition of opposing effects of FDI and FPI on the labor share in developing countries even though only the (positive) FDI variable is significant in a statistical sense, while the difference to FPI, our key statistic of interest is slightly insignificant at the 10 % level if no control variables are included (as indicated in the last column of the table). However, the opposing effects of FDI and FPI on the labor share in developing

[22] We take OECD data for long-term interest rates, a spread between short-term and long-term rates, and a share price index. These three series are smoothed with a Hodrick-Prescott filter, Pearson transformed, and the first two are inverted so that a rise in each variable indicates finance becoming more easily available. For the EU, we take an average of the largest FDI economies, i.e. UK, Germany, France, and Belgium.

countries, with FDI exercising a positive effect, is clearly supported by our baseline model reported in the second column of table 4.2. The results suggest that a 10 % point increase in the FDI stock relative to GDP will increase the labor share by slightly more than 1 %, with a negative effect of similar magnitude for FPI. Both parameter estimates are statistically significant (at the 5 and 10 % level, respectively), with their difference being significant at the 5 % level. Interestingly, the only other two variables that exercise a statistically significant influence on the labor share in this specification are the capital-to-labor (K/L) ratio and trade intensity. As expected, but at odds with standard neoclassical theory, a higher capital-to-labor ratio tends to lower the labor share, while the negative effect of trade supports the notion that globalization is indeed an important factor influencing the labor share in developing countries.[23]

In column (3), we check that the lag structure of our key explanatory variables is well-defined. Allowing for an additional lag of the differenced foreign investment stocks does not alter our main results and the additional lags are individually and jointly insignificant.[24] Column (4) shows different lags for the control variables, again with our main results concerning the opposing effect of FDI and FPI on the labor share in developing countries unchanged.[25]

4.4.2 IV results

As an alternative identification strategy, we rely on the instrumental variable approach discussed above to estimate our baseline model, with second-stage results presented in table 4.3. As already indicated, first-stage identification is weak (a presentation and discussion is provided in appendix C), so while the exogeneity assumption of our approach is economically credible, statistically we have to rely on weak-identification techniques.

In the first and second column of table 4.3, FDI and FPI are only individually instrumented, respectively. For both cases, the respective CLR statistics of the relevant parameters are depicted in figure 4.3 (together with the Wald statistics that are not robust to weak instruments). The vertical axes of the graphs show a statistical rejection probability for the

[23]The estimated magnitude is of similar order as for our capital flow variables. Given that trade/GDP increased by a considerable magnitude in those countries over the last decades, this might add up to a relevant decline in the labor share.

[24]The p-value of the F-statistics of the second lags of FDI and FPI is 0.78 and does therefore not allow us to reject the null of joint insignificance.

[25]We decided to lag the differences of the more structural (as opposed to cyclical) variables education and capital-labor ratio by one year as we assume that they might take more time to materialize, whereas we allow for the contemporaneous and one-year lagged difference of short-term variables (such as inflation), which might affect the labor share quickly.

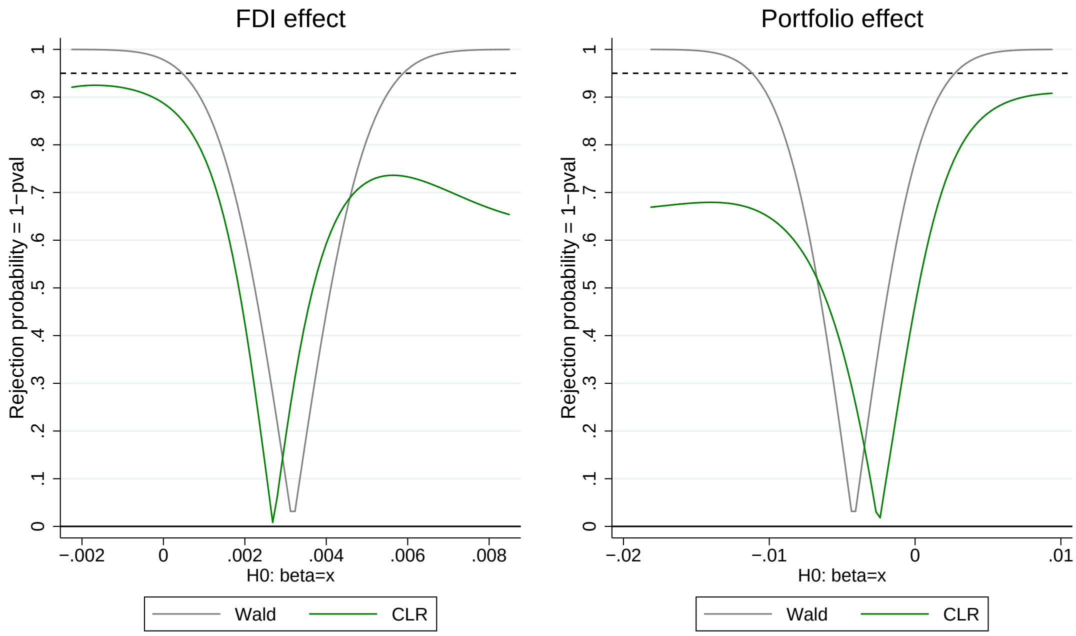
null hypothesis that the true parameter is equal to the corresponding value on the horizontal axes. For example, from the left panel we can infer that one can reject that the true FDI parameter equals -0.002 at a 90 % (but not a 95 %) statistical significance level, as the depicted CLR function exceeds the 0.9 (but not the 0.95) threshold. More generally, despite weak identification, we can reject a negative value of the FDI parameter at the 90 % level of statistical significance. Accordingly, we can reject (at the 10 % level at least) the hypothesis that the true FDI parameter is equal to the point estimate of the FPI parameter in column 1 (not instrumented) or 2 (instrumented). This is also visible from the CLR statistic in the last line of column (1). Conversely, an according statement cannot be made for the FPI parameter estimate from IV identification (depicted in column 2 of table 4.3 and in the right panel of figure 4.3). While the results suggest that a negative effect of FPI on the labor share in developing countries is more likely, weak identification only allows us to reject a parameter of rather high size (approximately above 0.01) which is clearly above the estimated FDI effect (of 0.002). However, it is worth emphasizing that rejection of a larger FPI parameter is much more probable than of a more negative one, while the opposite is true (with more confidence) for the FDI parameter.[26]

For a joint IV assessment of both our parameter estimates of interest, we also instrument them simultaneously, with results provided in column (3) of table 4.3. The point estimates are close to those obtained from individual IV estimates in the first two columns. For inference with respect to our key hypothesis, we work with the AR statistic, which is available for the case of 2 potentially endogenous regressors, and can reject (on a 10 % level) the joint hypothesis that the true parameter values are equal to their respective other foreign capital estimates. That is, we can reject the null $H_0 : \beta_{FDI} = \hat{\beta}_{FPI} \wedge \beta_{FPI} = \hat{\beta}_{FDI}$ in favor of the alternative that both parameters are unequal. Figure 4.4 plots a 90 % confidence set and a more detailed rejection surface of parameter combinations. The latter is a 3-dimensional extension of the previous CLR confidence area, reflecting that there are now 2 instead of 1 endogenous regressors. Since visual inspection is difficult, the left panel displays the area of parameter combinations where the surface in the right panel does not surpass the 90 % rejection probability.

Looking at the left panel, one could imagine a line where $\beta_{FDI} = \beta_{FPI}$, that would cross the 90 % confidence set, thus not allowing us to reject our relevant null hypothesis at those specific points. However, as is clearly visible, the confidence set is not symmetrically distributed around these parameter combinations of equality but extends much more to the

[26] Careful observers might have noticed that the point estimates in table 4.3 are not equal to the parameter values where the CLR function reaches its minimum in figure 4.3. By construction, this does not need to be the case. Rather, the fact that both are quite close suggests that the model is supported by the data.

Figure 4.3: **IV results (1 endogenous variable): CLR confidence area**



Source: See C.1 in appendix C.

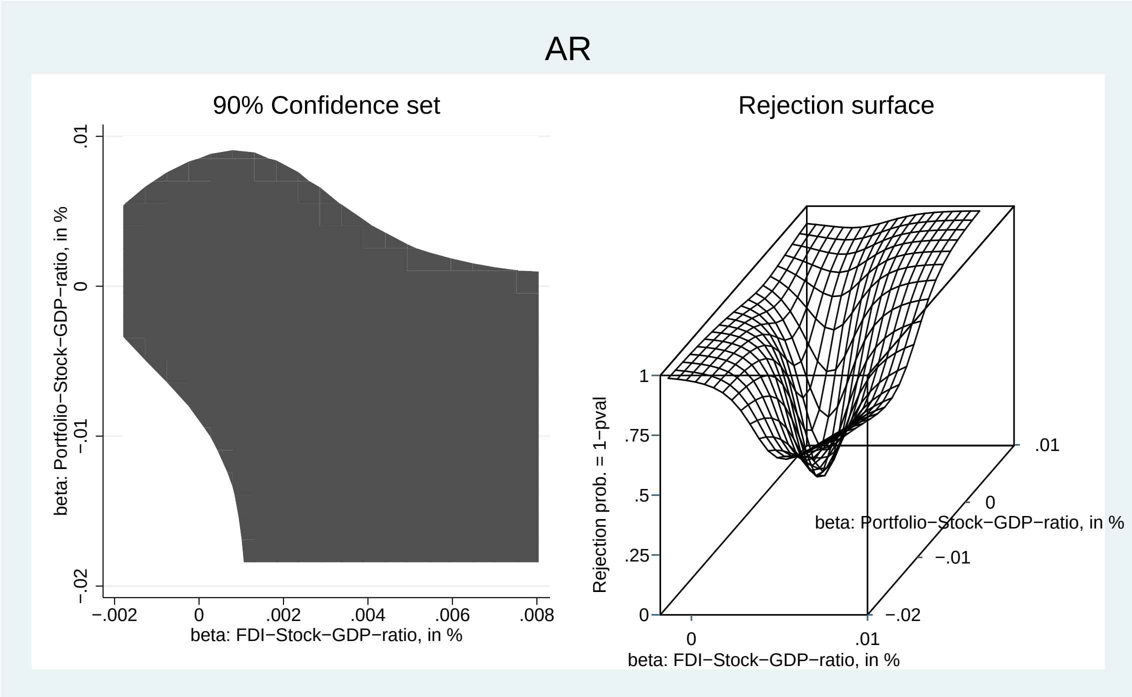
lower right into the area where the effect of FDI on the labor share is positive, while the effect of FPI is negative, in line with our discussion and previous results.

It is interesting to note that IV estimates suggest a larger effect (in absolute terms) of both foreign investment parameters than the first difference results. For the most part, however, this does not seem to be driven by an estimation bias but by the difference between estimation in levels and first differences[27], with the former possibly capturing more long-run effects.

Looking at other control variables, we can confirm the previous result that trade and a higher K/L ratio negatively correlate with the labor share. The positive correlation of the education index with the labor share turns statistically significant in the second column, with reasonable standard errors in the other two specifications. The negative correlation with GDP turns significant and government consumption also exhibits a negative effect. Taken at face value, both latter results are somewhat surprising and at odds with most findings in previous studies. However, a negative effect of GDP p.c. on the labor share was also found in Harrison (2005) and the conventional rationale that higher GDP (growth) leads to

[27] This can be seen when comparing the FD results with level results in table 4.1. Additionally, non-instrumented foreign capital variables in IV table 4.3 are still larger (in absolute size) than the FD results.

Figure 4.4: **IV results (2 endogenous variables): Rejection area**



Source: See C.1 in appendix C.

more scope for trade unions to redistribute to workers seems problematic in the context of developing countries that are often characterized by surplus labor, leaving little bargaining power to unions (at least in the broad economy). The negative correlation of the labor share with government expenses is an artefact of the PWT data and not robust to our alternative labor share measure, as demonstrated in the next section.[28]

The relative economic relevance of different explanatory variables can be inferred from the standardized beta coefficients in table 4.4. As one can see, foreign investment (and also trade) does matter for the labor share in developing countries from an economic perspective, although FDI and FPI seem to cancel each other out for the most part. No clear picture that is robust across specifications emerges for the other variables, though the more structural (as opposed to cyclical) variables – education, K/L ratio, and development level – seem to matter in the IV regression, which captures more long-run effects (with the education effect being potentially economically relevant but insignificant from a statistical perspective).

[28] A negative correlation could also arise if governments increasingly moved away from public job-creating investment programs to social benefits. In this likely case, social benefits would no longer be reflected in wages.

4.5 Robustness and further results

In this section, we provide several specification and robustness checks as well as some further results.

4.5.1 Diagnostic checks

We start with a diagnostic check on the functional (linear) form of the first-difference model.[29] The upper panel of figure C.1 therefore provides a plot of the model residuals against fitted values and a leverage-to-residual plot. As one can see, the only truly worrisome residuals concern Azerbaijan (2006) and Moldova (1999). Column (5) of table 4.5 thus re-estimates our model without these two observations. This somewhat lowers (in absolute terms) the point estimates of our two foreign investment variables of interest, without changing the qualitative implications of our results (as both individually and their difference remain statistically significant).

The lower panel of figure C.1 provides a component-plus-residual plot for the FDI and FPI variable, respectively. One can see that there is no reason to believe that the linear functional relationship would be inappropriate.

4.5.2 Alternative specifications and labor share measure

Column (1) of table 4.5 adds a crisis dummy and gross fixed capital formation (GFCF) as additional controls to the baseline first-difference model. Column (2) further adds labor productivity and the interest rate. Note that this also leads to a relevant decrease in the sample size. However, in neither of the two alternative specifications our key result is affected: Our foreign capital stock variables are both individually significantly different from zero and significantly different from each other (in a statistical sense). The same is true for the point estimates of the IV model when adding the crisis dummy and GFCF (column 6), although weak-instrument robust inference does not allow us to reject parameter equality at the margin (p-value 0.108). Notably, our results with respect to the K/L ratio and the negative effect of trade remain robust to the inclusion of further controls.

We also add an index for employment vulnerability, the implied PPP exchange rate, and mean years of schooling (as an alternative education measure) as control variables, respectively.[30] Neither of those variables turn out significant. With respect to our key hypothesis,

[29] An indirect assessment of the functional specification of the IV model can be inferred from the fact that the point estimate is close to the minimum of the rejection probability function of the CLR and AR tests.

[30] Results not reported but available upon request.

results remain unaffected in the first-difference model, with parameter equality rejected at the 5 % level in all three cases and individual FDI (and FPI) parameters being positive (negative) and statistically significant at least at the 5 (10) % level in all cases. For the IV model, our key result does no longer hold when including the employment vulnerability index, which most likely is driven by the enormous decline in sample size to 170 observations. Key results hold, however, when including the exchange rate or years of schooling.

Table 4.2: **First-difference results**

VARIABLES	(1) $\Delta\ln(LS_{PWT})$	(2) $\Delta\ln(LS_{PWT})$	(3) $\Delta\ln(LS_{PWT})$	(4) $\Delta\ln(LS_{PWT})$
ΔFDI stock/GDP	0.00100*	0.00119**	0.00118**	0.00105**
(-1)	[0.000541]	[0.000490]	[0.000554]	[0.000475]
ΔFDI stock/GDP			-0.000288	
(-2)			[0.000418]	
ΔPortfolio stock/GDP	-0.000191	-0.00108*	-0.000907	-0.000866*
(-1)	[0.000636]	[0.000554]	[0.000759]	[0.000509]
ΔPortfolio stock/GDP			0.000523	
(-2)			[0.00144]	
Δln(GDP p.c.)		-0.185	-0.183	
		[0.154]	[0.158]	
Δln(Inflation)		-0.00178	-0.00118	-0.000203
(-1)		[0.00337]	[0.00368]	[0.00244]
ΔRisk		0.00276	0.00238	0.00237
		[0.00167]	[0.00188]	[0.00181]
Δln(Government share)		0.0373	0.0401	0.0462
		[0.0745]	[0.0770]	[0.0734]
ΔEducation index		0.0851	0.143	
		[0.651]	[0.698]	
ΔK/L		-3.26e-06*	-2.99e-06*	
		[1.83e-06]	[1.68e-06]	
ΔTrade		-0.000958**	-0.00101**	-0.000830**
		[0.000424]	[0.000482]	[0.000408]
Δln(GDP p.c.)				-0.170*
(-1)				[0.0908]
Δln(Government share)				0.0285
(-1)				[0.0253]
ΔEducation index				0.403
(-1)				[0.523]
ΔK/L				-4.03e-06*
(-1)				[2.20e-06]
ΔTrade				-0.000257
(-1)				[0.000495]
Observations	361	245	220	244
Number of countries	47	35	33	34
R-squared	0.134	0.263	0.248	0.269
t-statistic	1.94	6.31**	-	5.72**

Cluster-robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

SNA and time dummies not reported

Table 4.3: **IV results**

VARIABLES	(1) $\ln(LS_{PWT})$	(2) $\ln(LS_{PWT})$	(3) $\ln(LS_{PWT})$
FDI stock/GDP	0.00318**	0.00188***	0.00312**
	[0.00138]	[0.000639]	[0.00125]
Portfolio stock/GDP	-0.00263**	-0.00422	-0.00419
	[0.00111]	[0.00354]	[0.00362]
ln(GDP p.c.)	-0.333***	-0.360***	-0.336***
	[0.0613]	[0.0747]	[0.0614]
ln(Inflation)	0.00201	0.00103	0.00252
(-1)	[0.00528]	[0.00455]	[0.00541]
Risk	0.00173	0.00205	0.00202
	[0.00160]	[0.00168]	[0.00170]
ln(Government share)	-0.0765***	-0.0685***	-0.0782***
	[0.0202]	[0.0222]	[0.0219]
Trade	-0.00186***	-0.00140***	-0.00169***
	[0.000555]	[0.000519]	[0.000474]
Education index	0.655	0.896**	0.676
	[0.586]	[0.400]	[0.557]
K/L	-2.67e-06**	-3.56e-06**	-3.17e-06*
	[1.33e-06]	[1.69e-06]	[1.63e-06]
Instrumented	FDI	FPI	FDI & FPI
Observations	308	308	308
Number of countries	37	37	37
R-squared	0.406	0.433	0.399
CLR / AR χ^2_4	6.63*	1.85	8.18*

Cluster-robust standard errors in brackets

*** p<0.01, ** p<0.05, * p<0.1

Time dummies partialled out, SNA not reported

CLR test for single parameter equality in columns 1 & 2,

AR test for joint equality of both endogenous regressors in column 3.

Table 4.4: **Standardized beta coefficients**

	(1) difference model	(2) IV model
FDI Stock GDP	0.207**	0.357**
	(2.43)	(2.49)
Portfolio stock/GDP	-0.096*	-0.199
	(-1.94)	(-1.16)
ln(GDP p.c.)	-0.196	-1.336***
	(-1.20)	(-5.47)
ln(Inflation)	-0.033	0.018
(-1)	(-0.53)	(0.47)
Risk	0.160	0.062
	(1.65)	(1.19)
ln(Government share)	0.080	-0.169***
	(0.50)	(-3.57)
Education index	0.008	0.566
	(0.13)	(1.21)
K/L	-0.086*	-0.451*
	(-1.78)	(-1.94)
Trade	-0.167**	-0.298***
	(-2.26)	(-3.56)
N	245	308

t statistics in parentheses; * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Results correspond to column (2) of table 4.2 and (3) of table 4.3, respectively.

Table 4.5: **Robustness checks**

VARIABLES	(1) $\Delta\ln(LS_{PWT})$	(2) $\Delta\ln(LS_{PWT})$	(3) $\Delta\ln(LS_{Trapp})$	(4) $\Delta\ln(LS_{Trapp})$	(5) $\Delta\ln(LS_{PWT})$	(6) $\ln(LS_{PWT})$	(7) $\ln(LS_{Trapp})$	(8) $\Delta\ln(LS_{PWT})$
FDI stock/GDP	0.00130**	0.00141***	0.00242**	0.00305**	0.000817***	0.00365***	0.00307**	0.00209***
	[0.000479]	[0.000425]	[0.00114]	[0.00122]	[0.000299]	[0.00125]	[0.00146]	[0.000663]
Portfolio stock/GDP	-0.00135**	-0.00144*	-0.00201*	-0.00279***	-0.000937*	-0.00678**	-0.00736	-0.00186*
	[0.000503]	[0.000719]	[0.00112]	[0.000971]	[0.000511]	[0.00333]	[0.00599]	[0.00102]
FDI Stock × K/L								-3.34e-08**
								[1.55e-08]
Portfolio Stock × K/L								2.94e-08*
								[1.69e-08]
ln(GDP p.c.)	-0.318***	-0.375*	-0.240*	-0.350***	-0.162*	-0.275***	0.00530	-0.171
	[0.107]	[0.186]	[0.133]	[0.123]	[0.0869]	[0.0590]	[0.0984]	[0.152]
ln(Inflation)	-0.00767**	-0.00726**	0.00703	0.00245	-0.000848	0.00236	0.0117	-0.00177
(-1)	[0.00313]	[0.00344]	[0.00508]	[0.00525]	[0.00303]	[0.00648]	[0.00795]	[0.00326]
Risk	-0.000442	0.00120	0.00558***	0.00428*	0.00168	0.000826	0.00607**	0.00259
	[0.00140]	[0.00128]	[0.00191]	[0.00227]	[0.00145]	[0.00183]	[0.00263]	[0.00168]
ln(Government share)	-0.0432	-0.0256	0.0916	0.0196	-0.0189	-0.0871***	0.232***	0.0393
	[0.0387]	[0.0365]	[0.0737]	[0.0419]	[0.0332]	[0.0168]	[0.0450]	[0.0757]
Education Index	0.606	1.229*	0.821	1.889**	-0.174	0.614	1.069	0.00689
	[0.563]	[0.686]	[0.964]	[0.915]	[0.614]	[0.645]	[0.783]	[0.675]
K/L	-5.80e-06***	-5.72e-06***	-8.36e-07	5.15e-07	-3.53e-06*	-5.08e-06***	-3.07e-06	-3.93e-06*
	[1.95e-06]	[1.75e-06]	[1.68e-06]	[2.60e-06]	[2.00e-06]	[1.93e-06]	[1.92e-06]	[2.29e-06]
Trade	-0.00102**	-0.000998**	-0.000943*	-0.00106*	-0.000933**	-0.00112***	-0.000884	-0.000983**
	[0.000454]	[0.000459]	[0.000498]	[0.000607]	[0.000444]	[0.000389]	[0.000574]	[0.000415]
Crisis	-0.0353**	-0.0336		-0.107*		-0.00883		
	[0.0153]	[0.0219]		[0.0635]		[0.0537]		
FCF/GDP	-0.000594	-0.000560		-0.00233*		-0.00134		
	[0.000639]	[0.000505]		[0.00116]		[0.000988]		
Labor productivity		-2.78e-06						
		[1.13e-05]						
Interest rate		0.000296						
		[0.000478]						
Observations	197	144	251	203	243	261	316	245
Number of countries	34	27	37	36	35	35	39	35
R-squared	0.406	0.551	0.221	0.289	0.235	0.459	0.342	0.275
Estimation	FD	FD	FD	FD	FD	IV	IV	FD
test statistic	8.52***	7.45**	5.14**	8.24***	6.30**	7.59 (AR)	7.62 (AR)	N/A

Robust standard errors in brackets, *** p<0.01, ** p<0.05, * p<0.1

Differences and lag structures not indicated in explanatory variables. IV instruments for both types of foreign investment.

Columns 3 and 7 of table 4.5 use the alternative labor share measure calculated by Trapp (2015) as the dependent variable in our baseline first-difference and IV model, respectively. Even with this alternative labor share measure, which differs considerably from the PWT measure (as demonstrated in the correlation matrix of appendix table C.2), our qualitative results remain unaffected. If anything, the (absolute) magnitude of the effects increase (especially in the first-difference model). Column 4 further adds the crisis dummy and GFCF to the first-difference model using the alternative labor share measure by Trapp (2015), with results still remaining robust.

4.5.3 Additional results: Marginal elasticity of substitution

We further experimented with different interaction terms. Column 8 of table 4.5 shows the results of the first-difference model when our two key foreign investment variables are interacted with the capital-to-labor ratio. Note that we principally estimate the model in first differences to control for unobserved heterogeneity, but interact the (first-differenced) foreign investment stocks with the *level* of the K/L ratio to obtain marginal effects of foreign investment on the labor share conditional on differences in the K/L ratio *across* (and not within) countries.

This provides an interesting result as the interaction has a different prefix for FDI as opposed to FPI, meaning that an increasing K/L ratio shrinks the effect of foreign investment towards 0, and eventually leads to a change in the prefix (though the latter is not significant).[31] Without over-emphasizing the robustness of these results, they have a relevant economic implication that could be explored further in future research: As we argued, 'classical' foreign capital in the form of FPI might possess some bargaining power, in tendency increasing the elasticity of substitution. However, this effect will be the more important, the more capital-scarce a country is, e.g. the lower the K/L ratio, consistent with our results. Conversely, our argument for the lower substitution elasticity of FDI essentially results from a capital market friction: Foreign direct investors (in developing countries) cannot easily withdraw their establishment. This constraint will become less binding, however, as capital markets deepen. The latter makes it easier to sell FDI assets to local investors and allow multinationals to become increasingly 'footlose'.

Consistent with this result, we also find squared terms of FDI and FPI to be negative (and significant) and positive (but insignificant), respectively. The former is at odds with

[31] For both effects, the threshold is slightly above a K/L ratio of 60,000, which is only the case for 5 countries in the sample. Also, the (interactive) effect does not turn significant at such high levels of the K/L ratio within the sample range. Plots of the marginal conditional effects are available upon request.

the findings of Maarek and Decreuse (2015), who find a negative FDI effect but a positive squared term, with the labor share only covering the manufacturing sector. Quantitatively, the effect of our squared FDI term is negligible: it only leads to a negative effect on developing countries' labor share if the first-differenced FDI stock reaches more than 40 % of GDP, which is only true for one observation in the sample. Interacting the FDI stock with the FPI stock leads to a positive (and significant) interaction term. Most importantly, in all those specifications, our main conclusions about the opposing effect of FDI and FPI on developing countries' labor share hold (for the main part of the sample). Furthermore, trade and the K/L ratio remain negative and significant (at the 1% level) in all of those specifications.

4.6 Discussion and conclusion

Our analysis has shown that de facto financial globalization in the form of foreign direct and portfolio investment cannot account for the decline in the labor share that has been observed in developing countries over the last two decades. This does not mean that foreign capital does not matter for the labor share in those countries. Rather, FDI and FPI have relevant but opposing effects in line with our key argument that only portfolio investors are globally flexible enough to exercise a relevant bargaining power, while FDI is more bound to the host market than often assumed and tends to pay a wage premium to attract well-educated and reliable employees to protect multinational firms' proprietary asset.

In practice, since FDI is much more important than FPI, the effect of those two aspects of financial de facto globalization on developing countries' labor share is positive. Quantitatively, the FDI stock (relative to GDP) in the sample developing countries increased from 16 to about 35 % over the last two decades, while FPI only rose from about 4.2 to 5.5 % of GDP. Meanwhile, the log of the labor share fell from 3.77 to 3.72. This implies that FPI can explain very little of the labor share decline (about 5 % of the overall decline) while the actually observed increase of FDI countered the labor share decline by about three quarters.[32] By and large, the effects of FDI are thus not only statistically significant but also economically very relevant, while the potential negative effects of FPI (if any) are relatively modest.

Our results contribute to a wider debate concerning the macroeconomic determinants and implications of the labor share (e.g. Karabarbounis and Neiman, 2014) and the role

[32] We assume parameters of -0.002 (FPI) and 0.002 (FDI). The contributions are then calculated as $(\Delta FI \times \beta)/-0.05$, where ΔFI is the change in foreign investment, β is the respective parameter, and -0.05 is the change in the log of the labor share.

and effects of financial globalization in developing countries (e.g. Jeanne et al., 2012, Kose et al., 2009a, Prasad et al., 2003). They do not preclude the possibility that financial liberalization policies have a relevant detrimental effect on the labor share, as de-jure financial openness also gives foreign direct investors that have not yet realized their project an outside option that increases their bargaining power and could hence lead to a 'race to the bottom' in wages. On the other hand, evidence by Görg et al. (2009) for OECD countries indicates that multinationals might favor redistributive welfare states for stability considerations, creating an argument against unbounded wage competition. While it is too demanding to explicitly model all those effects econometrically, theoretical work by Arseneau and Leduc (2011) suggests that the effect of such outside options is potentially large. Moreover, our results about the functional income distribution between capital and labor do not preclude the possibility that financial de-facto globalization has contributed importantly to the increase in inequality between households (that is, within labor) in developing countries.

It is also worth mentioning that our estimations show a robust negative labor-share effect of the capital-to-labor ratio, at odds with conventional neoclassical theory, and of trade. While being beyond the scope of this paper, we think a more detailed analysis of the latter effect using more disaggregated data that has become available recently is a promising and relevant area for future research, especially since the effect is potentially large in economic magnitude.[33] Similarly, the fact that different forms of FDI potentially lead to different modes of world market integration with differing socio-economic effects (see e.g. Wacker et al., 2016) calls for a more disaggregated analysis of the potentially heterogeneous FDI effects. Finally, it seems important to gauge to what extent different forms of financial de-jure liberalization can account for the observed decline of the labor share in developing countries.

[33] Assuming a parameter of -0.0015, as suggested by several of our results, a 12 % point increase in the trade/GDP ratio, as roughly observed in our sample between the pre-2000 and post-2000 period, is associated with a decline of the labor share of 1.8 %.

Chapter 5

Cash Crops as a Sustainable Pathway out of Poverty? Panel Data Evidence on the Heterogeneity of Cocoa Farmers in Sulawesi, Indonesia

Abstract

The cultivation of cash crops has a great potential for reducing poverty in the developing world that may not be fully harnessed because many smallholders are inefficient producers. Furthermore, income gains may be only static and poverty and vulnerability of smallholder households may not be reduced sustainably. Instead, cash crop farmers, in particular those without proper farm management skills, may experience boom and bust cycles, caused by volatile world market prices, local weather shocks and pests. To analyze the long-term poverty impacts of cash crop agriculture, we draw on a unique panel data set of smallholder cocoa farmers in Central Sulawesi, Indonesia, covering the years 2000, 2006 and 2013. We show that – over the analyzed time horizon of more than 10 years – cocoa cultivation is associated with strong and sustainable poverty reduction. Cocoa farmers fare better than non-cocoa farmers and the welfare gains can mainly be attributed to increasing cocoa yields. Yet, yield gaps remain large and are increasingly heterogeneous. We can trace back this productivity heterogeneity to farm management practices. Linking these findings to poverty transitions, we can show that better management practices facilitate the transition out of poverty and shields against income losses.

5.1 Introduction

In the developing world, growth originating in the agricultural sector has long been identified as an essential pathway out of poverty. Since 70 % of world's poor live in rural areas, diversification in cash crops for global food markets has been widely discussed as a prospective route for agricultural growth and poverty reduction (Feintrenie et al., 2010, Klasen et al., 2013, WB, 2008). The cultivation of commercial crops has also been found to foster rural infrastructure and public services which both entail positive effects on broader levels (Vanwambeke et al., 2007, Walker et al., 2002). Hence, increased commercialization within the agriculture sector might be a key driver to transform a semi-subsistence agrarian society to a more diversified economy including off-farm industries and higher levels of welfare (Achterbosch et al., 2014). Living standards of cash cropping smallholders can be, on average, higher and the long-term income improvements depend highly on the respective technological skills of individual households, in particular agronomic practices (Tittonell and Giller, 2013).

However, a successful integration into global crop markets requires the individual ability of poor households to mitigate or cope with the risks associated with cash crop production. These are, amongst other factors, price shocks as well as marketing and production risks (Barbier, 1989, Rist et al., 2010, Sunderlin et al., 2001, Wood et al., 2013). The exposure to production and marketing risks faced by smallholders are, to an important extent, determined by the specific conditions of input and output markets. These conditions combined with the idiosyncratic capacities and constraints determine the crop choices and production technology chosen by smallholders and, in turn, their risk exposure, in particular to environmental shocks, such as floods, droughts or plant diseases (Chuku and Okoye, 2009). Changing the crop portfolio from subsistence cultivation to intensified cash crop cultivation might increase this risk exposure since it adds the hazards of mono-cropping that can promote and accelerate the incidence of pests (Steffan-Dewenter et al., 2007). The capacity to deal with these hazards depends in particular on farmers' management practices including the timing of operations, the accurate application and composition of chemical inputs and plantation maintenance (Chuku and Okoye, 2009, Sabatier et al., 2013, Schreinemachers et al., 2015).

It is well known that the capacity of smallholders to apply optimal management practices is limited, as are other means to cope with shocks, for example through credit markets (Harvey et al., 2014, OECD, 2015). As a result, the income gains of cash crop farming may be volatile and the long-term benefits smaller than the well-documented short-term gains (Carletto et al., 2009, Klasen et al., 2013, Tittonell et al., 2007). Empirical evidence, however, on the long-term impact of cash crop farming remains scarce, in particular since such assessments require long-term panel data.

This paper addresses this gap by examining the long-term welfare impacts of smallholder cocoa farming. Our analysis draws on a unique three-wave panel data set of smallholder cocoa farmers in Central Sulawesi, Indonesia, which spans a period of 13 years. We first analyze income dynamics and poverty changes over this period comparing cocoa- and non-cocoa farmers. As cocoa yield improvements, as the key driver of increasing cocoa incomes, were accompanied by a higher variation in yields, we then look at the determinants of cocoa yields. This analysis allows us to distinguish between smallholders according to their management practices; a distinction that we, in a final step, use to assess whether well-managing farmers are faring better than those who fail to do so.

The paper is structured accordingly. We first provide a literature review on the welfare impacts of cash crop cultivation. After providing some background information on Indonesia, its cocoa sector and the study region, we describe the data. Our empirical analysis then looks into welfare changes, determinants of cocoa yields, and the influence of management skills on welfare trajectories. We close with summarizing our main results and suggestions for future research.

5.2 Literature review and research questions

In the transition from a low productivity, semi-subsistence agriculture to a high productivity, commercialized agriculture, cash crops can serve as a potential route for agricultural growth and thus poverty reduction in bringing substantial productivity increases and employment opportunities to the rural economy (Timmer, 1988). Transforming sectors can stimulate agricultural innovation by raising capital for agricultural investment and accelerating the build-up of institutions that enable further commercialization (Achterbosch et al., 2014).

For cash crops to be also a successful driver of poverty reduction, the transition from subsistence to commercial agriculture significantly depends on the participation of smallholder farmers who typically farm less than two hectares in developing countries (WB, 2008). Feintrenie et al. (2010) find that cash crops with low labor requirements and the absence of seasonality are most lucrative for traditional smallholder farmers. Then, cash crops can be easily integrated into the already prevailing farming systems through, for example, the planting of agroforests or the intercropping of new cash crops with previously cultivated crops. Moreover, fragmented markets let smallholders' choices to be non-separable for production and consumption. Decisions on cash- and food crops are thus interlinked and agricultural commercialization has therefore been found to have positive spill-over effects on households' food production (Govereh and Jayne, 2003). In turn, many farm households mitigate production risks of cash crops and vulnerability to price variability through diverse livelihoods relying also on food crop production or non-farm income (Eriksen et al., 2005). However, once markets for labor and inputs develop, intercropped areas are often converted into more intensified, productive land-use systems, possibly increasing farmers' exposure to shocks.

The benefits from cash crop farming have been shown, for example, by Bussolo et al. (2007) for the case of Uganda. They find that – in the 1990s – coffee market liberalization followed by a price boom was associated with substantial reductions in poverty that could be sustained when prices went down again. Cash crop cultivation has also been found to be poverty reducing by Klasen et al. (2013). Based on a shorter panel of the same households used in this paper (2001, 2004 and 2006), they show that households cultivating cocoa were on average able to achieve about 14 % higher income levels compared to cultivating other crops. The authors suggest that the switch to cocoa might be a strategy to raise income especially for the poorer segments of rural populations. In contrast, Carletto et al. (2009) present evidence on negative long-term welfare effects of agricultural commercialization. The authors focus on households' adoption of a non-traditional, agricultural export crop (snow pea) in the Central Highlands of Guatemala and use panel data between 1985 and 2005. Applying difference-in-differences estimation, the results suggest that while consumption levels have improved for all households in the surveyed communities, long-term cash crop adopters show on average lower gains with higher benefits only in the beginning. The authors point at agronomic problems – in addition to marketing and institutional problems – leading to decreasing profitability in snow pea production.

Weak management practices, combined with input and output market failures, are the the main cause behind such deficits and the considerable yield gaps of smallholder production in many cash crops around the world (Mueller et al., 2012, Neumann et al., 2010, Tittonell and Giller, 2013, Tittonell et al., 2007). The relationship between practices and yields, however, will depend on the specific crop and region and might be non-linear across scales. On the global level, Mueller et al. (2012) assess the link between yield variability and agricultural management using input-yield models. They postulate as key causes for worldwide yield gaps irrigation techniques, fertilizer application and climate condition – together the three factors explain 60-80 % of global yield variability for most of the major global crops. Complementary to this, studies on the regional and local level give insights into more subtle drivers of crop yield-gaps. For example, Neumann et al. (2010) estimate regional frontier yields to compute frontier production and inefficiencies in wheat, maize and rice cultivation. For Indonesia, they find that the variance in efficiency comes mostly from differences in market accessibility and availability of agricultural labor. Examining a more detailed case, Tittonell et al. (2007) explore maize yield gaps on the field level, analyzing within-farm differences of smallholder farms in Kenya. They show that variability of yields stems from soil and climate conditions, the land use change history of fields, and also from the operational management, such as planting time and density or timing of weeding. For selected African countries, Tittonell and Giller (2013) analyze yield-gaps of smallholder farming systems. They conclude that the lack of inputs such as machinery, labor and capital are the main sources of production inefficiencies. However, the authors suggest that – even in the absence of inputs like fertilizer – proper agronomic management, such as cultivars, plant spacing and weeding, is able to narrow yield gaps.

The brief literature review illustrates that the long-term implications of cash crop production and the link to productivity heterogeneity remain underexplored. Using a panel sample of smallholders in a cocoa-growing region in Sulawesi, Indonesia, we therefore examine how cocoa farmers fare vis-à-vis other farmers over a longer time horizon. We also explore the determinants of cocoa yield and investigate whether bad or improved management practices are associated to the sustainability of the benefits of cash crop cultivation.

5.3 Cocoa in Indonesia and the study region

In the last decades, Indonesia has emerged as a key exporter of agricultural products on global markets. Since the late 1960s, Indonesia experienced high and sustained economic growth, partly driven by the development of its agricultural sector – specifically promoting export oriented agricultural production (Feintrenie et al., 2010, Mundlak et al., 2002, Timmer, 2007). The vast expansion of the agricultural area, the adoption of subsidized technologies, such as irrigation, fertilizer, pesticides and improved seeds, were important drivers of this development that shifted cropping patterns towards the cultivation of cash crops and pushed commercialization (Maertens et al., 2006, Mundlak et al., 2002). The country's agricultural sector thus experienced a transformation from traditional cultivation systems (slash- and burn cropping systems and agroforestry) towards intensified monoculture plantations with cash crops such as coffee, cocoa, coconut, oil palm, and rubber (Feintrenie et al., 2010). In 2014, the agricultural sector contributed about 35 % to national employment (WB, 2016c).

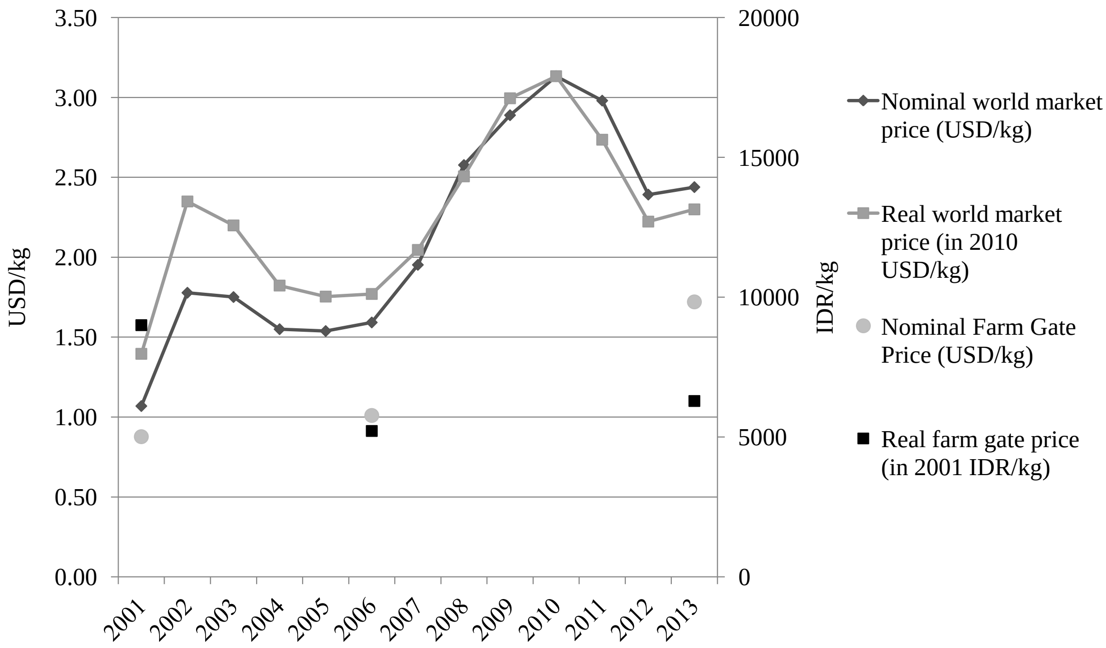
One of the main agricultural exports of Indonesia are cocoa products, after palm oil and rubber, representing an exported value of 450 million USD in 2013 (BPS, 2016b). Indonesia, which started to produce cocoa in the 1980s, now is the third largest producer and exporter of cocoa beans in the world, after the Ivory Coast and Ghana (ICCO, 2012). The country's total production of cocoa beans makes 709,330 tons for 2014 and smallholder farms contribute most to national cocoa production covering in total 1,198,962 hectares for cocoa plantations in the same year (BPS, 2016c). The main locations of cocoa production in Indonesia are Sulawesi, North-Sumatra, West Java, Papua, and East Kalimantan. In Sulawesi, smallholder farmers have started to cultivate cocoa beans extensively in the early 1990s (Akiyama and Nishio, 1997). Sulawesi contributes today with a production of over 386,130 tons (2014) the biggest part to the national cocoa production (BPS, 2016c). Our study focuses on the Lore Lindu region, which is part of the province Central Sulawesi and located south of Palu, the capital of this province. The region is predominantly rural and characterized by a high degree of diversity with respect to its geographical and climate conditions (Maertens et al., 2006). The region's centrally located Lore Lindu National Park forms one of the last and largest mountainous rainforests of Sulawesi.

Although cocoa beans are still one of the main exported cash crops, Indonesia's cocoa productivity started to decline in 2005. This decline is mainly attributable to the aging of cocoa trees and the increasing prevalence of cocoa pests and diseases which smallholder farmers who account for the majority of plantations often cannot handle due to the lack of plot management expertise (Nuryartono and Khumaida, 2016). The most common pest in Sulawesi is the cocoa pod borer, which already spread in the early 2000s (Neilson, 2007). In 2007, farmers of the Lore Lindu region report a yield loss of on average 24.3 % due to the cocoa pod borer and also 20.5 % due to the black pod disease (Juhrband et al., 2010). By the mid-2000s, decreasing cocoa yields – reinforced by aging plantations – had been perceived as a crisis in the sector (Clough et al., 2009). In this context, the application of intensification techniques – originally intended to raise yield levels – have been discussed to increase the susceptibility of cocoa trees to pests and diseases: Clough et al. (2009) discuss that specifically full-sun plantations and the corresponding removal of shading trees raise the physiological stress of the trees and make them more susceptible to the cocoa pod borer and the black pod disease.

In light of these developments, the cocoa sector in Sulawesi has been considered to follow a 'boom and bust cycle' (Clough et al., 2009, Ruf and Yoddang, 2004).[1] This is also reflected in official statistics: Cocoa yields in Central Sulawesi have decreased from about 1 ton in 2002 to 0.7 tons per hectare in 2014 (BPS, 2005, 2010, 2015). The Indonesian government has reacted to these developments with a plan to raise productivity setting itself a target of one million tons of cocoa beans per year by 2013-2014. In particular, the plan intended to address the problems of aging of trees, insufficient planting material, and the lack of knowledge on plantation maintenance (Ministry of Industry, 2016). As one policy, the government started the national program 'GERNAS' in 2009 to boost cocoa production

[1] This concept describes the process, when firstly young cocoa trees are planted within the tropical rainforest, which provides ideal conditions such as fertile soils, shade trees, and low weed pressure (Clough et al., 2009, Rice and Greenberg, 2000). Due to low investment costs economic gains can be realized once the tree matured at the age of 3 to 5 years and continues to produce cocoa until the age of 20-25 years (Wood and Lass, 2001). During the boom phase, other local farmers might be attracted by promising benefits and start to adapt cocoa cultivation. Then, in-migration is triggered to the rainforest frontiers and primarily agroforests are more and more transformed to mono-cropping systems. This process stagnates, when pest and diseases increasingly spread and trees start to age (Clough et al., 2009).

Figure 5.1: **World market and farm gate prices for cocoa (in USD/kg and IDR/kg)**



Note: Nominal farm gate prices are calculated as the median value of village prices. Village prices on cocoa are in turn derived as median values from the household-level output prices for cocoa. Real farm gate prices are in 2001 IDR prices, based on inflation data for Palu from BPS (2016a). Nominal and real world market prices are drawn from WB (2016b).
Source: WB (2016b) and authors' calculation and graphical representation based on STORMA and EFForTS data.

through intensification, rehabilitation and rejuvenation activities of around 450,000 hectares (BKMP, 2010). However, actual total production in 2014 was only 70.9 % of the set target. Indonesia's efforts to revive cocoa production thus obviously failed in reaching the achievable yields.[2]

These developments in the cocoa sector took place in a period of relatively favorable world market prices that showed a slight upward trend between 2000 and 2013 (see figure 5.1). After 2000, world market prices for cocoa increased and remained – after the food price hike in 2009 – on a level of around 2500 USD per ton, i.e. 2.5 USD per kg. Farm gate prices, derived from the survey data, increase correspondingly and are 30 to 70 US-Cents below the world market prices. Because of unfavorable exchange rate movements, this trend did not translate into rising farm gate prices. Real farm gate prices (below in 2001 Indonesian Rupiah (IDR)) fell between 2001 and 2006 and only slightly recovered until

[2]Nuryartono and Khumaida (2016) discuss various reasons for the failure of the government program, such as institutional barriers and inadequate assistance of smallholders.

2013.

5.4 Data and sampling

In the context of two collaborative research centres (STORMA – Stability of Rainforest Margins in Indonesia, and EFForTS – Ecological and Socioeconomic Functions of Tropical Lowland Rainforest Transformation Systems, Indonesia), household panel data have been collected in 2001, 2006 and 2013 in the Lore Lindu region. The surveys include information on socio-demographics, land holdings, agricultural as well as non-agricultural activities, and endowments. Each survey represents a random sample of 13 villages, which were randomly chosen in 2001 out of official village census data with 115 villages (Zeller and van Rheenen, 2002). Households are then randomly drawn, with the number proportional to village size. In 2006 and 2013, households that split off from their original households and formed a new one within the Lore Lindu region were additionally interviewed and added to the respective sample.

In total, the sample includes 316 households in 2001, 380 in 2006 and 387 households in 2013. We include all households into our analysis that could be interviewed more than once, which gives 300, 338 and 322 observations in 2001, 2006 and 2013 respectively. As cocoa farmer we classify all farmers with a cocoa plantation of at least 0.25 hectare.

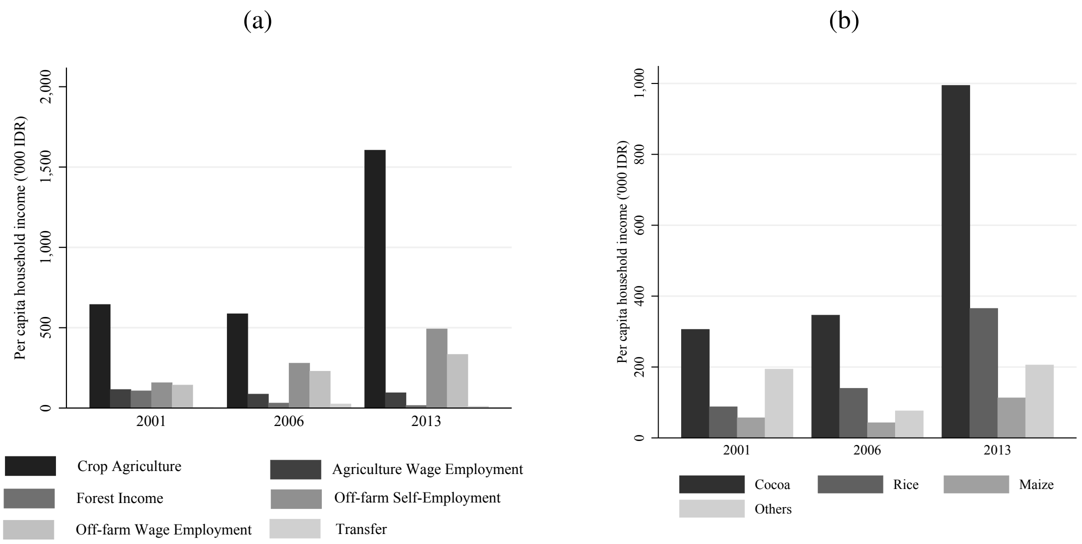
5.5 Cocoa income and poverty dynamics

In the Lore Lindu region, income from crop agriculture is the main livelihood and it has increased significantly in recent years (see figure 5.2a). Per capita household income from crop agriculture has risen from 644,590 Indonesian Rupiah (IDR) in 2001 to 1,605,030 IDR in 2013, implying an annual growth rate of 7.9 % over these 12 years.[3] Hence, household income per capita drawn from crop agriculture more than doubles in this period to around 170 USD in 2013 (see figure 5.2a). Cocoa is the central source of income for many smallholder households in the Lore Lindu region, as it is also discussed by van Edig and Schwarze (2011) and Klasen et al. (2013). Figure 5.2b shows a large increase in cocoa income over time with an annual growth of on average 11.6 % in per capita terms.[4]

[3] Agricultural wage employment only represents a marginal source of income for our sample households. In addition to crop agriculture, non-farm activities also play an increasingly important role for rural incomes.

[4] Rice, the second most important crop, also increased substantially but only generates less than half of the income generated by cocoa cultivation All others crops display only minor income changes in relative terms and did not contribute significantly to increases in income.

Figure 5.2: **Mean per capita (p.c.) income by sector of employment and main cultivated crops, 2001-2013**



Note: Monetary values are real Indonesian Rupiahs with base year 2001, using the provincial Consumer Price Index (CPI) for Palu provided by BPS (2016b). Incomes are yearly. The data represent the mean of all per capita household income per income source. To calculate the per capita household income, households' income (per source) is divided by the respective and idiosyncratic household size. The mean values consider also income sources with zero income.
Source: Authors' calculation and graphical representation based on STORMA and EFForTS data.

Agricultural growth and cocoa expansion has been a driving force of poverty reduction in the study region. Table 5.1 shows the poverty headcount ratio and poverty gap for all farm households, for cocoa and non-cocoa farmers, as well as separately for households that earn at least one third of their income from off-farm employment. The poverty headcount ratio declined from 62.33 % to 32.61 % for all households over the whole period. Especially notable is the stark decline between 2006 and 2013. The poverty gap, which estimates the depth of poverty and indicates the resources needed to lift the poor out of poverty by perfectly targeted transfers, decreased substantially from 36.30 % to 17.66 % from 2001 to 2013.

These significant improvements mainly arise from the poverty reduction amongst cocoa farmers. Table 5.1 show that poverty levels amongst cocoa farmers are lower and poverty reduction much stronger compared to non-cocoa farmers. Sampled households in the Lore Lindu region primarily shifted towards cocoa cultivation between 2001 and 2006, which is around 10 years later than the farmers in the South and South-West of Sulawesi. While in

2001, 176 out of 300 sampled households grew at least 0.25 hectare of cocoa, the share went up to 233 out of 338 households in 2006.

Table 5.1: **Comparison of poverty measures for USD 1/day PPP poverty line from 2001-2013**

	Poverty headcount ratio			*Poverty gap*			*Observations*		
	2001	2006	2013	2001	2006	2013	2001	2006	2013
All households	62.33	53.60	32.61	36.30	23.38	17.66	300	338	322
Cocoa farmers	54.55	46.35	24.36	31.30	19.30	13.18	176	233	234
with at least 1/3 off-farm inc.	33.33	21.15	13.89	10.37	3.90	7.64	30	52	36
Non-cocoa farmers	73.39	69.52	54.55	43.43	32.56	29.55	124	105	88
with at least 1/3 off-farm inc.	54.55	52.63	35.71	23.59	23.37	16.54	33	38	42

Note: Currency conversion based on the World Bank PPP (Purchasing Power Parity) conversion factor for private consumption (Local Currency Unit (LCU) per international $). Households with a cocoa plantation of at least 0.25 hectare are classified as cocoa farmers.
Source: Authors' calculation and graphical representation based on STORMA and EFForTS data.

The poverty depth decreased from 31.30 to 19.3 % during this time while the poverty incidence amongst cocoa farmers fell from 54.55 % to 46.35 %. This underpins the findings of Klasen et al. (2013) that the shift of households towards cocoa did not have a very strong immediate effect on the poverty incidence as cocoa trees had not yet reached their full maturity by 2006. Thus, poor cocoa farmers could increase their incomes and close the poverty gap but were not able to jump out of poverty. Between 2006 and 2013, the shift to cocoa turns out to be highly rewarding, when the cocoa trees developed their full productive potential. During this time, the poverty headcount ratio amongst cocoa farmers decreased from 46.35 to 24.36 % and the poverty gap from 19.3 to 13.18 %. Only households that partly engage in off-farm activities record even lower poverty rates. Cocoa farmers that derive at least one third of their income from off-farm employment show the lowest incidence and depth of poverty of all household groups, as classified in table 5.1. However, they also only represent a small share of the sample.

We now complement this static poverty analysis, which suggests an important role for cocoa production for poverty reduction, by poverty transition matrices that exploit the panel structure of our data. Table 5.2 shows the absolute numbers of cocoa farmers and non-cocoa farmers in different poverty groups and the shares of households changing poverty status (poor vs. non-poor at a poverty line of USD/day PPP) by main farming activity (cocoa vs. non-cocoa farming) for the two sample periods 2001-2006 and 2006-2013. In the first period, farmers that cultivated cocoa in 2001 performed better than non-cocoa farmer with a lower share of poor households remaining poor (43.6 % of all initially poor cocoa farmers) and a higher share escaping poverty while remaining cocoa farmer (45.7 %). The share of initial non-cocoa farmers who stick to their activity and remain poor is slightly higher with 48.9 %. Interestingly, and in line with the above assessment of poverty changes amongst cocoa farmers, the transition to cocoa cultivation might not pay off immediately: Some initially non-poor non-cocoa farmers switching to cocoa fall into poverty (21.2 % of all initially non-poor non-cocoa farmers) over the first period. Similarly, 20 % of initially poor cocoa adopters cannot escape poverty. Moreover, within the first period cocoa cultivation seems even to raise the vulnerability to poverty: A considerable amount of (initially) non-poor cocoa farmers (33.3 %) fall into poverty between 2001 and 2006. The first period is thus characterized by more chronic manifestations of poverty and a higher share of non-poor households falling back into poverty. In the second period, a much more dynamic upward mobility can be observed amongst cocoa farmers. The share of cocoa farmers escaping poverty increases significantly to 58.7 % (of initially poor cocoa farmers) and is considerably higher than the share of those remaining poor or falling into poverty. This trend holds also for the (initially) non-poor cocoa farmers whose share of farmers remaining non-poor rises from 60.3 % in the first period to a 79.8 % in the second period. Non-cocoa farmers' income levels also improve, but less than for cocoa farmers. The share of non-cocoa farmers escaping poverty or remaining non-poor is substantially lower than for cocoa households. Moreover, the share of non-cocoa households falling into poverty is higher than in the first period.

Hence, the results clearly suggest that cocoa production is a long-term driver of overall poverty reduction. Yet, despite the increasing opportunity to escape poverty between 2006 and 2013, it is important to recognize that a significant share of cocoa farmers remains poor. This heterogeneity in poverty dynamics and outcomes raises questions concerning the individual determinants of cocoa income and its poverty-reducing potential.

5.6 Productivity heterogeneity of cocoa farmers

The direct determinants of cocoa income, i.e. cocoa yield, cocoa area and farm gate prices are shown in table 5.3.

Whereas cocoa area per household is only slightly rising over time, we observe that average productivity increases significantly over the whole sample period. Cocoa yields increase slightly between 2001 and 2006, but more than double between 2006 and 2013,

Table 5.2: **Transition matrix for USD 1/Day PPP poverty line for cocoa farmers (C) and non-cocoa farmers (NC), 2001-2013**

2001 \ *2006*		*Poor (USD 1/day)*		*Non-Poor*		
		C	NC	C	NC	Σ
Poor (USD 1/day)	C	43.6 [41]	7.5 [7]	45.7 [43]	3.2 [3]	100 [94]
	NC	20.0 [18]	48.9 [44]	15.6 [14]	15.6 [14]	100 [90]
Non-Poor	C	33.3 [26]	1.3 [1]	60.3 [47]	4.1 [4]	100 [78]
	NC	21.2 [7]	33.3 [11]	21.2 [7]	24.2 [8]	100 [33]
	Σ	31.2 [92]	21.4 [63]	37.6 [111]	9.8 [29]	100 [295]

2006 \ *2013*		*Poor (USD 1/day)*		*Non-Poor*		
		C	NC	C	NC	Σ
Poor (USD 1/day)	C	28.8 [30]	8.7 [9]	58.7 [61]	3.8 [4]	100 [104]
	NC	15.9 [11]	39.1 [27]	15.9 [11]	29.0 [20]	100 [69]
Non-Poor	C	12.6 [15]	1.7 [2]	79.8 [95]	5.9 [7]	100 [119]
	NC	4.0 [1]	40.0 [10]	24.0 [6]	32.0 [8]	100 [25]
	Σ	18.0 [57]	15.1 [48]	54.6 [173]	12.3 [39]	100 [317]

Note: Currency conversion based on the World Bank PPP conversion factor for private consumption (Local Currency Unit (LCU) per international $). Values are rounded. Numbers of households are in brackets. Since most households in our region have adopted cocoa during the first period, we assume as cocoa farmers all households with at least two observations and with a cocoa plantation of at least 0.25 hectare.
Source: Authors' calculation and graphical representation based on STORMA and EFForTS data.

explaining most of the long-term increase in cocoa income over time. As shown above, real cocoa price fell between 2001 and 2006 and recovered somewhat until 2013.

The increase in average cocoa yields in the second period was accompanied by a considerable increase in their variance, i.e. rising heterogeneity. One important explanatory factor for these trends is the yield cycle of the cocoa tree. The average tree age of cocoa farmers increases from 3.8 years in 2001 (sd = 3.2 years) to 6.3 years in 2006 (sd = 4.1 years) up to 11.2 years in 2013 (sd = 6.3 years). As cocoa trees start to produce at the age of 3 to 5 until the age of 20 to 25 and reach their productivity peak at the age of 10 (Wood and Lass, 2001), the cocoa plantations of the farmers in the study region have on average reached their most productive age in 2013.

Table 5.3: **Measures of variance for cocoa income and its components for cocoa farmers, 2001-2013**

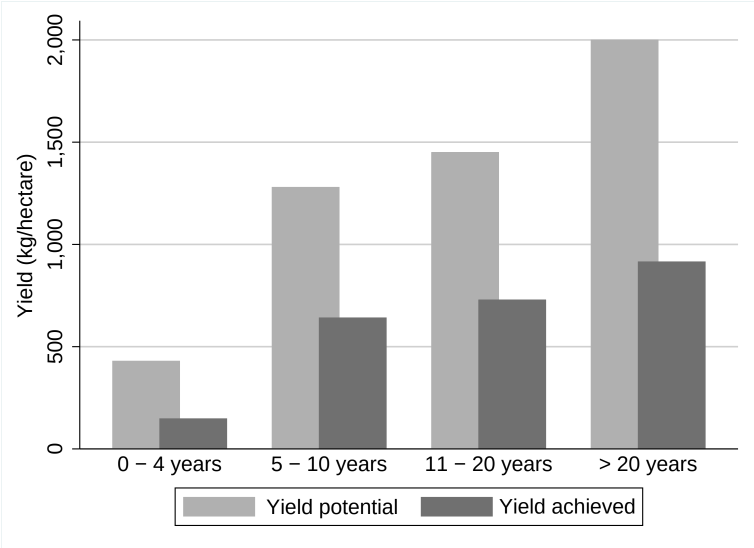
	2001	2006	2013
	mean (standard deviation)		
P.c. household cocoa inc.	513,551 (1,255,471)	496,847 (603,385)	1,353,738 (1,875,858)
Crop area (are)	1.4 (1.3)	1.4 (1.2)	1.5 (1.7)
Yield (kg/are)	211.6 (328.9)	349.0 (273.0)	815.6 (822.3)
Price (IDR/kg)	8,527 (1,206.4)	5,266.9 (423.7)	6,446.5 (279.6)

Note: Households with an cocoa plantation of at least 0.25 hectare are included. Monetary values are real IDR with base year 2001, using the provincial CPI for Palu provided by BPS (2016a). Local land units are measured in are. One are is equal to 100 m^2. Prices are village medians of farm gate prices.
Source: Authors' calculation based on STORMA and EFForTS data.

The strong variation of yields means that many cocoa farmers are not exploiting full potential yields. Figure 5.3 illustrates the average yield gap, i.e. the yield potential and the mean achieved yield for four tree age groups. Following Ittersum et al. (2013), we estimate yield potentials by upper percentiles in the yield distribution from the surveys. We rely on the 90^{th} percentile of yields amongst our survey farmers to estimate the maximum potential yield. Most farmers obtain yield levels that are well below the potential yields for the region: On average, they achieve about half of the yield potential. For example, while the farmer at the 90^{th} yield percentile produces 1280 kilogram cocoa per hectare for cocoa trees aged 5 to 10 years, the average cocoa farmer only achieves 642 kilogram per hectare. Yield gaps are present for all age groups, suggesting that the plantation age is not the only determinant of heterogeneity amongst cocoa farmers.

We therefore analyze cocoa yield determinants (or 'correlates' acknowledging the limited causal content of this type of exercise) using pooled ordinary least squares (OLS) and static panel data methods (Fixed Effects (FE) model). We estimate the following equation

Figure 5.3: **Yield gaps per tree age group, 2001-2013**



Source: Authors' calculation and graphical representation based on STORMA and EFForTS data.

that relates productivity, management practices as well as farm and farmer characteristics:

$$\ln Y_{it} = \alpha + \sum_j \beta_j P_{i,it} + \sum_k \beta_k M_{k,it} + \sum_l \beta_l H_{l,it} + \delta D_{it} + \gamma_i + \lambda_t + \varepsilon_{it} \tag{5.1}$$

where Y_{it} is productivity defined as household's yield measured in cocoa beans harvested (in kg) per hectare, P is a matrix of j variables of plot characteristics, M is a set of k variables on management practices, H is a set of l household characteristics, D_{it} is a dummy controlling for the presence of pests, λ_t are time fixed effects and ε_{it} is the idiosyncratic error. The Fixed Effects (FE) model also includes household fixed effects γ_i that control for unobserved and time-invariant characteristics, such as unobservable ability of farmers. Time fixed effects λ_t (year dummies) further capture time-specific shocks common to all households, like time trends in average productivity or weather shocks that affect all households in the same year. All estimations are performed using cluster-robust standard errors. Summary statistics on the key variables used in our econometric analyses are given in the appendix D, Table D.1.

Management practices are proxied by both chemical inputs (fertilizer[5] and herbicides) and manual techniques, such as manual weeding, pruning, the removal of diseased fruits and the frequency of harvests. Fertilizer application is included as the household's expenditures for fertilizer per hectare. All other management proxies are included as dummies. We

[5]For our sample, only about one quarter of farmers applies fertilizer.

also have information on participation in the GERNAS Pro Kakao program and include a corresponding dummy in some regressions without implying that this dummy will be able to capture causal program impacts. We control for tree age by adding cocoa tree age and its squared term. Moreover, we include a dummy for pests, mainly the cocoa pod borer and the black pod disease. We further account for wealth (assets), education and migrant status as household characteristics.

We estimate a log-linear model[6] and some explanatory variables (agricultural area, expenditure on inputs and households' assets) are transformed to their natural logarithm to comply with the assumption of normal distribution, mitigate the problem of heteroskedasticity, and to make the model less sensitive to outliers. The estimated coefficients can thus be interpreted as (semi-)elasticities. The model potentially suffers from endogeneity, in particular without household fixed effects. The OLS estimates of the effects of management practices are likely to be affected by omitted variable bias, as it is plausible that they are related to the same – unobserved – farmer ability as cocoa yields. To mitigate reverse causality of wealth, which might be determined by cocoa yields giving the farmer financial capacity to engage in input-intensive activities, we use lagged values of assets.

Table 5.4 shows the results of our analysis of yields. Columns (1) to (4) present the results of the pooled OLS model with time effects and column (5) without time effects. Our baseline model (column 1) regresses yield on the main plot conditions as well as labor input. The coefficient of cocoa area is statistically significant and indicates that an 1 % increase in total cocoa area under cultivation is on average associated with a 0.18 to 0.32 % decrease in yields. This result indicates that larger cocoa plantations of smallholders are less intensively managed (for example, by intercropping with other plants). As expected, the estimated coefficient for tree age is significantly positive while the estimate for its squared term is negative. This reflects the yield curve for cocoa with first increasing and then decreasing yields and a turning point at about 16 to 19 years in our estimation. Labor input as measured by expenditures for hired workers is also associated with higher yields; the number of family members working on the plot does not seem to play a role though. Column 2 adds variables on management practices and we find input-intensive as well as labor-intensive activities to be an essential means to achieve high yields. The yield elasticity of fertilizer expenditure is 0.02. Similarly, the application of herbicides is positive and significant. Furthermore, manual practices seem to be an important ingredient for successful cocoa cultivation. A

[6] Using the log value of yield removes observations with zero yields (e.g. during the initial phase of cocoa cultivation) from the estimation. As a robustness check, we also include observations with zero yields into the regression by adding 1 to each observation before transforming into logs. Results are similar and displayed in the appendix D, Table D.2.

striking example is that farmers who prune their cocoa trees on average achieve about 1.5 times the yield than those refraining from doing it (referring to column 2). Also removing diseased cocoa pods is essential, whereas controlling the growth of weeds by hand does not make a difference (only statistically significant in column 5).

Results on household characteristics (added in column 3) are mixed. Financial conditions of farm households – as measured by the ownership of assets – are statistically significant and positively correlated with yield. In other specifications, we use lagged values of assets to avoid reverse causality and the effect is no longer significant. The dummy on migration status is significantly negative (equals 1 in case of a local farmer) and thus indicates that migrants are more successful in cocoa cultivation than the local population. We further control for education of the household head and find the completion of primary and tertiary education to be positively correlated with cocoa yield.

Column (4) adds a pest dummy which is available for observations in 2006 and 2013. As expected, we find a negative effect which is insignificant though. However, we are hesitant to take this insignificant result at face value because pests are endogenous to a number of other regressors, in particular to management practices. Instead, we below investigate the correlates of crop failure to shed more light on the effects of pests.

Column (5) controls for the frequency of harvests and participation in the national cocoa program GERNAS that, amongst other things, trains farmers on cocoa cultivation (data is only available for 2013). Productivity remains unaffected by harvest frequency but there is evidence of a strong impact of GERNAS: Farmers that participate in the GERNAS program achieve on average 82 % higher yields.[7]

Column (6) shows the findings of the long-term analysis based on the FE model.[8] The FE model is preferable to OLS as it takes the panel structure into account and controls for time-invariant heterogeneity across farm households which may bias estimation results.

The FE model confirms our finding that both chemical (application of fertilizer) as well as labor inputs (pruning, removal of diseased fruits) have a positive impact on yields. To sum up, cocoa yields mainly depend on proper management practices which include both the application of chemical inputs and manual strategies. The farmers' choice of management practices can therefore explain a large share of the observed heterogeneity amongst our sample. Following a strategy of agricultural intensification (heavy use of fertilizer as

[7]This result is likely to suffer from endogeneity given the self-selection into the GERNAS program.

[8]An alternative panel data method is the Random Effects (RE) model. Performing the (robust) Hausman tests, however, allows us to reject the null hypothesis of exogeneity of explanatory variables with the time and household fixed effects at the 1% level of significance for our baseline model and confirms therefore our choice for the FE model specification.

well as application of herbicides) helps to increase yields. Also plot maintenance practices (especially pruning and the removal of diseased pods) have a great potential to considerably increase yields. These management practices appear to primarily affect yields in a direct way and rather not through preventing disease infestations.

While the FE model addresses endogeneity arising from household-specific time-invariant omitted variables, there might still be endogeneity originating from time-varying unobserved effects if correlated with the explanatory variables. To handle this problem of endogeneity, we adopt an Instrumental Variable (IV) approach to estimate equation 5.1. The various management practices – our main explanatory variables – are instrumented with the average management practice in the village (excluding the specific farmer), the rationale being that farmers' management practices are influenced by those of their neighbors.[9] Applying this IV approach yields very similar results and confirms that management practices have a strong impact on cocoa yields (see table D.3 in appendix D).

To further explore the heterogeneity of production we apply a quantile regression, i.e. an approach that allows the parameters in equation 5.1 to vary across different quantiles of cocoa yields (here the 10^{th}, 25^{th}, 50^{th}, 75^{th} and 90^{th} quantile). The Breusch-Pagan test for heteroskedasticity rejects the null hypothesis of homoskedasticity and thus rules out that heteroskedastic errors are driving our results.

Table 5.5 shows again the estimation results for our main covariates. It becomes apparent that yields of less productive and more productive farmers are determined by different factors. We find coefficients on plot conditions, management practices as well as household characteristics to vary across quantiles and to differ from the OLS model. The pseudo R^2 which varies between 0.25 and 0.28, however, indicates that the quantile regression model explains yield more or less equally well at different parts of the distribution.

With regard to plot conditions, the coefficients on plantation age are very instructive. They reveal that the shape of the cocoa yield curve varies markedly across quantiles. In contrast to the successful farmers, the productivity of low performers has a much steeper rise in the beginning, reaches the turning point at an earlier stage (e.g. at a tree age of 13 years for the 10^{th} quantile compared to 17 years for the 90^{th} quantile) and records a steeper downturn afterwards. Moreover, the quantile regression results suggest that low and high performers have varying degrees of success with regard to management strategies.

At the lower tail of the yield distribution (10^{th} quantile), farmers' agricultural practices do not have an effect on yield at all. Only the dummy on migrant status has a significant

[9]This correlation is likely in a region where cocoa was only introduced in the early 2000s, whereas the neighbors' management practices should not have a direct effect on the farmer's yield.

impact showing that being local has a strong negative effect on yield for the low performers. The low- to medium-performers (25th and 50th quantile) successfully rely on labor-intensive strategies (pruning and removal of diseased fruits, hired labor) to increase their yields. The effective application of fertilizer at the 50th and 75th quantile suggests that a well-managed intensification strategy could also help the lower quantiles to increase their yields. The high performers' (75th and 90th quantile) labor input (hiring labor and plot maintenance practices such as pruning and removal of diseased fruit) has also a positive effect, though with a slightly lower magnitude compared to the low- to medium-performers. To sum up, the quantile regression reveals that heterogeneity in yield amongst cocoa farmers illustrates the importance of both the choice of management practices and their effective implementation for the observed productivity heterogeneity of farmers.

In a final exercise of our empirical analyses, we examine the incidence and determinants of crop failures, which may be a threat to sustainable income gains of cocoa farmers. In line with the above mentioned reports on problems in Indonesia's cocoa sector at large we observe a sharp increase in crop failures in our sample (see table 5.6): In 2006, 9 % of cocoa farmer report on crop failure for the last 5 years. This share increases to 44 % alone for the year 2013. These losses are mostly due to pests and diseases, which explain 96 % of all crop failures in 2006 and 78 % in 2013 (other reasons are drought, flood or other weather phenomena). Hence in 2013, about one third of farmers is affected by pests and diseases. The reported pests and diseases are mainly the black pod disease and – to a slightly lesser extent – the cocoa pod borer.

The incidence and intensity of crop failure increase both across tree age groups within the respective year as well as over time. To explore this trend further, we run an auxiliary regression that relates crop failure, management practices and agricultural shocks (see table 5.7). We first regress crop failure on basic plot conditions and management practices (column 1), then add household characteristics (column 2), and finally the pest dummy (column 3). We measure crop failure by the percentage of regular yield lost, due to natural disasters (droughts, storms) or infestations with pest and diseases. Results are available only for 2006 and 2013, for which data on agricultural shocks do exist.

As expected, proper management practices that are related to disease and pest management such as the application of herbicides, manual weeding and the removal of diseased pods are associated with lower yield losses. The same is true for harvest frequencies: Harvesting the cocoa trees more than once per month decreases the magnitude of yield loss.

Additionally controlling for household characteristics (column 2) does not affect the estimated coefficients on the management practice proxies, which reinforces that we are actually observing an effect of those practices rather than the effect of some unobserved farmer ability that would be correlated with them. We find further evidence that especially the production of local farmers is affected by pests as the migrant status dummy is highly significant and positive. When we add a pest dummy (column 3) we can see that pests indeed explain the largest proportion of the variance in crop failures, as R-squared increases from 0.233 to 0.595. The effect is large: If a pest occurs, yield is on average diminished by 30 %. The coefficients on management practices, in particular the use of herbicides, weeding, and removal of diseased pods, are smaller when the pest dummy is included. In other words, the omission of the pest dummy induced an upward bias of the mitigating effect of these practices in the first two specifications of table 5.7. This indicates that a major transmission channel of better management practices on yields runs through the prevention and mitigation of pests. In addition, there is a significantly positive time trend in crop failures indicating that crop failures become more frequent in the region. In contrast to productivity, the magnitude of yield loss is largely unrelated to cocoa tree age and plantation size (when controlled for management practices). Further, the use of hired labor is significantly raising crop losses, but turns insignificant when including the pest dummy. This might indicate that farmers count on labor in the event of a crop failure, especially for pesticide spraying. Also the migrant status dummy gets insignificant in column (3), suggesting that the yield loss of locals, and probably lower yields in general, is partly due to pest infestations.

5.7 Heterogeneity in cocoa yields and poverty outcomes

To connect our findings, we explore in a final step how productivity heterogeneity and the associated management practices are linked to long-term poverty reduction amongst cocoa farming households in the Lore Lindu region. To proxy good management practices of cocoa plantations, we draw on three key determinants of cocoa productivity derived from the OLS and FE model above. First, we include the practice of tree pruning, which is highly positively correlated with cocoa yield and thus crucial for farmers' successful management of cocoa trees. Second, we consider the regular removal of diseased fruits as a key method to reduce the susceptibility to pests, especially the cocoa pod borer and the black pod disease. Third, we use the application of fertilizer, herbicides or both as proxy for advanced management practices with chemical inputs. Accordingly, to be classified as a cocoa farmer with good management practices, a farmer has to prune his cocoa trees, has to remove diseased fruits from his trees and has to apply any chemical input. Applying these criteria, we separate our sample into well-managing and not-well managing farmers, resulting in 33 farmers with good management practices in 2001, 82 in 2006 and 131 farmers in 2013 (see table 5.8). Management practices on average thus improve considerably over time.

We combine this information with the respective poverty status of farmers' households and illustrate in a next step all transitions in both farmers' management quality and income status over the total sample period. To this end, table 5.9 shows all transitions of cocoa farmers between 2001, 2006 and 2013.[11]

The results indicate that initially poor households can benefit from applying better management practices (23.4 % of all initially poor and not-well managing farmers), but that a transition out of poverty is also possible without doing so (a third of all initially poor and not-well managing farmers). Staying poor is associated with continued worse farm management while well-managing farm households find it much easier to escape poverty (59.3 % from the initially poor, well-managing households).

Looking at non-poor households confirms an important role for farming practices. The majority of cases (N=54 and 72 %) of initially non-poor, well-managing households are households continuing their good management practices and maintain non-poor income levels. The latter holds also for the 43 farmers that improve management practices. And while only 10 initially non-poor farmers who manage well fall into poverty, this happens to 27 households without good management practices.

5.8 Conclusion

The present study shows that cash crop farming can be associated with strong and sustainable poverty reduction. In our study region in Central Sulawesi and over the analyzed time horizon of more than 10 years, cocoa farmers fare considerably better than non-cocoa farmers and the welfare gains are less volatile than might be anticipated in light of the problems, in particular the occurrence of pests, faced by the Indonesian cocoa sector at large in the period under consideration. The large increases in cocoa income can mainly be attributed to increasing cocoa yields. However, yield gaps remain large and are increasingly heterogeneous. We can trace back this productivity heterogeneity to farm management practices that include both the application of chemical inputs and manual practices. The farmers' choice of management practices can therefore explain a large share of the observed productivity heterogeneity in our sample. These management practices seem to have a direct positive

[11] In total, 275 farmers could be interviewed concerning their management practices in 2001, 2006 and/or 2013. Of those 275 households, 141 could be interviewed three times (i.e. two transitions), 86 could be interviewed twice (i.e. one transition) and 48 could be interviewed once (i.e. no transition), adding up to 643 observations and 368 transitions.

effect on yields as well as indirect positive effect through the prevention and mitigation of crop failures, which tend to become increasingly common because of more frequent pest infestations in the region.

Taken together, increased cocoa yields and the importance of management techniques suggest that the improvement of management practices can be linked to improved livelihoods. And indeed, we can empirically establish this link: We can show that better management practices facilitate the transition out of poverty and shields against income losses. In light of the still gasping yield gaps of cocoa farmers in the region, our findings are good news as they show the potential of improving agricultural productivity to raise living standards. However, poverty persistence and the persistence of bad management amongst a substantial fraction of farmers may imply that these farmers may be much harder to reach. Finally, the increasing incidence of pests, especially the cocoa pod borer and the black pod disease, might require more focused interventions. While intensification strategies have in the past helped cocoa farmers to considerably increase yields, they may, together with aging plantations, aggravate the incidence of pests and diseases. Thus, management skills may have to improve beyond the simple intensification techniques and replanting will have to accelerate. This may be required to sustain the livelihood improvements that the cocoa sector has brought to many smallholders in Sulawesi.

Table 5.4: **Determinants of cocoa productivity (pooled OLS and FE model), 2001-2013**

VARIABLES	(1) Cocoa yield (log) OLS	(2) Cocoa yield (log) OLS	(3) Cocoa yield (log) OLS	(4) Cocoa yield (log) OLS	(5) Cocoa yield (log) OLS	(6) Cocoa yield (log) FE
Cocoa area (log)	-0.175***	-0.211***	-0.267***	-0.296***	-0.320***	-0.460***
	(0.002)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tree age	0.221***	0.195***	0.183***	0.118***	0.099**	0.164***
	(0.000)	(0.000)	(0.000)	(0.002)	(0.015)	(0.000)
Tree age^2	-0.006***	-0.006***	-0.005***	-0.003***	-0.003**	-0.005***
	(0.000)	(0.000)	(0.000)	(0.006)	(0.016)	(0.000)
Labor exp. (log)	0.049***	0.035***	0.032***	0.020*	0.015	0.017
	(0.000)	(0.000)	(0.000)	(0.052)	(0.414)	(0.139)
Family workers (#)	-0.017	-0.016	-0.014	0.018	0.028	0.011
	(0.582)	(0.571)	(0.635)	(0.608)	(0.646)	(0.804)
Fertilizer exp. (log)		0.018**	0.007	0.014	0.007	0.031**
		(0.046)	(0.463)	(0.148)	(0.605)	(0.034)
Use of herbicides		0.323*	0.305*	0.553**	1.146***	0.330
		(0.081)	(0.100)	(0.015)	(0.003)	(0.120)
Manual weeding		0.046	0.086	0.212	0.775**	0.084
		(0.795)	(0.626)	(0.331)	(0.035)	(0.688)
Pruning		0.445***	0.405**	0.417**	0.189	0.734***
		(0.007)	(0.022)	(0.044)	(0.432)	(0.000)
Removing pods		0.661***	0.667***	0.617***	0.486**	0.383*
		(0.000)	(0.000)	(0.000)	(0.048)	(0.078)
Migrant status			-0.273***	-0.274***	-0.525***	
			(0.004)	(0.008)	(0.003)	
Primary edu.			0.143	0.234	0.656**	
			(0.258)	(0.141)	(0.025)	
Secondary edu.			-0.187	-0.123	0.126	
			(0.271)	(0.576)	(0.715)	
Tertiary edu.			-0.002	0.275	0.585**	
			(0.988)	(0.104)	(0.046)	
Assets (log)			0.062**			
			(0.018)			
Lagged assets (log)				0.035	0.023	
				(0.221)	(0.558)	
Pest				-0.091	-0.019	
				(0.423)	(0.892)	
GERNAS					0.598***	
					(0.001)	
Harvest frequency					0.152	
					(0.255)	
Year = 2006	0.081	0.065	0.148			0.265*
	(0.508)	(0.584)	(0.216)			(0.066)
Year = 2013	0.537***	0.481***	0.590***	0.445***		0.771***
	(0.001)	(0.001)	(0.000)	(0.000)		(0.000)
Constant	4.273***	3.290***	3.050***	3.524***	3.615***	3.222***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	554	554	551	368	209	554
R-squared	0.312	0.384	0.405	0.355	0.306	0.472
Adj. R-squared	0.303	0.370	0.386	0.324	0.241	
Number of id						257
Within R-squared						0.472
Between R-squared						0.151

Note: Pval in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, year dummies included, cluster-robust standard errors. Households with a cocoa plantation of at least 0.25 hectare are included.
Source: Authors' calculation based on STORMA and EFForTS data.

Table 5.5: **Quantile regression of determinants of yields (pooled OLS), 2001-2013**

VARIABLES	(1) Cocoa yield (log) OLS	(2) Cocoa yield (log) Q(10th)	(3) Cocoa yield (log) Q(25th)	(4) Cocoa yield (log) Q(50th)	(5) Cocoa yield (log) Q(75th)	(6) Cocoa yield (log) Q(90th)
Cocoa area (log)	-0.240***	-0.276*	-0.193*	-0.272***	-0.215***	-0.290***
	(0.000)	(0.059)	(0.064)	(0.000)	(0.000)	(0.000)
Tree age	0.189***	0.397***	0.252***	0.172***	0.129***	0.101**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.011)
Tree age^2	-0.006***	-0.015***	-0.009***	-0.005***	-0.004***	-0.003*
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.075)
Labor exp. (log)	0.035***	0.040	0.041**	0.034***	0.024**	0.022*
	(0.000)	(0.147)	(0.024)	(0.000)	(0.015)	(0.092)
Family workers (#)	-0.012	-0.037	-0.010	-0.008	-0.023	-0.001
	(0.679)	(0.637)	(0.858)	(0.706)	(0.446)	(0.983)
Fertilizer exp. (log)	0.010	0.014	0.008	0.012**	0.016*	0.011
	(0.252)	(0.565)	(0.611)	(0.042)	(0.075)	(0.345)
Use of herbicides	0.348*	0.233	0.438	0.219*	0.040	0.076
	(0.055)	(0.481)	(0.202)	(0.092)	(0.824)	(0.722)
Manual weeding	0.096	0.094	0.269	-0.027	-0.123	-0.076
	(0.578)	(0.762)	(0.416)	(0.828)	(0.472)	(0.721)
Pruning	0.428**	0.351	0.554*	0.474***	0.456***	0.346
	(0.014)	(0.203)	(0.081)	(0.000)	(0.006)	(0.136)
Removing pods	0.662***	0.421	0.666***	0.786***	0.569***	0.397**
	(0.000)	(0.201)	(0.004)	(0.000)	(0.000)	(0.022)
Migrant status	-0.300***	-0.696***	-0.442**	-0.142**	-0.109	-0.189*
	(0.001)	(0.010)	(0.013)	(0.034)	(0.254)	(0.088)
Primary edu.	0.158	0.302	0.095	0.057	0.074	0.235
	(0.213)	(0.439)	(0.720)	(0.561)	(0.599)	(0.164)
Secondary edu.	-0.150	-0.130	-0.412	-0.350***	0.092	0.315
	(0.377)	(0.777)	(0.200)	(0.003)	(0.587)	(0.151)
Tertiary edu.	0.089	0.287	0.015	0.083	0.110	0.283
	(0.552)	(0.521)	(0.959)	(0.450)	(0.477)	(0.121)
Year = 2006	0.090	0.110	0.201	0.179**	0.078	-0.245
	(0.451)	(0.723)	(0.380)	(0.029)	(0.513)	(0.135)
Year = 2013	0.559***	0.333	0.624**	0.656***	0.593***	0.455**
	(0.000)	(0.372)	(0.024)	(0.000)	(0.000)	(0.011)
Constant	3.413***	1.941***	2.533***	3.517***	4.540***	5.383***
	(0.000)	(0.006)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	554	554	554	554	554	554
R-squared	0.400					
Adj. R-squared	0.382					
Pseudo R-squared		0.273	0.267	0.245	0.227	0.253

Note: Pval in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, year dummies included. Households with a cocoa plantation of at least 0.25 hectare are included.
Source: Authors' calculation based on STORMA and EFForTS data.

Table 5.6: **Cocoa tree age: Yield and crop failures, 2006-2013**

	2006				*2013*			
Tree age	Cases	Yield (kg/ha)	Crop failure	Lost yield (%)	Cases	Yield (kg/ha)	Crop failure	Lost yield (%)
Years	*n*	*mean (sd)*	*N*	*mean (sd)*	*N*	*mean (sd)*[10]	*n*	*mean (sd)*
0 – 4	89	154.3 (200.2)	2	0.6 (3.7)	22	236.9 (386.3)	0	0
5 – 10	115	462.0 (240.9)	13	3.6 (12.2)	110	905.0 (967.8)	52	18.5 (23.8)
11 – 20	28	497.9 (247.8)	7	8.25 (16.1)	84	823.8 (656.1)	40	18.1 (24.0)
> 20	1	513.3 (-)	0	0	18	938.0 (689.9)	10	28.0 (31.6)
0 – 36	233	349.0 (273.0)	22	3.0 (10.7)	234	815.6 (822.3)	102	17.4 (24.1)

Note: Households with a cocoa plantation of at least 0.25 hectare are included.
Source: Authors' calculation based on STORMA and EFForTS data.

Table 5.7: **Determinants of crop failure (pooled OLS), 2001-2013**

VARIABLES	(1) Crop failure	(2) Crop failure	(3) Crop failure
Cocoa area (log)	-0.802	-0.676	-1.053
	(0.556)	(0.672)	(0.366)
Tree age	0.873	1.143*	0.410
	(0.109)	(0.061)	(0.345)
Tree age^2	-0.020	-0.025	-0.001
	(0.269)	(0.175)	(0.945)
Labor exp. (log)	0.411**	0.525***	-0.023
	(0.015)	(0.006)	(0.873)
Family workers (#)	1.034	1.198	1.382**
	(0.123)	(0.116)	(0.011)
Fertilizer exp. (log)	-0.168	0.012	-0.195
	(0.429)	(0.960)	(0.243)
Use of herbicides	-24.279***	-23.701***	-13.018**
	(0.000)	(0.000)	(0.013)
Manual weeding	-21.173***	-19.955***	-12.370**
	(0.000)	(0.001)	(0.021)
Pruning	3.363	9.670**	4.195
	(0.608)	(0.047)	(0.137)
Removing pods	-6.550**	-7.344**	-5.323**
	(0.023)	(0.021)	(0.024)
Harvest frequency	-3.721*	-4.859**	-4.076**
	(0.066)	(0.026)	(0.011)
Migrant status		4.498**	-0.461
		(0.041)	(0.782)
Primary edu.		-0.987	0.923
		(0.719)	(0.677)
Secondary edu.		5.572	6.030*
		(0.160)	(0.076)
Tertiary edu.		1.075	6.000**
		(0.741)	(0.027)
Lagged assets (log)		-0.538	-0.374
		(0.394)	(0.370)
Pest			31.316***
			(0.000)
Year = 2013	14.469***	12.066***	4.872***
	(0.000)	(0.000)	(0.001)
Constant	21.541**	13.813	10.042
	(0.017)	(0.171)	(0.187)
Observations	430	365	365
R-squared	0.224	0.233	0.595
Within R-squared	.	.	.
Between R-squared	.	.	.

Note: Pval in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, cluster-robust standard errors. Households with a cocoa plantation of at least 0.25 hectare are included.
Source: Authors' calculation based on STORMA and EFForTS data.

Table 5.8: **Numbers of well managing and not-well managing cocoa farmers**

	2001	*2006*	*2013*
No. of well managing farmers	33	82	131
No. of not-well managing farmers	143	151	103
No. of all farmers	176	233	234

Note: Households with a cocoa plantation of at least 0.25 hectare are classified as cocoa farmers.
Source: Authors' calculation based on STORMA and EFForTS data.

Table 5.9: **Transition matrix for USD 1/day PPP poverty lines for cocoa farmers with well and not-well agricultural practices, 2001-2013, total transition cases**

$TRANS_{i,t}$ \ $TRANS_{i,t+n}$ with $n = \{1;2\}$		*Poor (USD 1/day)* WELL	*Poor (USD 1/day)* NOT WELL	*Non-Poor* WELL	*Non-Poor* NOT WELL	Σ
Poor (USD 1/day)	WELL	3.7 [1]	14.8 [4]	59.3 [16]	22.2 [6]	100 [27]
	NOT WELL	10.4 [16]	33.1 [51]	23.4 [36]	33.1 [51]	100 [154]
Non-Poor	WELL	13.3 [10]	0.0 [0]	72.0 [54]	14.7 [11]	100 [75]
	NOT WELL	4.0 [5]	24.1 [27]	38.4 [43]	33.0 [37]	100 [112]
	Σ	8.7 [32]	22.3 [82]	40.5 [149]	28.5 [105]	100 [368]

Note: Currency conversion based on the World Bank PPP conversion factor for private consumption (LCU per international $). Households with a cocoa plantation of at least 0.25 hectare are classified as cocoa farmers. Transitions are considered for at least one change.
Source: Authors' calculation based on STORMA and EFForTS data.

Bibliography

Achterbosch, Thom, Siemen van Berkum, and Gerdien Meijerink (2014) “Cash crops and food security: Contributions to income, livelihood risk and agricultural innovation,” LEI Report, 2014-015, LEI Wageningen UR, Wageningen.

Akiyama, Takamasa and Akihiko Nishio (1997) “Sulawesi’s Cocoa Boom: Lessons of Smallholder Dynamism and a Hands-Off Policy,” *Bulletin of Indonesian Economic Studies*, Vol. 33(2), pp. 97–121.

Albuquerque, Rui (2003) “The composition of international capital flows: Risk sharing through Foreign Direct Investment,” *Journal of International Economics*, Vol. 61(2), pp. 353–383.

Alfaro, Laura and Maggie Xiaoyang Chen (2014) “The global agglomeration of multinational firms,” *Journal of International Economics*, Vol. 94, pp. 263–276.

Anderson, T. W. and H. Rubin (1949) “Estimators of the Parameters of a Single Equation in a Complete Set of Stochastic Equations,” *Annals of Mathematical Statistics*, Vol. 21, pp. 570–582.

Antweiler, Werner, Brian R. Copeland, and M. Scott Taylor (2001) “Is Free Trade Good for the Environment?” *American Economic Review*, Vol. 91(4), pp. 877–908.

Arestis, Philip and Asena Caner (2010) “Capital Account Liberalisation and Poverty: How Close is the Link?” *Cambridge Journal of Economics*, Vol. 34(2), pp. 295–323.

Arpaia, Alfonso, Esther Perez, and Karl Pichelmann (2009) “Understanding Labor Income Share Dynamics in Europe,” Economic Papers, 379, European Commission, Brussels.

Arseneau, David M. and Sylvain Leduc (2011) “Threatening to Offshore in a Search Model of the Labor Market,” Paper presented at the Conference ’Globalization: Strategies and Effects’, Aarhus University, Aarhus.

Atkinson, Anthony B. (2009) “Factor shares: the principal problem of political economy?” *Oxford Review of Economic Policy*, Vol. 25(1), pp. 3–16.

Atkinson, Anthony B. and Francois Bourguignon (2015) *Handbook of Income Distribution*: Elsevier, North Holland.

Badinger, Harald and Peter Egger (2010) “Horizontal vs. Vertical Interdependence in Multinational Activity,” *Oxford Bulletin of Economics and Statistics*, Vol. 72(6), pp. 744–768.

Barbier, Edward B. (1989) “Cash crops, food crops, and sustainability: The case of Indonesia,” *World Development*, Vol. 17(6), pp. 879–895.

Barbier, Edward B. and Joanne C. Burgess (2017) “The Sustainable Development Goals and the systems approach to sustainability,” Economics Discussion Papers, 2017-28, Kiel Institute for the World Economy, Kiel.

Bargain, Olivier and Prudence Kwenda (2011) “Earnings structures, informal employment, and self-employment: New evidence from Brazil, Mexico and South Africa,” *The Review of Income and Wealth*, Vol. 57(1), pp. S100–S122.

Beddington, John, Mohammed Asaduzzaman, Adrian Fernandez, Megan Clark, Marion Guillou, Molly Jahn, Lin Erda, Tekalign Mamo, Nguyen Van Bo, Carlso Nobre, Robert Scholes, Rita Sharma, and Judi Wakhungu (2011) “Achieving food security in the face of climate change,” Consultative Group on International Agricultural Research, Copenhagen, Consultative Group on International Agricultural Research, Copenhagen.

Behrens, Arno, Stefan Giljum, Jan Kovanda, and Samuel Niza (2007) “The material basis of the global economy: Worldwide patterns of natural resource extraction and their implications for sustainable resource use policies,” *Ecological Economics*, Vol. 64, pp. 444–453.

Bengtsson, Erik and Daniel Waldenström (2015) “Capital Share and Income inequality: Evidence from the Long Run,” IZA Discussion Paper Series, 9581, Insitute for the Study of Labour, Bonn.

Bentolila, Samuel and Gilles Saint-Paul (2003) “Explaining Movements in the Labor Share,” *Contributions to Macroeconomics*, Vol. 3(1).

Berg, Andrew G. and Jonathan D. Ostry (2011) “Inequality and Unsustainable Growth: Two Sides of the Same Coin?,” IMF Staff Discussion Note, 8, International Monetary Fund, Washington D.C.

van Bergeijk, Peter A.G. and Rolph van der Hoeven (2017) *Sustainable Development Goals and Income Inequality*: Edward Elgar, Cheltenham, forthcoming.

Bernanke, Ben and Refet Gürkaynak (2001) "Is Growth Exogenous? Taking Mankiw, Romer and Weil Seriously," *NBER Macroeconomics Annual*, Vol. 16(8365).

Besley, Timothy and Louise J. Cord (2007) *Delivering on the promise of pro-poor growth*: World Bank, Washington D.C. and Palgrave Macmillan, New York.

Binswanger, Hans, Klaus Deininger, and Gershon Feder (1995) *Handbook of Development Economics*, Chap. Power, distortions, revolt and reform in agricultural land relations, pp. 2659–2772: Elsevier, North-Holland.

BKMP (2010) "Cocoa plantation and cocoa industry. Agribusiness update," Indonesia Investment Coordinating Board, Jakarta.

Blanchard, Olivier (1997) "The medium run," *Brookings Papers on Economic Activity*, Vol. 2, pp. 89–158.

Blander, Rembert De and Geert Dhaene (2012) "Unit root tests for Panel Data with AR(1) Errors and Small T," *The Econometrics Journal*, Vol. 15(1), pp. 101–124.

Blonigen, Bruce A., Ronald B. Davies, and Keith Head (2003) "Estimating the knowledge-capital model of the multinational enterprise: Comment," *American Economic Review*, Vol. 93(3), pp. 980–994.

Blonigen, Bruce A., Ronald B. Davies, Glen R. Waddell, and Helen T. Naughton (2007) "FDI in space: Spatial autoregressive relationships in Foreign Direct Investment," *European Economic Review*, Vol. 51(5), pp. 1303–1325.

Bourguignon, Francois (2015) *The Globalization of Inequality*, Princeton: Princeton University Press.

Bovenberg, Lans (1999) "Green Tax Reforms and the Double Dividend: An Updated Reader's Guide," *International Tax and Public Finance*, Vol. 6(3), pp. 421–443.

Bovenberg, Lans and Frederick van der Ploeg (1996) "Optimal taxation, public goods and environmental policy with involuntary unemployment," *Journal of Public Economics*, Vol. 62, pp. 59–83.

Bowman, Maria S. and David Zilberman (2013) "Economic Factors Affecting Diversified Farming Systems," *Ecology and Society*, Vol. 18(1).

BPS (2005) "Sulawesi Tengah in figures," National Statistical Office Indonesia, Jakarta.

——— (2010) "Sulawesi Tengah in figures," National Statistical Office Indonesia, Jakarta.

——— (2015) "Sulawesi Tengah in figures," National Statistical Office Indonesia, Jakarta.

——— (2016a) "Consumer Price Index data for Palu," National Statistical Office Indonesia, Jakarta, URL: http://www.bps.go.id/index.php/linkTabelStatis/911, accessed on 8 December 2016.

——— (2016b) "Data on cocoa export," National Statistical Office Indonesia, Jakarta, URL: https://www.bps.go.id/linkTabelStatis/view/id/1018, accessed on 8 Dec 2016.

——— (2016c) "Plantation data, area and production," National Statistical Office Indonesia, Jakarta, URL: https://www.bps.go.id, accessed on 8 December 2016.

Bussolo, Maurizio, Olivier Godart, Jann Lay, and Rainer Thiele (2007) "The impact of coffee price changes on rural households in Uganda," *Agricultural Economics*, Vol. 37(2-3), pp. 293–303.

Carletto, Calogero, Talip Kilic, and Angeli Kirk (2009) "Non-traditional crops, traditional constraints long-term welfare impacts of export crop adoption among Guatemalan smallholders," Policy Research Working Paper, 5142, World Bank, Washington D.C.

Castañeda, André, Dung Doan, David Newhouse, Minh Cong Nguyen, Hiroki Uematsu, and João Pedro Azevedo (2016) "Who Are the Poor in the Developing World?," Policy Research Working Paper, 7844, Background paper for the 'Poverty and Shared Prosperity Report 2016: Taking on Inequality'.

Charpe, Matthieu (2011) "The labour share of income: Determinants and potential contribution to exiting the financial crisis," World of Work Report, Chapter 3, International Labour Organization, Geneva.

Charpe, Matthieu, Sangheon Lee, Daniela Arias, and Slim Bridji (2014) "Does income distribution matter for development? Trends in labour share of income and their economic impacts in developing countries," World of Work Report, Chapter 8, International Labour Organization, Geneva.

Checchi, Daniele and Cecilia Garcia-Penalosa (2010) "Labour Market Institutions and the Personal Distribution of Income in the OECD," *Economica*, Vol. 77(307), pp. 413–450.

Chen, Vivian, Abhay Gupta, Andre Therrien, Gad Levanon, and Bart van Ark (2010) "Recent Productivity Developments in the World Economy: An Overview from The Conference Board Total Economy Database," *International Productivity Monitor*, Vol. 19(1), pp. 3–19.

Cho, Yoonyoung, David Robalino, and Jose Manuel Romero (2015) "Entering and Leaving Self-Employment: A Panel Data Analysis for 12 Developing Countries," IZA Discussion Paper Series, 9358, Institute for the Study of Labor, Bonn.

Chuku, Chuku A. and Chidinma Okoye (2009) "Increasing resilience and reducing vulnerability in sub-Saharan African agriculture: Strategies for risk coping and management," *African Journal of Agricultural Research*, Vol. 4(13), pp. 1524–1535.

Clough, Yann, Heiko Faust, and Teja Tscharntke (2009) "Cacao boom and bust: sustainability of agroforests and opportunities for biodiversity conservation," *Conservation Letters*, Vol. 2(5), pp. 197–205.

Cobb, Charles W. and Paul H. Douglas (1928) "A Theory of Production," *The American Economic Review*, Vol. 18(1), pp. 139–65.

Cole, Matthew A. (2003) "Determining the Trade - Environment Composition Effect: The Role of Capital, Labor and Environmental Regulations," *Journal of Environmental Economics and Management*, Vol. 46(3), pp. 363–383.

——— (2004) "Trade, the pollution haven hypothesis and the environmental Kuznets curve: examining the linkages," *Ecological Economics*, Vol. 48, pp. 71–81.

Cole, Matthew A. and Robert J. R. Elliott (2005) "FDI and the Capital Intensity of "Dirty" Sectors: A Missing Piece of the Pollution Haven Puzzle," *Review of Development Economics*, Vol. 9(4), pp. 530–548.

Collier, Paul and Stefan Dercon (2014) "African Agriculture in 50 Years: Smallholders in a Rapidly Changing World?" *World Development*, Vol. 63, pp. 92–101.

Dabla-Norris, Era et al. (2015) "Causes and Consequences of Income Inequality: A Global Perspective," IMF Staff Discussion Note, 15/13, International Monetary Fund, Washington D.C.

Dabla-Norris, Era, Jiro Honda, Amina Lahreche, and Geneviéve Verdier (2010) “FDI flows to low-income countries: Global drivers and growth implications,” Working Paper, 10/132, International Monetary Fund, Washington D.C.

Daly, Herman E. and Joshua Farley (2011) *Ecological economics: Principles and applications*: Island Press, Washington D.C.

Daude, Christian and Marcel Fratzscher (2008) “The pecking order of cross-border investment,” *Journal of International Economics*, Vol. 74(1), pp. 94–119.

Daudey, Emilie and Cecilia García-Peñalosa (2007) “The Personal and the Factor Distributions of Income in a Cross-Section of Countries,” *Journal of Development Studies*, Vol. 43(5), pp. 812–29.

Davies, James B., Susanna Sandström, Anthony Shorrocks, and Edward N. Wolff (2011) “The Level and Distribution of Global Household Wealth,” *Economic Journal*, Vol. 121, pp. 223–254.

Davies, Ronald B. and Helga Kristjánsdóttir (2010) “Fixed Costs, Foreign Direct Investment, and Gravity with Zeros,” *Review of International Economics*, Vol. 18(1), pp. 47–62.

Deininger, Klaus and Derek Byerlee (2011) “The Rise of Large Farms in Land Abundant Countries: Do They Have A Future?,” Policy Research Working Paper, 5588, World Bank, Washington D.C.

di Giovanni, Julian (2005) “What drives capital flows? The case of cross-border M and A activity and financial deepening,” *Journal of International Economics*, Vol. 65(1), pp. 127–149.

Dickey, David A. and Wayne A. Fuller (1979) “Distribution of the Estimators for Autoregressive Time Series with a Unit Root,” *Journal of American Statistical Association*, Vol. 74(366), pp. 427–431.

Diwan, Ishac (2001) “Debt as Sweat: Labor, Financial Crisis, and the Globalization of Capital,” mimeo, World Bank, Washington D.C.

Dollar, David and Aart Kraay (2004) “Trade, Growth, and Poverty,” *Economic Journal*, Vol. 144, pp. F22–F49.

Douglas, Paul H. (1967) "Comments on the Cobb-Douglas production function," in M. Brown ed. *The Theory and Empirical Analysis of Production*: Columbia University Press, New York, pp. 15–22.

——— (1976) "The Cobb-Douglas Production Function Once Again: Its History, Its Testing, and Some New Empirical Values," *Journal of Political Economy*, Vol. 84(5), pp. 903–916.

Dube, Arindrajit and Sanjay G. Reddy (2014) "Threat Effects and Trade: Wage Discipline through Product Market Competition," *Journal of Globalization and Development*, Vol. 4(2), pp. 213–252.

van Edig, Xenia and Stefan Schwarze (2011) "Short-Term Poverty Dynamics of Rural Households: Evidence from Central Sulawesi, Indonesia," *Journal of Agriculture and Rural Development in the Tropics and Subtropics*, Vol. 112(2), pp. 141–155.

Edinson, Hali J., Michael W. Klein, Luca Ricci, and Torsten Sloek (2002) "Capital Account Liberalization and Economic Performance: Survey and Synthesis," Working Paper, No. 9100, National Bureau of Economic Research, Cambridge, MA.

Ellis, Lucy and Kathrin Smith (2007) "The global upward trend in the profit share," BIS Working Paper, 213, Bank for International Settlements, Basel.

Elsby, Michael and Bart Hobijnand Aysegül Sahin (2013) "The Decline of the U.S. Labor Share," *Brookings Papers on Economic Activity*, pp. 1–52.

Eriksen, Siri H., Katrina Brown, and P. Mick Kelly (2005) "The dynamics of vulnerability: locating coping strategies in Kenya and Tanzania," *The Geographical Journal*, Vol. 171(4), pp. 287–305.

Escobar, Arturo (2000) "Beyond the Search for a Paradigm? Post- Development and beyond," *Development*, Vol. 43, pp. 11–14.

Ethier, Wilfred and Lars E. O. Svensson (1986) "Theorems of international trade with factor mobility," *Journal of International Economics*, Vol. 20(1/2), pp. 21–42.

Euler, Michael, Munir Hoffmann, Zakky Fathonic, and Stefan Schwarze (2016) "Exploring yield gaps in smallholder oil palm production systems in eastern Sumatra, Indonesia," *Agricultural Systems*, Vol. 146, pp. 111–119.

FAO (2012) *Statistical Yearbook*, Food and Agricultural Organization, Rome.

Feenstra, Robert, Robert Inklaar, and Marcel P. Timmer (2015) "The Next Generation of the Penn World Table," *American Economic Review*, Vol. 105(10), pp. 3150–3182.

Feintrenie, Lauréne, Wan Kian Chong, and Patrice Levang (2010) "Why do farmers prefer oil palm? Lessons learnt from Bungo District, Indonesia," *Small-scale Forestry*, Vol. 9(3), pp. 379–396.

Fernandez-Arias, Eduardo (1996) "The new wave of private capital inflows: Push or pull?" *Journal of Development Economics*, Vol. 48(2), pp. 389–418.

Fields, Gary S. (2011) "Poverty and Low Earnings in the Developing World," ILR School Working Paper, 7, Cornell University, New York.

——— (2014) "Self-employment and poverty in developing countries," IZA World of Labor, 60, Institute for the Study of Labor, Bonn.

Fofana, Ismael, Andre Lemelin, and John Cockburn (2005) "Balancing a Social Accounting Matrix: Theory and Application," Université Laval, Québec.

Fox, Louise and Thomas Pave Sohnesen (2012) "Household Enterprises in Sub-Saharan Africa: Why They Matter for Growth, Jobs, and Livelihoods," Policy Research Working Paper, World Bank, Washington D.C.

Francese, Maura and Carlos Mulas-Granados (2015) "Functional Income Distribution and Its Role in Explaining Inequality," IMF Working Paper, 15/244, International Monetary Fund, Washington D.C.

Fratzscher, Marcel (2011) "Capital ows, push versus pull factors and the global financial crisis," Working Paper, 1364, European Central Bank, Frankfurt.

Garnett, T., M. C. Appleby, A. Balmford, I. J. Bateman, T. G. Benton, P. Bloomer, B. Burlingame, M. Dawkins, L. Dolan, D. Fraser, M. Herrero, I. Hoffmann, P. Smith, P. K. Thornton, C. Toulmin, S. J. Vermeulen, and H. C. J. Godfray (2013) "Sustainable Intensification in Agriculture: Premises and Policies," *Science*, Vol. 341(6141), pp. 33–34.

Giovannoni, Olivier (2014) "What Do We Know About the Labor Share and the Profit Share?," Levy Economics Institute Working Paper Collection, 803, Bard College, New York.

Glyn, Andrew (2009) *The Oxford Handbook of Economic Inequality*, Chap. Functional Distribution and Inequality, pp. 101–126: Oxford University Press, Oxford.

Goldberg, Pinelopi Koujianou and Nina Pavcnik (2007) "Distributional Effects of Globalization in Developing Countries," *Journal of Economic Literature*, Vol. 45(1), pp. 39–82.

Gollin, Douglas (2002) "Getting Income Shares Right," *Journal of Political Economy*, Vol. 110(2), pp. 458–74.

——— (2014) "The Lewis Model: A 60-Year Retrospective," *Journal of Economic Perspectives*, Vol. 28(3), pp. 71–88.

Görg, Holger, Hassan Molana, and Catia Montagna (2009) "Foreign direct investment, tax competition and social expenditure," *International Review of Economics & Finance*, Vol. 18(1), pp. 31–37.

Görg, Holger and Eric Strobl (2005) "Spillovers from Foreign Firms through Worker Mobility: An Empirical Investigation," *Scandinavian Journal of Economics*, Vol. 107(4), pp. 693–709.

Govereh, Jones and T.S. Jayne (2003) "Cash cropping and food crop productivity: Synergies or trade-offs?" *Agricultural Economics*, Vol. 28(1), pp. 39–50.

Granger, Clive William John and Paul Newbold (1974) "Spurious Regressions in Econometrics," *Journal of Econometrics*, Vol. 2(2), pp. 111–120.

Grunewald, Nicole, Stephan Klasen, Inmaculada Martinez-Zarzoso, and Chris Muris (2017) "The Trade-off Between Income Inequality and Carbon Dioxide Emissions," *Ecological economics*, forthcoming.

Guerriero, Marta and Kunal Sen (2012) "What Determines the Share of Labour in National Income? A Cross-Country Analysis," IZA Discussion Paper Series, 6643, Institute for the Study of Labor, Bonn.

Günther, Isabel and Andrey Launov (2012) "Informal employment in developing countries: Opportunity or last resort?" *Journal of Development Economics*, Vol. 97(1), pp. 88–98.

Guscina, Anastasia (2006) "Effects of Globalization on Labor's Share in National Income," IMF Working Paper, 294, International Monetary Fund, Washington D.C.

Harding, Torfinn and Beata S. Javorcik (2012) “Foreign Direct Investment and Export Upgrading,” *Review of Economics and Statistics*, Vol. 94(4), pp. 964–980.

Harrison, Ann (2005) “Has Globalization Eroded Labor’s Share? Some Cross-Country Evidence,” MPRA Paper, University of Munich, Munich.

Harvey, Celia A., Zo Lalaina Rakotobe, Nalini S. Rao, Radhika Dave, Hery Razafimahatratra, Rivo Hasinandrianina Rabarijohn, Haingo Rajaofara, and James L. MacKinnon (2014) “Extreme vulnerability of smallholder farmers to agricultural risks and climate change in Madagascar,” *Philosophical Transactions of the Royal Society B*, Vol. 369(1639).

Hashimoto, Yuko and K. M. Wacker (2016) “The role of information for international capital flows: new evidence from the SDDS,” *Review of World Economics*, Vol. 152(3), pp. 529–557.

Havranek, Tomas and Zuzana Irsova (2011) “Estimating vertical spillovers from FDI: Why results vary and what the true effect is,” *Journal of International Economics*, Vol. 85(2), pp. 234–244.

Helpman, Elhanan, Marc J. Melitz, and Stephen R. Yeaple (2004) “Export Versus FDI with Heterogeneous Firms,” *American Economic Review*, Vol. 94(1), pp. 300–316.

Hettig, Jann Lay, Elisabeth and Kacana Sipangule (2016) “Drivers of Households Land-Use Decisions: A Critical Review of Micro-Level Studies in Tropical Regions,” *Land*, Vol. 5(4).

Hijzen, Alexander, Pedro S. Martins, Thorsten Schank, and Richard Upward (2013) “Foreign-owned firms around the world: A comparative analysis of wages and employment at the micro-level,” *European Economic Review*, Vol. 60, pp. 170 – 188.

Holtz-Eakin, Douglas and Thomas M. Selden (1995) “Stoking the fires? CO2 emissions and economic growth,” *Journal of Public Economics*, Vol. 57(1), pp. 85–101.

Hutchinson, John and Damiaan Persyn (2012) “Globalisation, Concentration and Footlose Firms: In Search of the Main Cause of the Declining Labor Share,” *Review of World Economics*, Vol. 148(1), pp. 17–43.

ICCO (2012) “Annual Report,” URL: http://www.icco.org/about-us/icco-annual-report.html, International Cocoa Organization, Abidjan.

IFPRI (2015) "Social Accounting Matrices," International Food Policy and Research Institute, Washington D.C. URL: https://dataverse.harvard.edu/dataverse/IFPRI, accessed on 11 February 2017.

ILO (2010) "Wage policies in times of crisis," Global Wage Report 2010/11, International Labour Organization, Geneva.

——— (2013) "Wages and equitable growth," Global Wage Report 2012/13, International Labour Organization, Geneva.

——— (2014a) "Developing with jobs," World of Work Report 2014, International Labour Organization, Geneva.

——— (2014b) "Risk of a jobless recovery?," Global Employment Trends, International Labour Organization, Geneva.

——— (2015) "Wages and income inequality," Global Wage Report 2014/15, International Labour Organization, Geneva.

——— (2016) "Trends 2016," World Employment and Social Outlook, International Labour Organization, Geneva.

——— (2017a) "ILO modeled estimates," ILOSTAT, International Labor Organization, Geneva.

——— (2017b) "Key Indicators of the Labour Market (KILM)," URL: http://www.ilo.org/ilostat/faces/ilostat-home/home?_adf.ctrl-state=1b2e7htvgk_4&_afrLoop=286517921545847, accessed on 11 February 2017.

ILO, OECD, IMF and WB (2015) "Income Inequality and labour income share in G20 countries: Trens, Impacts and Causes," Prepared for the G20 Labour and Employment Ministers Meeting and Joint Meeting with the G20 Finance Ministers, Ankara, Turkey, 3-4 September 2015.

IMF (2007) "Globalization and inequality," World Economic Outlook, International Monetary Fund, Washington D.C.

IMF (2009) *Balance of Payments and International Investment Position Manual*, International Monetary Fund, Washington D.C.

——— (2017) "Gaining Momentum," World Economic Outlook, International Monetary Fund, Washington D.C.

Imrohorolu, Ayse and Murat Üngör (2016) "Is Zimbabwe More Productive Than the United States? Some Observations From PWT 8.1," Economics Discussion Paper, 1606, University of Otago, Dunedin.

Inklaar, Robert and Marcel Timmer (2013) "Capital, Labor and TFP in PWT 8.0," Groningen Growth and Development Center, University of Groningen.

IPCC (2007) "Climate Change 2007: The Physical Science Basis," Intergovernmental Panel on Climate Change, Geneva, Contribution of Working Group I to the Fourth Assessment Report of the Intergovernmental Panel on Climate Change.

Islam, Rizwanul (2006) "Fighting Poverty: The Development - Employment Link," *Development and Change*, Vol. 39(2), pp. 338–340.

Ittersum, Martin K.van, Kenneth G. Cassman, Patricio Grassini, Joost Wolf, Pablo Tittonell, and Zvi Hochman (2013) "Yield gap analysis with local to global relevance - A review," *Field Crops Research*, Vol. 143(1), pp. 4–17.

Izyumov, Alexei and John Vahaly (2015) "Income Shares Revisited," *Review of Income and Wealth*, Vol. 61(1), pp. 179–188.

Jakob, Michael, Jan Christoph Steckel, Stephan Klasen, Jann Lay, Nicole Grunewald, Inmaculada MartÃnez-Zarzoso, Sebastian Renner, and Ottmar Edenhofer (2014) "Feasible mitigation actions in developing countries," *Nature Climate Change*, Vol. 4, pp. 961–968.

Jaumotte, Florence and Irina Tytell (2007) "How Has The Globalization of Labor Affected the Labor Income Share in Advanced Countries?," IMF Working Paper, 298, International Monetary Fund, Washington D.C.

Javorcik, Beata S. and Shang-Jin Wei (2009) "Corruption and cross-border investment in emerging markets: Firm-level evidence," *Journal of International Money and Finance*, Vol. 28(4), pp. 605–624.

Jayadev, Arjun (2007) "Capital Account Openness and the Labor Share of Income," *Cambridge Journal of Economics*, Vol. 31(3), pp. 423–43.

Jeanne, Olivier, Arvind Subramanian, and John Williamson (2012) *Who Needs to Open the Capital Account?*: Peterson Institute for International Econometrics, Washington D.C.

Jerven, Morten (2012) "Comparability of GDP estimates in Sub-Saharan Africa: The effect of Revisions in Sources and Methods Since Structural Adjustment," *Review of Income and Wealth*, Vol. 59(S1), pp. S16–36.

Johnson, Simon, Daniel Kaufmann, Andrei Shleifer, Marshall I. Goldman, and Martin L. Weitzman (1997) "The Unofficial Economy in Transition," Brookings Papers on Economic Activity, 2, Brookings Institutions, Washington D.C.

Juhrband, Jana, Thomas Duwe, Jan Barkmann, Gerhard Gerold, and Rainer Marggraf (2010) "Structure and Management of Cocoa Agroforestry Systems in Central Sulawesi across an Intensification Gradient," in Teja Tscharntke, Christoph Leuschner, Edzo Veldkamp, Heiko Faust, Edi Guhardja, and Arifuddin Bidin eds. *Tropical Rainforests and Agroforests under Global Change*: Springer, Berlin, pp. 351–376.

Kaldor, Nicholas (1957) "A Model of Economic Growth," *The Economic Journal*, Vol. 67(268), pp. 591–642.

Kanbur, Ravi and Joseph Stiglitz (2015) "Wealth and income distribution: New theories needed for a new era," URL: http://voxeu.org/article/wealth-and-income-distribution-new-theories-needed-new-era, accessed on 24 May 2017.

Kao, Chihwa (1999) "Spurious regression and residual-based tests for cointegration in panel data," *Journal of Econometrics*, Vol. 90(1), pp. 1–44.

Karabarbounis, L. and B. Neiman (2014) "The Global Decline of the Labor Share," *The Quarterly Journal of Economics*, Vol. 129(1), pp. 61–103.

Kaufmann, Daniel and Aleksander Kaliberda (1996) "Integrating the Unofficial Economy into the Dynamics of Post-Socialist Economies: A Framework of Analysis and Evidence," Policy Research Working Paper, 1691, World Bank, Washington D.C.

Kesternich, Iris and Monika Schnitzer (2010) "Who is afraid of political risk? Multinational firms and their choice of capital structure," *Journal of International Economics*, Vol. 82(2), pp. 208 – 218.

Klasen, Stephan (2016) "What to do about rising inequality in developing countries?," PEGNet Policy Brief, 5/2016, Institute of the World Economy, Kiel.

Klasen, Stephan, Katrin M. Meyer, Claudia Dislich, Michael Euler, Heiko Faust, Marcel Gatto, Elisabeth Hettig, Nengah Surati Jaya, Fenna Otten, César Pérez-Cruzado, Stefanie Steinebach, Suria Tarigan, and Kerstin Wiegand (2016) "Economic and ecological trade-offs of agricultural specialization at different spatial scales," *Ecological Economics*, Vol. 122, pp. 111–120.

Klasen, Stephan, Jan Priebe, and Robert Rudolf (2013) "Cash crop choice and income dynamics in rural areas: evidence for post-crisis Indonesia," *Agricultural Economics*, Vol. 44, pp. 349–364.

Kose, M. Ayhan, Eswar S. Prasad, Kenneth Rogoff, and Shang-Jin Wei (2009a) "Financial Globalization: A Reappraisal," IMF Staff Papers, 56(1), International Monetary Fund, Washington D.C.

Kose, M. Ayhan, Eswar S. Prasad, and Marco E. Terrones (2009b) "Does openness to international financial flows raise productivity growth?," *Journal of International Money and Finance*, Vol. 28, pp. 554–580.

Kravis, Irving B. (1959) "Relative Income Shares in Fact and Theory," *The American Economic Review*, Vol. 49(5), pp. 917–949.

Krueger, Alan B. (1998) "Measuring Labor's Share," *The American Economic Review*, Vol. 89(2), pp. 45–51.

Le Blanc, David (2015) "Towards integration at last? The sustainable development goals as a network of targets," DESA Working Paper, 141, United Nations Department of Economic and Social Affairs, New York.

Lewis, Arthur W. (1954) "Economic Development with Unlimited Supplies of Labour," *The Manchester School*, Vol. 22, pp. 139–191.

Lipsey, Robert E. (2002) "Home and host country effects of FDI," Working Paper, No. 9293, National Bureau of Economics Research, Cambridge, MA.

Lipton, Michael (2005) "The Family Farm in a Globalizing World: The Role of Crop Science in Alleviating Poverty," 2020 Discussion Paper, 40, International Food Policy Research Institute, Washington D.C.

Loayza, Norman and Claudio Raddatz (2006) "The composition of growth matters for poverty alleviation," Policy Research Working Paper, 4077, World Bank, Washington D.C.

Lübker, Malte (2002) "Assessing the impact of past distributional shifts on global poverty levels," Employment Paper, 37, International Labour Organization, Geneva.

Maarek, Paul and Bruno Decreuse (2015) "FDI and the labor share in developing countries: A theory and some evidence," *Annals of Economics and Statistics*, Vol. 119-120, pp. 289–319.

Maddala, Gangadharrao Soundalyarao and Shaowen Wu (1999) "A Comparative Study of Unit Root Tests with Panel Data and a New Simple Test," *Oxford Bulletin of Economics and Statistics*, Vol. 61, pp. 631–652.

Maertens, Miet, Manfred Zeller, and Regina Birner (2006) "Sustainable agricultural intensification in forest frontier areas," *Agricultural Economics*, Vol. 34(2), pp. 197–206.

Markusen, James R., Anthony J. Venables, Denise Eby-Konan, and Kevin Honglin Zhang (1996) "A unified treatment of horizontal direct investment, vertical direct investment and the pattern of trade in goods and services," Working Paper, No. 5696, National Bureau of Economic Research, Cambridge, MA.

Marterbauer, Markus and Ewald Walterskirchen (2003) "Bestimmungsgründe der Lohnquote und der realen Lohnstückkosten," WIFO-Monatsberichte, 2, Austrian Insitute of Economic Research, Vienna.

Mayer, Thierry and Soledad Zignago (2011) "Notes on CEPII's distances measures the GeoDist Database," Working Paper, 2011-25, CEPII, Paris.

McCullough, Ellen B. (2017) "Labor productivity and employment gaps in Sub-Saharan Africa," *Food Policy*, Vol. 67, pp. 133–152.

Melamed, Claire (2012) "After 2015: Contexts, politics and processes for a post-2015 global agreement on development," Working Paper, Overseas Development Institute, London.

Melamed, Claire, Renate Hartwig, and Ursula Grant (2011) "Jobs, growth and poverty: what do we know, what donât we know, what should we know?," Background Note, Overseas Development Institute, London.

Milanovic, Branko (2012) "Global income inequality by the numbers: In history and now – an overview," Policy Research Working Paper, 6259, World Bank: Washington DC.

——— (2015) *Global Inequality: A New Approach for the Age of Globalization*: Harvard University Press, Cambridge.

Ministry of Industry (2016) “Industri Scrap 800 Ribu Ton Kakao,” Jakarta, URL: http://www.kemenperin.go.id/artikel/4740/2015,-Industri-Scrap-800-Ribu-Ton-Kakao, accessed on 6 June 2016.

Moreira, Marcelo J. (2003) “A Conditional Likelihood Ratio Test for Structural Models,” *Econometrica*, Vol. 71(4), pp. 1027–1048.

Mueller, Nathaniel D., James S. Gerber, Matt Johnston, Deepak K. Ray, Navin Ramankutty, and Jonathan A. Foley (2012) “Closing yield gaps through nutrient and water management,” *Nature*, Vol. 490, pp. 254–257.

Mundell, Robert A. (1957) “International Trade and Factor Mobility,” *American Economic Review*, Vol. 47(3), pp. 321–335.

Mundlak, Yair, Donald F. Larson, and Rita Butzer (2002) “Determinants of Agricultural Growth in Indonesia, the Philippines, and Thailand,” Policy Research Working Paper, 2803, World Bank, Washington D.C.

Neilson, Jeff (2007) “Global markets, farmers and the state: Sustaining profits in the Indonesian cocoa sector,” *Bulletin of Indonesian Economic Studies*, Vol. 43(2), pp. 227–250.

Neumann, Kathleen, Peter H. Verburg, Elke Stehfest, and Christoph Müller (2010) “The yield gap of global grain production: A spatial analysis,” *Agricultural Systems*, Vol. 103(5), pp. 316–326.

Nolte, Kerstin and Martin Ostermeier (2017) “Labour Market Effects of Large-Scale Agricultural Investment : Conceptual Considerations and Estimated Employment Effects,” *World Development*, forthcoming.

Nunn, Nathan and Nancy Qian (2014) “U.S. Food Aid and Civil Conflict,” *American Economic Review*, Vol. 104(6), pp. 1630–1666.

Nuryartono, Nunung and N. Khumaida (2016) “Indonesia cocoa productivity: How high should we go?,” Petuah Policy Brief, 3.

OECD (2004) “OECD Employment Outlook,” OECD Publishing, Organisation for Economic Co-operation and Development, Paris.

——— (2009) *Promoting Pro-Poor Growth: Employment*: Organisation for Economic Co-operation and Development, Paris.

OECD (2012) "OECD Employment Outlook," OECD Publishing, Organisation for Economic Co-operation and Development, Paris.

OECD (2015) "Indonesia," OECD Economic Surveys, Organisation for Economic Co-operation and Development, Paris.

Onaran, Ozlem (2009) "From the Crisis of Distribution to the Distribution of the Costs of the Crisis: What can We Learn from Previous Crises about the Effects of the Financial Crisis on Labor Share?" Working Paper 195, Political Economy Research Institute, University of Massachusetts at Amherst.

Onaran, Özlem, Engelbert Stockhammer, and Lucas Grafl (2011) "Financialisation, income distribution and aggregate demand in the USA," *Cambridge Journal of Economics*, Vol. 35(4), pp. 637–661.

Ortega, Daniel and Francisco Rodriguez (2001) "Openness and Factor Shares," Economic Commission for Latin America and the Caribbean, Santiago de Chile.

Piketty, Thomas (2014) *Capital in the twenty-first century*: Harvard University Press, Cambridge.

Prasad, Eswar S., Kenneth Rogoff, Shang-Jin Wei, and M. Ayhan Kose (2003) "Effects of Financial Globalization on Developing Countries: Some Empirical Evidence," Occasional Paper 220, International Monetary Fund.

PWT (2013) "Penn World Tables, Release 8.0," URL: http://www.rug.nl/ggdc/productivity/pwt/pwt-releases/pwt8.0, accessed on 11 February 2017.

Pyatt, Graham and Jeffery I. Round (1985) "Social accounting matrices: a basis for planning," World Bank Symposium, World Bank, Washington D.C.

Rani, Uma and Marianne Furrer (2016) "Decomposing income inequality into factor income components: Evidence from selected G20 countries," ILO Research Working Paper, 15, International Labour Organization, Geneva.

Ravallion, Martin (2001) "Growth, Inequality and Poverty: Looking Beyond Averages," *World Development*, Vol. 29(11), pp. 1803–1815.

Ravallion, Martin, Mark Heil, and Jyotsna Jalan (2000) "Carbon emissions and income inequality," *Oxford Economic Papers*, Vol. 52(4), pp. 651–669.

Ray, Debraj (1998) *Development Economics*: Princeton University Press, Princeton.

Razin, Assaf, Efraim Sadka, and Chi-Wa Yuen (1998) "A pecking order of capital inflows and international tax principles," *Journal of International Economics*, Vol. 44(1), pp. 45–68.

Reinhart, Carmen, Guillermo Calvo, and Leonardo Leiderman (1993) "Capital Inflows and The Real Exchange Rate Appreciation in Latin America: The Role of External Factors," *IMF Staff Papers*, Vol. 40, pp. 108–151.

Rey, Helene (2013) "Dilemma not Trilemma: The global financial cycle and monetary policy independence," Paper presented at the Jackson Hole Symposium.

Rice, Robert A. and Russell Greenberg (2000) "Cacao cultivation and the conservation of biological diversity," *Ambio: A Journal of the Human Environment*, Vol. 29(3), pp. 167–173.

Richardson, J. David and Elena Borisovna Khripounova (1998) "U.S. Labor Market Power and Linkages to International Trade: Identifying Suspects and Measures," mimeo, Draft for U.S. Department of Labor, Washington D.C.

Rist, Lucy, Laurène Feintrenie, and Patrice Levang (2010) "The livelihood impacts of oil palm: smallholders in Indonesia," *Biodiversity and Conservation*, Vol. 19, pp. 1009–1024.

Robertson, Philip, Eldor A. Paul, and Richard R. Harwood (2000) "Greenhouse Gases in Intensive Agriculture: Contributions of Individual Gases to the Radiative Forcing of the Atmosphere," *Science*, Vol. 289(5486), pp. 1922–1925.

Robinson, Sherman, Andrea Cattaneo, and Moataz El-Said (2001) "Updating and Estimating a Social Accounting Matrix Using Cross Entropy Methods," *Economic Systems Research*, Vol. 13(1), pp. 47–64.

Rodriguez, Francisco and Arjun Jayadev (2010) "The Declining Labor Share of Income," Human Development Reports Research Paper, 25, United Nations Development Programme, New York.

Rodrik, Dani (1997) *Has Globalization Gone Too Far?*: Institute for International Economics, Washington D.C.

Rognlie, Matthew (2015) “Deciphering the fall and rise in the net capital share,” *Brookings Papers on Economic Activity*, pp. 1–54.

Round, Jeffrey I. (2001) “Constructing SAMs for Development Policy Analysis: Lessons Learned and Challenges Ahead,” *Economic Systems Research*, Vol. 15(2), pp. 161–183.

Ruf, François and Yoddang (2004) “Adoption of cocoa,” in Frederic Lançon François Ruf ed. *From slash-and-burn to replanting: Green revolutions in the Indonesian uplands*: World Bank, Washington D.C., pp. 173–191.

Sabatier, Rodolphe, Kerstin Wiegand, and Katrin Meyer (2013) “Production and robustness of a Cacao agroecosystem: effects of two contrasting types of management strategies,” *PLoS One*, Vol. 8(12).

Sachs, Jeffrey D. (2015) *The Age of Sustainable Development*: Columbia University Press, New York.

Sachs, Jeffrey D. and Shiv Someshwar (2012) “Green Growth and Equity in the Context of Climate Change: Some Considerations,” ADBI Working Paper Series, 371, Asian Development Bank Institute, Tokyo.

Sachs, Wolfgang (1992) *The Development Dictionary: A Guide to Knowledge as Power*: Zed Books, New York.

Sandmo, Agnar (2015) *Handbook of Income Distribution*, Chap. The principal problem in political economy: Income distribution in the history of economic thought: Elsevier, North Holland.

Schneider, Friedrich and Andreas Bühn (2016) “Estimating the Size of the Shadow Economy: Methods, Problems and Open Questions,” IZA Discussion Paper Series, 9820, Institute for the Study of Labor, Bonn.

Schreinemachers, Pepijn, Swaminathan Balasubramaniam, N. Manikanda Boopathi, Cuong Viet Ha, Lawrence Kenyon, Suwanna Praneetvatakul, Aer Sirijinda, Nghia Tuan Led, Ramasamy Srinivasan, and Mei-Huey Wu (2015) “Farmers’ perceptions and management of plant viruses in vegetables and legumes in tropical and subtropical Asia,” *Crop Protection*, Vol. 75, pp. 115–123.

SDSN (2013) “Solutions for Sustainable Agriculture and Food Systems,” Technical Report for the post-2015 Development Agenda, Sustainable Development Solution Network, New York.

Sen, Amartya (2000) *Employment, Technology and Development*: Oxford University Press, New York.

Seyfang, Gill and Jouni Paavola (2008) "Inequality and sustainable consumption: bridging the gaps," *Local Environment*, Vol. 13(8), pp. 669–684.

Silici, Laura, Calisto Bias, and Eunice Cavane (2015) "Sustainable agriculture for small-scale farmers in Mozambique," Country report, International Institute for Environment and Development, London.

Slaughter, Matthew J. (2001) "International Trade and Labor Demand Elasticities," *Journal of International Economics*, Vol. 54(1), pp. 27– 56.

Solow, Robert M. (1956) "A Contribution to the Theory of Economic Growth," *The Quarterly Journal of Economics*, Vol. 70(1), pp. 65–94.

Steffan-Dewenter, Ingolf, Michael Kessler, Jan Barkmann, Merijn M. Bos, Damayanti Buchori, Stefan Erasmi, Heiko Faust, Gerhard Gerold, Klaus Glenk, S. Robbert Gradstein, Edi Guhardja, Marieke Harteveld, Dietrich Hertel, Patrick Höhn, Martin Kappas, Stefan Köhler, Christoph Leuschner, Miet Maertens, Rainer Marggraf, Sonja Migge-Kleian, Johanis Mogea, Ramadhaniel Pitopang, Matthias Schaefer, Stefan Schwarze, Simone G. Sporn, Andrea Steingrebe, Sri S. Tjitrosoedirdjo, Soekisman Tjitrosoemito, André Twele, Robert Weber, Lars Woltmann, Manfred Zeller, and Teja Tscharntke (2007) "Tradeoffs between income, biodiversity, and ecosystem functioning during tropical rainforest conversion and agroforestry intensification," *PNAS*, Vol. 104, pp. 4973–4978.

Steffen, Will, Katherine Richardson, Johan RockstrÃ¶m, Sarah E. Cornell, Ingo Fetzer, Elena M. Bennett, Reinette Biggs, Stephen R. Carpenter, Wim de Vries, Cynthia A. de Wit, Carl Folke, Dieter Gerten, Jens Heinke, Georgina M. Mace, Linn M. Persson, Veerabhadran Ramanathan, Belinda Reyers, and Sverker SÃ¶rlin (2015) "Planetary boundaries: Guiding human development on a changing planet," *Science*, Vol. 347(6223).

Stiglitz, Amartya Sen, Joseph and Jean-Paul Fitoussi (2009) "Report by the Commission on the Measurement of Economic Performance and Social Progress."

Stiglitz, Joseph E. (2000) "Capital Market Liberalization, Economic Growth, and Instability," *World Development*, Vol. 28(6), pp. 1075–1086.

Stockhammer, Engelbert (2013) "Why Have Wage Shares Fallen? An Analysis of the Determinants of Functional Income Distribution," Conditions of Work and Employment Series, 35, International Labour Organization, Geneva.

Summers, Lawrence H. (2014) "The Inequality Puzzle," *Democracy - A Journal of Ideas*, Vol. 33, pp. 124–138.

Sunderlin, William D., Arild Angelsen, Daju Pradnja Resosudarmo, Ahmad Dermawan, and Edy Rianto (2001) "Economic crisis, small farmer well-being, and forest cover change in Indonesia," *World Development*, Vol. 29(5), pp. 767–782.

Swan, Trevor W. (1956) "Economic Growth and Capital Accumulation," *The Economic Record*, Vol. 32, pp. 334–361.

Thiele, Rainer and Daniel Piazolo (2002) "Constructing a Social Accounting Matrix with a Distributional Focus - The Case of Bolivia," Kiel Working Paper, 1094, Institute of the World Economy, Kiel.

Thurlow, James, David Evans, and Sherman Robinson (2004) "A 2001 Social Accounting Matrix for Zambia," International Food Policy Research Institute, Washington D.C.

Tilman, David, Kenneth G. Cassman, Pamela A. Matson, Rosamond Naylor, and Stephen Polasky (2002) "Agricultural sustainability and intensive production practices," *Nature*, Vol. 418, pp. 671–677.

Timmer, C. Peter (1988) "The Agricultural Transformation," in H Chenery and TN Srinivasan eds. *Handbook of Development Economics*: Elsevier, North-Holland, pp. 275–331.

Timmer, C. Peter (2007) "A Historical Perspective on Pro-Poor Growth in Indonesia," in Michael Grimm, Stefan Klasen, and Andrew McKay eds. *Determinants of Pro Poor Growth. Analytical Issues and Findings from Country Case*: Palgrave Macmillan, London.

Timmer, Marcel P., Erik Dietzenbacher, Bart Los, Robert Stehrer, and Gaaitzen de Vries (2015) "An Illustrated User Guide to the World Input-Output Database: the Case of Global Automotive Production," *Review of International Economics*, Vol. 23(3), pp. 575–605.

Tittonell, Peter and Ken E. Giller (2013) "When yield gaps are poverty traps: The paradigm of ecological intensification in African smallholder agriculture," *Field Crops Research*, Vol. 143, pp. 76–90.

Tittonell, Peter, B Vanlauwe, N de Ridder, and Ken E. Giller (2007) "Heterogeneity of crop productivity and resource use efficiency within smallholder Kenyan farms: Soil fertility gradients or management intensity gradients?" *Agricultural Systems*, Vol. 94.

Todaro, Michael P. and Stephen C. Smith (2009) *Economic Development*: Pearson Education Limited, Essex.

Trapp, Katharina (2015) "Measuring the Labour Income Share of Developing Countries: Learning from Social Accounting Matrices," UNU-WIDER Working Paper, 41, United Nations University World Institute for Development Economics Research, Helsinki.

UN (2009) "System of national accounts 2008," United Nations, European Commission, International Monetary Fund, OECD and World Bank.

——— (2012) "Report of the Friends of the Chair on the barriers to the implementation of the System of National Accounts 1993," Economic and Social Council Statistical Commission, New York.

——— (2015) "The Millenium Development Goals Report," United Nations, New York.

——— (2016) "Millenium Development Goals," URL: http://www.un.org/millenniumgoals, accessed on 18 June 2017.

UN DESA (2015) "Social Accounting Matrices," United Nations Department of Economic and Social Affairs, New York, URL: https://www.un.org/esa/desa, accessed on 23 January 2015.

UN SNA (2015) "United Nations System of National Accounts, National Accounts Official Country Data," United Nations, New York, URL: http://data.un.org/Explorer.aspx?d=SNA, accessed on 11 February 2017.

UNCTAD (2014) "Growth with Structural Transformation: A post 2015 development agenda," The least developed countries report, United Nations Conference on Trade and Development, Geneva.

——— (2015) "Smallholder Farmers and Sustainable Commodity Development," Commodities and Development Report, United Nations Conference on Trade and Development, Geneva.

UNDP (1997) "Human Development to Eradicate Poverty," Human Development Report 1997, United Nations Development Programme, New York.

——— (2013) *Humanity Divided*: Bureau for Development Policy, New York.

UNIDO (2015) “Industrial Statistics Database - 2015 edition,” URL: http://www.unido.org/resources/statistics/statistical-databases/indstat2-2015-edition.html, accessed on 15 May 2017.

UNSD (2016) “SDG Indicators Metadata repository,” United Nations Statistics Division, New York, URL: https://unstats.un.org/sdgs/metadata/, accessed on 6th April 2017.

UNU-WIDER (2017) “World Income Inequality Database - WIID 3.4,” United Nations University World Institute for Development Economics Research, URL: https://www.wider.unu.edu/database/world-income-inequality-database-wiid34, accessed on 13 July 2017.

US Bureau of Economic Analysis (2009) “Concepts and Methods of the U.S. National Income and Product Accounts,” United States Department of Commerce, Washington D.C.

van Nieuwerburgh, Stijn and Laura Veldkamp (2009) “Information Immobility and the Home Bias Puzzle,” *Journal of Finance*, Vol. 64(3), pp. 1187–1215.

Vandemoortele, Jan (2011) “The MDG Story: Intention Denied,” *Development and Change*, Vol. 42, pp. 1–21.

Vanwambeke, Sophie O., Pradya Somboon, and Eric F. Lambin (2007) “Rural transformation and land-use change in northern Thailand,” *Journal of Land Use Science*, Vol. 2(1), pp. 1–29.

Verhoogen, Eric (2008) “Trade, Quality Upgrading and Wage Inequality in the Mexican Manufacturing Sector,” *Quarterly Journal of Economics*, Vol. 123(2), pp. 489–530.

Wacker, Konstantin, Philipp Großkurth, and Tabea Lakemann (2016) “FDI, Export Prices, and Quality Upgrading: What is so special about South Asia?,” *Asian Development Review*, Vol. 33(1), pp. 28–55.

Wacker, Konstantin M. (2013) “On the Measurement of Foreign Direct Investment and its Relationship to Activities of Multinational Corporations,” Working Paper, 1614, European Central Bank, Frankfurt.

——— (2016) “(When) Should We Use Foreign Direct Investment Data to Measure the Activities of Multinational Corporations? Theory and Evidence,” *Review of International Economics*, Vol. 24(5), pp. 980–999.

Wacker, Konstantin M., David Lodge, and Giulio Nicoletti (2014) "Measuring Financial Conditions in Major Non-Euro Area Economies," Working Paper, 1743, European Central Bank, Frankfurt.

Walker, Robert, Stephen Perz, Marcellus Caldas, and Luiz Guilherme Teixeira Silva (2002) "Land Use and Land Cover Change in Forest Frontiers: The Role of Household Life Cycles," *International Regional Science Review*, Vol. 25(2), pp. 169–199.

WB (2006) "Equity and Development," World Development Report, World Bank, Washington D.C.

——— (2008) "Agriculture for Development," World Development Report, World Bank, Washington D.C.

——— (2013) "Jobs," World Development Report, World Bank, Washington D.C.

——— (2016a) "Agriculture, value added," World Bank, Washington D.C. URL: http://data.worldbank.org/indicator/NV.AGR.TOTL.ZS, accessed on 26 June 2017.

——— (2016b) "Commodity price data (the pink sheet)," World Bank, Washington D.C. URL: http://www.worldbank.org/en/research/commodity-markets, accessed on 4 February 2017.

——— (2016c) "Indonesia," World Bank, Washington D.C. URL: http://data.worldbank.org/country/indonesia, accessed on 6 December 2016.

WB (2016d) "Taking on Inequality," Poverty and shared prosperity, World Bank, Washington D.C.

——— (2017) "World Development Indicators," World Bank, Washington D.C. URL: http://data.worldbank.org/data-catalog/world-development-indicators, accessed on 11 February 2017.

Wei, Shang-Jin (2000) "Local Corruption and Global Capital Flows," *Brookings Papers on Economic Activity*, Vol. 2, pp. 303–354.

Wiggins, Steve, Johann Kirsten, and Luis Llambí (2010) "The Future of Small Farms," *World Development*, Vol. 38(10), pp. 1341–1348.

WIOD (2013) "World Input Output Database, Socio Economic Accounts," URL: http://www.wiod.org/database/seas13, accessed on 4 August 2017.

Wood, Benjamin, Carl Nelson, Talip Kilic, and Siobhan Murray (2013) “Up in smoke? Agricultural commercialization, rising food prices and stunting in Malawi,” Policy Research Working Paper, 6650, World Bank, Washington D.C.

Wood, George Alan R. and RA Lass (2001) *Cocoa*: Blackwell Science, Oxford.

Yeaple, Stephen Ross (2003) “The complex integration strategies of multinationals and cross country dependencies in the structure of Foreign Direct Investment,” *Journal of International Economics*, Vol. 60(2), pp. 293–314.

Young, Andrew T. and Robert A. Lawson (2014) “Capitalism and labor shares: A cross-country panel study,” *European Journal of Political Economy*, Vol. 33(1), pp. 20–36.

Yusuf, Arief Anshory (2006) “Constructing Indonesian Social Accounting Matrix for Distributional Analysis in the CGE Modelling Framework,” MPRA Paper, 1730, University of Munich, Munich.

Zeller, Stefan Schwarze, Manfred and Teunis van Rheenen (2002) “Statistical Sampling Frame and Methods Used for the Selection of Villages and Households in the Scope of the Research Program on Stability of Rainforest Margins in Indonesia (STORMA),” STORMA Discussion Paper Series, 1, Research Project on Stability of Rain Forest Margins (STORMA).

Zhang, Longmei (2016) “Rebalancing in China - Progress and Prospects,” IMF Working Paper, 186, International Monetary Fund, Washington D.C.

Zhen, Lin, Jayant K. Routray, Michael A. Zoebisch, Guibao Chend, Gaodi Xie, and Shengkui Cheng (2005) “Three dimensions of sustainability of farming practices in the North China Plain A case study from Ningjin County of Shandong Province, PR China,” *Agriculture, Ecosystems and Environment*, Vol. 105, pp. 507–522.

Ziai, Aram (2012) “Postcolonial perspectives on development,” ZEF Working Paper, 103, Center for Development Research, Bonn.

Appendix A

Chapter 2

Countries included in the data set:

Algeria, Argentina, Armenia, Azerbaijan, Bahrain, Belarus, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Chile, China, Colombia, Costa Rica, Cote d'Ivoire, Croatia, Cuba, Czech Republic, Democratic Republic of Congo, Djibouti, Dominican Republic, Ecuador, Egypt, Estonia, Fiji, Gabon, Georgia, Greece, Guatemala, Guinea, Honduras, Hungary, India, Iran, Iraq, Jamaica, Jordan, Kazakhstan, Kenya, Kyrgyz Republic, Lao People's Democratic Republic, Latvia, Lebanon, Lesotho, Lithuania, Macedonia, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Morocco, Mozambique, Namibia, Nicaragua, Niger, Nigeria, Oman, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Portugal, Romania, Russia, Saudi Arabia, Senegal, Serbia, Seychelles, Sierra Leone, Slovak Republic, Slovenia, South Africa, South Sudan, Sri Lanka, Sudan, Suriname, Tajikistan, Tanzania, Thailand, Trinidad and Tobago, Tunisia, Turkey, Ukraine, Uruguay, Venezuela, Zimbabwe.

Appendix B

Chapter 3

Countries included in the data sets:

UN SNA, PWT and Trapp data: Algeria, Argentina, Armenia, Azerbaijan, Bahrain, Belarus, Benin, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Bulgaria, Burkina Faso, Burundi, Cameroon, Central African Republic, Chad, Chile, China, Colombia, Costa Rica, Cote d'Ivoire, Croatia, Cuba, Czech Republic, Democratic Republic of Congo, Djibouti, Dominican Republic, Ecuador, Egypt, Estonia, Fiji, Gabon, Georgia, Guatemala, Guinea, Honduras, Hungary, India, Iran, Iraq, Jamaica, Jordan, Kazakhstan, Kenya, Kyrgyz Republic, Lao People's Democratic Republic, Latvia, Lebanon, Lesotho, Lithuania, Macedonia, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Morocco, Mozambique, Namibia, Nicaragua, Niger, Nigeria, Oman, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Romania, Russia, Saudi Arabia, Senegal, Serbia, Seychelles, Sierra Leone, Slovak Republic, Slovenia, South Africa, Sri Lanka, Sudan, Suriname, Tajikistan, Tanzania, Thailand, Trinidad and Tobago, Tunisia, Turkey, Ukraine, Uruguay, Venezuela, Zimbabwe.

ILO data: Algeria, Argentina, Armenia, Azerbaijan, Bahrain, Belarus, Benin, Bolivia, Botswana, Brazil, Bulgaria, Cameroon, Chile, China, Columbia, Costa Rica, Cote d'Ivoire, Croatia, Cuba, Czech Republic, Djibouti, Dominican Republic, Ecuador, Egypt, Estonia, Fiji, Guatemala, Honduras, Hungary, India, Iran, Iraq, Jordan, Kazakhstan, Kenya, Kyrgyz Republic, Latvia, Lithuania, Macedonia, Mauritius, Mexico, Moldova, Mongolia, Morocco, Mozambique, Namibia, Nicaragua, Niger, Nigeria, Oman, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Romania, Russia, Saudi Arabia, Senegal, Serbia, Seychelles, Slovak Republic, South Africa, Sri Lanka, Tanzania, Thailand, Trinidad and Tobago, Tunisia, Turkey, Ukraine, Uruguay, Venezuela.

WIOD data: Bulgaria, Brazil, China, Czech Republic, Estonia, Hungary, India, Indonesia, Lithuania, Latvia, Mexico, Poland, Romania, Russia, Slovakia, Turkey.

UNIDO data: Algeria, Argentina, Armenia, Azerbaijan, Bangladesh, Belarus, Belize, Bolivia, Bosnia, and Herzegovina, Botswana, Brazil, Bulgaria, Burundi, Cambodia, Cameroon, Central African Republic, Chile, China, Columbia, Costa Rica, Cote d'Ivoire, Croatia, Czech Republic, Ecuador, Egypt, El Salvador, Eritrea, Estonia, Ethiopia, Fiji, Gabon, Gambia, Georgia, Ghana, Honduras, Hungary, India, Indonesia, Iran, Iraq, Jamaica, Jordan, Kenya, Kyrgyz Republic, People's Democratic Republic, Latvia, Lebanon, Lithuania, Macedonia, Madagascar, Malawi, Malaysia, Mauritius, Mexico, Moldova, Mongolia, Morocco, Nepal, Nigeria, Oman, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Poland, Puerto Rico, Romania, Russia, Rwanda, Saudi Arabia, Senegal, Sierra Leone, Slovak Republic, South Africa, Sri Lanka, St. Lucia, Sudan, Suriname, Swaziland, Syria, Tanzania, Thailand, Trinidad and Tobago, Tunisia, Turkey, Uganda, Ukraine, Uruguay, Venezuela, Vietnam, West Bank & Gaza, Yemen, Zambia.

Appendix C

Chapter 4

Table C.1: **Summary statistics**

Variable	Mean	(Std. Dev.)	N	Source
$\ln(LS_{PWT})$	3.883	(0.197)	309	PWT 8.0
$\ln(LS_{Trapp})$	3.756	(0.241)	307	own calculation
FDI stock/GDP	26.376	(22.488)	309	IFS, UN SNA
Portfolio stock/GDP	6.4	(9.351)	309	IFS, UN SNA
ln(GDP p.c.)	8.129	(0.783)	309	PWT 7.0
ln(Inflation) (-1)	1.948	(1.371)	309	WDI
Risk	66.52	(6.076)	309	ICRG
ln(Government share)	2.035	(0.425)	309	PWT 7.0
Education index	0.526	(0.165)	309	UNDP
K/L	30,504	(28,043)	309	own calculation
Trade	77.471	(34.781)	309	PWT 7.0
Crisis	0.03	(0.172)	263	own calculation
GFCF/GDP	21.226	(7.411)	309	WEO, UN SNA

Countries included (in baseline estimation of table 4.1), incl. number of observations: Armenia (11), Azerbaijan (8), Belarus (9), Bolivia (13), Brazil (3), Bulgaria (8), Burkina Faso (6), China (5), Colombia (17), Cote d'Ivoire (7), Dominican Republic (4), Egypt (6), Guatemala (5), Honduras (6), India (14), Jamaica (2), Jordan (10), Kazakhstan (8), Latvia (3), Lithuania (2), Moldova (12), Morocco (8), Mozambique (6), Namibia (3), Niger (11), Nigeria (5), Panama (3), Paraguay (15), Peru (18), Philippines (1), Poland (2), Russian Federation (9), Senegal (12), Tanzania (16), Thailand (15), Tunisia (15), Ukraine (9), Venezuela (2).

Table C.2: **Variable correlation matrix**

	$\ln(LS_{PWT})$	$\ln(LS_{Trapp})$	FDI	FPI	ln(GDP)	Inflation	Risk	ln(G/GDP)	Educ	K/L	Trade
$\ln(LS_{PWT})$	1										
$\ln(LS_{Trapp})$	0.462	1									
FDI stock/GDP	-0.149	0.0558	1								
Portfolio stock/GDP	-0.198	-0.198	0.193	1							
ln(GDP p.c.)	-0.141	-0.0273	0.222	0.369	1						
ln(Inflation) (-1)	0.159	0.119	-0.309	-0.0768	0.140	1					
Risk	-0.221	-0.0854	0.373	0.273	0.446	-0.356	1				
ln(Government share)	0.241	0.0764	-0.151	0.0379	-0.121	0.0216	-0.0861	1			
Education index	0.0523	0.0724	0.403	0.330	0.805	0.191	0.303	-0.149	1		
K/L	0.0520	-0.000133	0.178	0.417	0.595	0.141	0.314	-0.0326	0.524	1	
Trade	0.0609	0.168	0.431	0.244	0.311	-0.116	0.293	-0.0117	0.430	0.349	1
N	309										

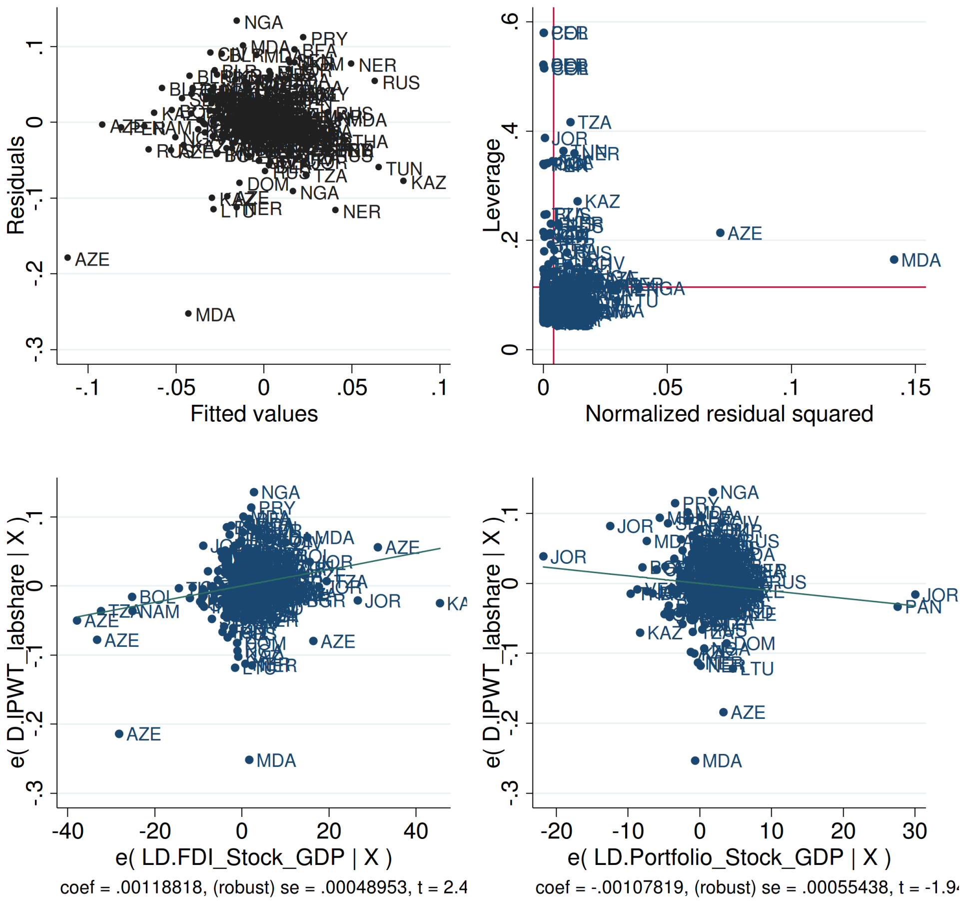
Table C.3 provides the first-stage results of our model, that is the equation explaining foreign investment by financial conditions in the financial centers and the distance therefrom. It should be noted that the model includes country and year fixed effects. The negative coefficient on the US FCI is hence not worrisome and should not be interpreted because it is only identified because of some year fixed effects dropping out. The measure of relevance is the (mostly positive) interaction of the respective FCIs with distance. This suggests that in times where it is easy for investors to attain access to finance, they are more likely to invest in more distant countries than otherwise. This is consistent with theory and can be compared to investors moving towards the long end of the yield curve (with more risky assets) if financial conditions are easy (and hence risk-taking increases).

Table C.3: **First-stage results**

VARIABLES	(1) FDI/GDP	(2) FPI/GDP
US FCI	-33.843**	-5.9290
	(14.428)	(5.2580)
US FCI x Dist(USA)	0.00020	0.00022**
	(0.00015)	(0.00009)
Euro FCI x Dist(BEL)	-0.00057	0.00059***
	(0.00057)	(0.00021)
Japan FCI x Dist(JPN)	0.00021	-0.00016
	(0.00054)	(0.00030)
included instruments: ln(GDP) ln(inflation)(-1), ICRG risk, ln(govt share), educ index, K/L, trade		
observations (clusters)	308 (37)	308 (37)
F-stat: overall / excluded IV	6.38 / 1.66	5.44 / 5.11
Kleibergen-Papp underidentification	p-value: 0.1226	
Hansen J overidentification	p-value: 0.4570	

The Hansen J statistic does not allow to reject the null hypothesis of joint validity of instruments and overidentifying restrictions (suggesting that the set of instruments are coherent in the sense that they identify the same vector of parameters).

Figure C.1: **Diagnostic checks (first-difference model)**



Note: The upper panel provides a plot of the model residuals against fitted values and a leverage-to-residual plot. The lower panel provides a component-plus-residual plot for the FDI and FPI variable, respectively.

Appendix D

Chapter 5

Table D.1: **Summary statistics**

VARIABLES	Unit	Year	Average	Min	Max	Median	Std. Dev.	N
Dependent variables								
Cocoa yield	kg/hectare	2001	211.6	0.0	2933.3	93.0	328.9	176
		2006	349.0	0.0	1140.0	300.0	273.0	233
		2013	815.6	0.0	4800.0	592.9	822.3	234
Crop failure	% of yield	-	-	-	-	-	-	-
	lost	2006	3.0	0.0	75.0	0.0	10.7	233
		2013	17.4	0.0	90.0	0.0	24.1	234
Basic agricultural parameters								
Cocoa area	hectare	2001	1.4	0.25	8.3	1.0	1.3	176
		2006	1.4	0.25	8.0	1.0	1.2	233
		2013	1.5	0.25	15.0	1.0	1.6	234
Tree age	years	2001	3.8	1.0	20.0	3.0	3.2	166
		2006	6.3	0.3	22.0	5.0	4.1	233
		2013	11.2	0.3	36.0	10.0	6.3	234
Labor exp.	000 IDR/ha	2001	25.3	0	500.0	0	76.9	176
		2006	39.0	0	966.7	0	111.9	233
		2013	52.2	0	1982.3	0	250.1	234
No. of family workers	number	2001	3.0	0	8	3	1.6	176
		2006	2.5	0	7	2	1.3	233
		2013	1.9	0	6	2	1.2	233
Management practices								
Fertilizer exp.	000 IDR/ha	2001	29.5	0	710	0	110.5	176
		2006	17.5	0	433.7	0	60	233
		2013	69.3	0	1397.2	0	170.7	234
Use of herbicides	dummy	2001	0.1	0	1	0	0.3	176
	0=no	2006	0.4	0	1	0	0.5	233
	1=yes	2013	0.5	0	1	0	0.5	234
Manual weeding	dummy	2001	0.6	0	1	1	0.5	176
	0=no	2006	0.5	0	1	1	0.5	233
	1=yes	2013	0.5	0	1	1	0.5	234
Pruning	dummy	2001	0.7	0	1	1	0.5	176
	0=no	2006	0.9	0	1	1	0.3	233
	1=yes	2013	0.9	0	1	1	0.3	234
Removing pods	dummy	2001	0.9	0	1	1	0.3	176
	0=no	2006	0.8	0	1	1	0.3	233
	1=yes	2013	0.9	0	1	1	0.4	234
Harvest freq.	dummy	-	-	-	-	-	-	-
	0=less than 2 times/month	2006	0.7	0	1	1	0.5	210
	1=more than 2 times/month	2013	0.4	0	1	0	0.5	221
GERNAS	dummy	-	-	-	-	-	-	-
	0=no	-	-	-	-	-	-	-
	1=yes	2013	0.1	0	1	0	0.3	234
Pest incidence								
Pest	dummy	-	-	-	-	-	-	-
	0=no	2006	0.1	0	1	0	0.3	233
	1=yes	2013	0.3	0	1	0	0.5	234
Household characteristics								
Migrant status	dummy	2001	0.7	0	1	1	0.5	176
	0=migrant	2006	0.7	0	1	1	0.5	233
	1=local	2013	0.8	0	1	1	0.4	233
Primary Edu.	dummy	2001	0.6	0	1	1	0.5	176
	0=no	2006	0.5	0	1	1	0.5	233
	1=yes	2013	0.6	0	1	1	0.5	233
Secondary Edu.	dummy	2001	0.2	0	1	0	0.4	176
	0=no	2006	0.1	0	1	0	0.3	233
	1=yes	2013	0.1	0	1	0	0.3	233
Tertiary Edu.	dummy	2001	0.2	0	1	0	0.4	176
	0=no	2006	0.2	0	1	0	0.4	233
	1=yes	2013	0.2	0	1	0	0.4	233
Assets	000 IDR	2001	4321.1	15.0	58050.0	1025.0	7775.1	175
	000 IDR	2006	3555.0	3.7	97473.6	68.1	9264.0	232
	000 IDR	2013	6820.0	3.1	331381.9	2698.4	24533.8	231

Source: Authors' calculation based on STORMA and EFForTS data.

Table D.2: **Robustness check: Inclusion of zero yields, determinants of cocoa productivity (pooled OLS and FE model), 2001-2013**

VARIABLES	(1) Cocoa yield (log) OLS	(2) Cocoa yield (log) OLS	(3) Cocoa yield (log) OLS	(4) Cocoa yield (log) OLS	(5) Cocoa yield (log) OLS	(6) Cocoa yield (log) FE
Cocoa area (log)	0.020	-0.010	-0.053	-0.194**	-0.319***	-0.078
	(0.816)	(0.903)	(0.525)	(0.017)	(0.000)	(0.638)
Tree age	0.568***	0.458***	0.448***	0.238***	0.099**	0.370***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.014)	(0.000)
Tree age^2	-0.017***	-0.014***	-0.013***	-0.007***	-0.003**	-0.012***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.016)	(0.000)
Labor exp. (log)	0.040***	0.016	0.015	0.025**	0.015	-0.010
	(0.006)	(0.228)	(0.255)	(0.029)	(0.413)	(0.557)
Family workers (#)	0.047	0.018	0.012	0.050	0.028	0.000
	(0.329)	(0.689)	(0.798)	(0.235)	(0.647)	(0.996)
Fertilizer exp. (log)		0.018	0.009	0.008	0.007	0.038**
		(0.107)	(0.457)	(0.476)	(0.605)	(0.043)
Use of herbicides		0.501*	0.477*	1.090***	1.143***	0.422
		(0.061)	(0.078)	(0.002)	(0.003)	(0.171)
Manual weeding		0.218	0.223	0.797**	0.773**	0.090
		(0.413)	(0.408)	(0.025)	(0.034)	(0.773)
Pruning		1.496***	1.489***	1.590***	0.190	1.490***
		(0.000)	(0.000)	(0.000)	(0.429)	(0.000)
Removing pods		0.958***	0.963***	0.810***	0.482**	0.767***
		(0.000)	(0.000)	(0.002)	(0.048)	(0.010)
Migrant status			-0.240*	-0.256*	-0.522***	
			(0.074)	(0.080)	(0.003)	
Primary edu.			-0.065	0.251	0.652**	
			(0.700)	(0.156)	(0.025)	
Secondary edu.			-0.403*	-0.140	0.125	
			(0.093)	(0.579)	(0.715)	
Tertiary edu.			-0.244	0.314*	0.582**	
			(0.235)	(0.098)	(0.046)	
Assets (log)			0.030			
			(0.400)			
Lagged assets (log)				0.000	0.023	
				(0.992)	(0.556)	
Pest				-0.004	-0.019	
				(0.974)	(0.888)	
GERNAS					0.596***	
					(0.001)	
Harvest frequency					0.151	
					(0.256)	
Year = 2006	0.527**	0.436**	0.452**			0.805***
	(0.011)	(0.024)	(0.023)			(0.000)
Year = 2013	0.530**	0.416*	0.497**	0.273*		0.918***
	(0.035)	(0.071)	(0.032)	(0.091)		(0.005)
Constant	1.700***	0.014	0.197	1.056*	3.627***	0.505
	(0.000)	(0.965)	(0.634)	(0.073)	(0.000)	(0.205)
Observations	632	632	628	381	209	632
R-squared	0.447	0.551	0.553	0.464	0.307	0.524
Adj. R-squared	0.440	0.542	0.540	0.439	0.241	
Number of id						273
Within R-squared						0.524
Between R-squared						0.538

Note: Pval in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, year dummies included, cluster-robust standard errors. Households with a cocoa plantation of at least 0.25 hectare are included. Zero yields are included by adding 1 to yield before transforming into log.
Source: Authors' calculation based on STORMA and EFForTS data.

Table D.3: **Robustness check: Instrumental variable approach, determinants of cocoa productivity (2SLS and Maximum Likelihood), 2001-2013**

VARIABLES	(1) Cocoa yield (log) OLS	(2) Cocoa yield (log) IV-2SLS	(3) Cocoa yield (log) IV-ML	(4) Cocoa yield (log) IV-ML	(5) Cocoa yield (log) IV-ML	(6) Cocoa yield (log) IV-ML
Cocoa area (log)	-0.267***	-0.283***	-0.270***	-0.259***	-0.262***	-0.244***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tree age	0.183***	0.166***	0.185***	0.185***	0.183***	0.162***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Tree age^2	-0.005***	-0.005***	-0.006***	-0.006***	-0.005***	-0.005***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Labor exp. (log)	0.032***	0.030***	0.028***	0.031***	0.032***	0.027***
	(0.000)	(0.002)	(0.005)	(0.002)	(0.001)	(0.010)
Family workers (#)	-0.014	-0.010	-0.012	-0.013	-0.016	-0.027
	(0.635)	(0.741)	(0.704)	(0.679)	(0.593)	(0.407)
Fertilizer exp. (log)	0.007	0.072**	0.005	0.007	0.010	0.005
	(0.463)	(0.042)	(0.584)	(0.467)	(0.316)	(0.610)
Use of herbicides	0.305*	0.253	0.968***	0.717	0.615*	0.260
	(0.100)	(0.184)	(0.006)	(0.368)	(0.082)	(0.200)
Manual weeding 0.086	0.081	0.645**	0.529	0.391	0.092	
	(0.626)	(0.655)	(0.035)	(0.534)	(0.256)	(0.632)
Pruning	0.405**	0.308*	0.129	0.206	-0.203	0.295
	(0.022)	(0.091)	(0.542)	(0.617)	(0.737)	(0.113)
Removing pods	0.667***	0.641***	0.654***	0.668***	0.702***	1.630***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Migrant status	-0.273***	-0.120	-0.279***	-0.287***	-0.269***	-0.289***
	(0.004)	(0.315)	(0.006)	(0.006)	(0.008)	(0.006)
Primary edu.	0.143	0.164	0.150	0.148	0.163	0.167
	(0.258)	(0.228)	(0.309)	(0.313)	(0.275)	(0.277)
Secondary edu.	-0.187	-0.098	-0.191	-0.194	-0.188	-0.140
	(0.271)	(0.594)	(0.275)	(0.267)	(0.284)	(0.445)
Tertiary edu.	-0.002	0.013	-0.014	-0.002	-0.015	0.006
	(0.988)	(0.934)	(0.932)	(0.992)	(0.930)	(0.973)
Assets (log)	0.062**	0.031	0.064***	0.062**	0.062**	0.065***
	(0.018)	(0.339)	(0.008)	(0.011)	(0.011)	(0.007)
Year = 2006	0.148	0.222*	0.076	0.118	0.205	0.332**
	(0.216)	(0.073)	(0.552)	(0.382)	(0.127)	(0.022)
Year = 2013	0.590***	0.579***	0.493***	0.545***	0.625***	0.753***
	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
Constant	3.050***	3.168***	2.802***	2.857***	3.243***	2.314***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Observations	551	551	551	551	551	551
Instrument relevance:						
- F-statistic		29.2				
- correlation		0.43	0.36	0.14	0.21	0.19
Endogenous regressor		Fertilizer exp. (log)	Use of herbicides	Manual weeding	Pruning	Removing pods

Note: Pval in parentheses, *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$, year dummies included, cluster-robust standard errors. Households with a cocoa plantation of at least 0.25 hectare are included. Zero yields are included by adding 1 to yield before transforming into log.
Source: Authors' calculation based on STORMA and EFForTS data.

Own contribution

Chapters 1, 2 and 3 of this cumulative dissertation have been written in single authorship. Chapters 4 and 5 have been written in co-authorship.

The paper presented in chapter 4 (*Financial Globalization and the Labor Share in Developing Countries: The Type of Capital Matters*) has been written in co-authorship with Konstantin M. Wacker. The paper is based on previous research and conceptualization of mine. We jointly conceptualized the paper further, designed and performed the empirical analysis and wrote the paper.

The paper presented in chapter 5 (*Cash crops as a sustainable pathway out of poverty? Panel data evidence on heterogeneity from cocoa farmers in Sulawesi, Indonesia*) has been written in co-authorship with Elisabeth Hettig, Jann Lay, Martin Bruness, Dewi Nur Asih and Nunung Nuryartono. The paper was conceptualized by Elisabeth Hettig, Jann Lay and Katharina van Treeck. Katharina van Treeck, Martin Bruness, Dewi Nur Asih collected the data in the field (with support by Nunung Nuryartono). Elisabeth Hettig and Katharina van Treeck developed the theoretical background and did the literature review, as well as the data cleaning, panel structure and variable set up. Elisabeth Hettig, Katharina van Treeck and Martin Bruness carried out the descriptive analyses. Elisabeth Hettig and Katharina van Treeck performed the empirical analyses. Elisabeth Hettig, Katharina van Treeck and Jann Lay contributed to writing the draft.