

USING QUANTITATIVE TOOLS TO MEASURE GENDER DIFFERENCES WITHIN VALUE CHAINS

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Introduction

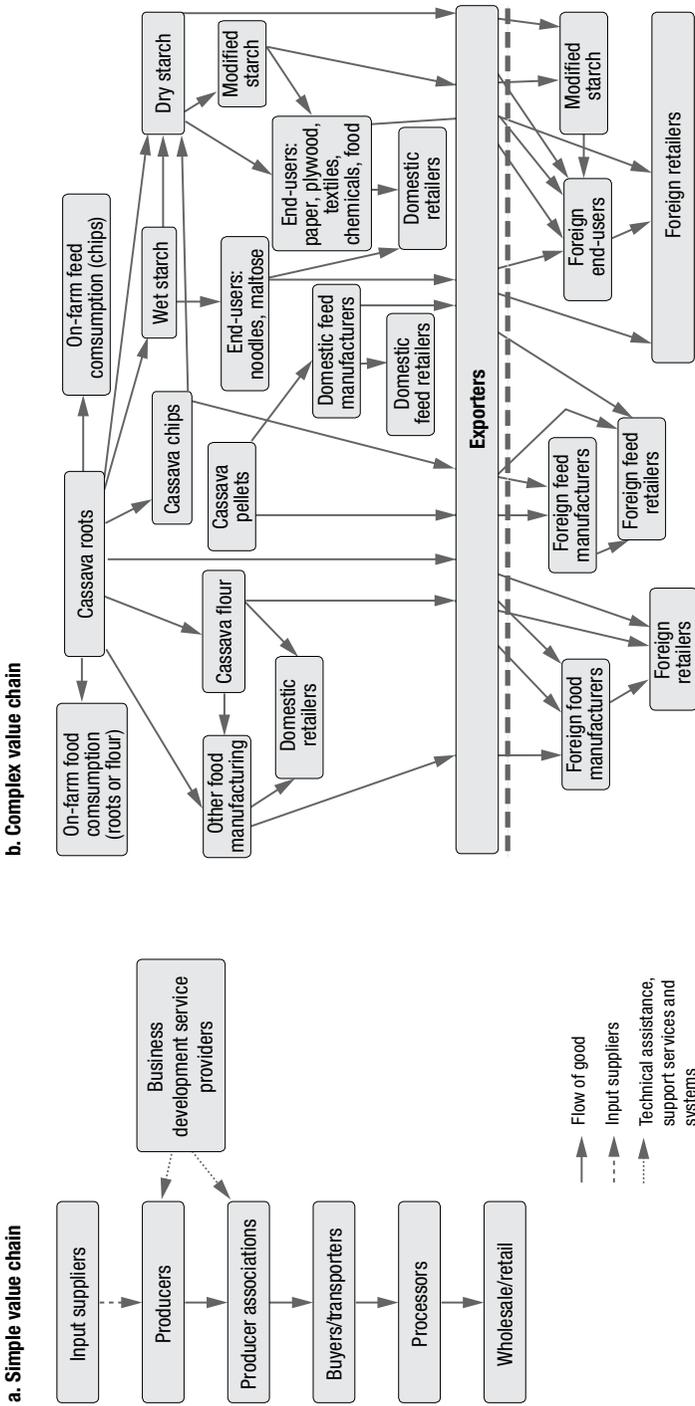
A value chain is a linked set of activities that take a product from conception through production, delivery, and finally disposal (see Figure 14.1a). While some value chains are simple and straightforward, others can be complex. Many different economic agents can be directly involved in each step of the chain; in addition, inputs used during one stage of production might re-enter the chain at another stage if their residual value is recyclable. Figure 14.1b provides an example of a more complex value chain with more than one final product stemming from the initial inputs, each following a parallel process.

Multiple barriers affect people's ability to participate in and benefit from value chains; these include a lack of access to capital and markets. Detailed study of value chains can address these barriers by identifying critical issues and bottlenecks that limit opportunities for specific populations.

One such population is women. Female workers make up a considerable proportion of the agricultural workforce worldwide, but significant gender inequalities remain when it comes to access to assets, land, labor, credit, and infrastructure (see Deere and Leon 2003 for Latin American countries; Doss 2006, and Quisumbing, Estudillo, and Otsuka 2004 for Africa south of the Sahara). Research has shown evidence of gender discrimination in wages and employment conditions in rural markets, suggesting that women could benefit from labor-market interventions (Maertens and Swinnen 2012). Further identifying such gender imbalances is the first step in improving the design of policies and interventions that will lead to greater gender equality and productivity (both labor and agricultural) in developing countries, as well as to reduced poverty and hunger.

Using quantitative tools to study gender-related questions is essential for increasing gender inclusion and promoting economic growth in developing countries. In this chapter, we look at how to use such tools to examine gender in value chains. The proposed tools (available via CRP-PIM 2015) are based on widely known methods and have a straightforward empirical

FIGURE 14.1 Value-chain maps



Source: a. Authors; b. MAP (2008).

implementation; they have been tested in several studies and haven't proven to be useful indicators of gender differentials.

Specifically, we have developed indicators that quantitatively estimate the time women and men spend on diverse activities during the day, especially focusing on tasks performed at work. Measuring labor burden by gender could give useful insights into how to improve the gender balance and opportunities. When looking at the conditions in which men and women work, we present an indicator on working conditions and develop an index on equality. The objective of this index is to assess key variables that characterize access to work and working conditions. The index has two categories: variables that characterize working conditions, and variables that describe access to work. Finally, we have developed two indicators to assess differences in payments and occupations for females and males. The wage gap calculates the gender wage gap and assesses the extent to which observed gender wage gaps correspond to gaps in individuals' demographic and job-related characteristics. How different is remuneration by gender in each node/value chain? How much of that difference is due to observable characteristics? How much of that difference is due to unobservable characteristics? Finally, the Duncan Index estimates gender segregation at each node in the value chain by occupation. It could be extended to capture hierarchical segregation by occupation and tasks (skilled and non-skilled) depending on data available. Essentially, it tries to answer the question of how participation by occupation, node, or value chain differs between men and women.

In summary, these tools allow us to map different gender roles and to identify opportunities that could lead to increased productivity, cost reduction, or product upgrades that, in turn, can spur economic growth.

Why Is Quantitative Analysis Needed and What Can It Do?

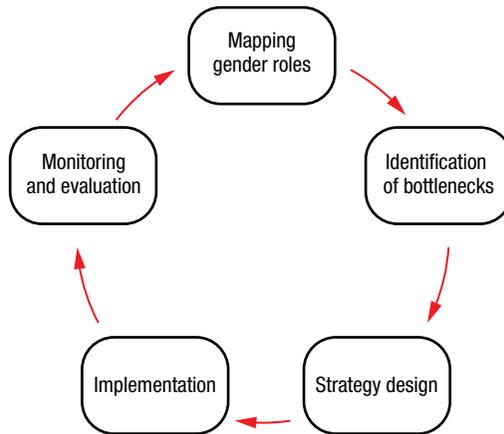
Since the mid-2000s, there has been an increasing amount of literature that seeks to integrate gender issues into the study of value chains. Much of this literature relies heavily on qualitative sources such as scoping studies (rapid field appraisals), focus groups, and diagramming tools (see Senders et al. 2012; Mayoux and Mackie 2009; Laven and Pyburn 2012; Rubin, Manfre, and Barrett 2009; Dulón 2009; Chan and Barrientos 2010). Although qualitative analysis provides the context needed to understand certain situations, it is mostly based on subjective responses that are difficult to categorize. Much of this literature fails to provide quantitative methods that can be used to

analyze information efficiently and to estimate gender differentials consistently; it also does not discuss recommended sample size for information gathering or sampling methodology. We thus see the need to enrich these existing manuals with sound quantitative analysis that can give a more precise idea of gender differentials.

To best address the issue of gender disparities in agriculture, researchers should utilize a combination of both qualitative and quantitative data. Quantitative data in which participants' responses are coded, organized, and statistically analyzed would complement and enrich the qualitative analysis, helping improve investments and program targeting and leading to more effective design, monitoring, and evaluation of policies and programs (Farnworth 2011). The quantitative tools we propose utilize indicators derived from survey questionnaires that could be easily adapted to different value-chain contexts. Implementing the modules and questions proposed would require few or no additional resources either to modify the existing sections of the questionnaire or to incorporate complete modules.

Using qualitative tools begins with identifying, or mapping, women's roles in a value chain. Mapping gender roles provides a picture of the relationships between different actors in the value chain. Understanding these relationships can help policymakers and researchers identify constraints and opportunities for women in each part of the chain and design strategies to increase gender equality. After implementation, quantitative tools can be used to track the effect of the chosen strategy and to quantify changes. Figure 14.2 shows the phases in value-chain analysis; indicators created by quantitative tools can be used to support analysis throughout the entire process.

How can quantitative tools improve analysis of a specific problem? One major gender-related issue is employment. Increasing women's equal participation in productive activities, as well as providing income-earning opportunities for both poor women and poor men through wage employment or self-employment, are essential steps in reducing poverty. Maertens and Swinnen (2012) suggest that labor-market channels are more effective in reducing poverty than product-upgrading channels. They find that women benefit more, and more directly, through labor-market effects than through product-market effects. Also, women benefit more if they are hired employees in agro-industry because they have direct access to wages and because the wages they receive improve their household bargaining power; income derived from contract farming, on the other hand, is mainly controlled by male contractors.

FIGURE 14.2 Phases in value-chain analysis

Source: Authors.

However, few studies have looked specifically at (1) the distribution of employment by gender in a value-chain context; (2) the circumstances in which workers seek or find employment; and (3) the job conditions generated by the production of a specific commodity or livestock (Barrientos and Dolan 2003; Dolan and Sutherland 2005 are the most relevant studies). Moreover, as mentioned by Maertens and Swinnen (2012), development policies have focused mainly on the inclusion of smallholder farms in modern value chains and the promotion of smallholder contract farming, rather than on labor markets and employment by gender. Using qualitative tools to examine these latter indicators can complement existing efforts and lead to more effective, better-targeted policies.

Table 14.1 presents gender-related research questions that could benefit from the use of quantitative measurements. These questions are not meant to be all-inclusive; rather, they are designed to give a basic idea of the kind of analysis that could be done using the tools we propose. Depending on the available data, each tool can be extended to analyze different dimensions of the research question. The examples provided show some basic indicators that can be obtained with minimal data; these examples are not exhaustive, however.

TABLE 14.1 Gender-related research questions

Quantitative tool	What questions can it answer?
Non-parametric Oaxaca Blinder decomposition analysis to measure gender-earnings gaps (Using a unit identification and employment module)	<ul style="list-style-type: none"> • How is remuneration different for men and women in each node of the value chain or in the value chain as a whole? • How much of that difference is due to observable characteristics, such as age or skill level? • How much of that difference is due to unobservable characteristics, such as people's preferences or possible gender-based discrimination?
Time-use analysis (Using a unit identification and time-use module)	<ul style="list-style-type: none"> • Do men and women spend their time differently throughout the value chain, especially for the major tasks in each node? • How do women's burdens in terms of time spent compare with men's? • How do women's workloads in terms of leisure time, family care, and household chores compare with those of men? • Do transport time, transport fees, or childcare mobility form barriers for women in terms of market access?
Duncan Index for occupational segregation (Using a unit identification and employment module)	<ul style="list-style-type: none"> • Within each node of the value chain or within the value chain as a whole, which occupations do men have and which occupations do women have? • Are men and women equally represented within an occupation in proportion to their share of the population?
Working-conditions/access-to-work equality index (Using a unit identification and employment module)	<ul style="list-style-type: none"> • Is there unequal access to employment for men and women? • Do working conditions differ by gender? • What barriers to entry do men and women face in each node of the value chain or in the value chain as a whole? • Which barriers are more significant for women and which are more significant for men?

Source: Authors.

Quantitative Tools to Help Understand the Role of Gender in Value Chains

In this section, a series of quantitative tools is presented that can be used to help understand how value chains work, characterize labor distribution, and evaluate working conditions and access to work in the context of value chains and gender.

Tool: Non-Parametric Oaxaca Blinder Decomposition Analysis

Although women have made strides in entering the global labor force since the mid-1990s, this increased participation has not translated into equal earnings. In addition, labor and gender economics literature since the mid-2000s has found that women are often in the lowest economic percentiles of income distributions and face barriers in access to income-producing opportunities (see Atal, Ñopo, and Winder 2009; Ñopo, Daza, and Ramos 2011; World Bank 2012). In order to address these disparities, it is first necessary to analyze both the size of the wage gap and the reasons behind the differences in pay. This information can then be used to generate solid gender-oriented strategies.

The objective of this tool is to calculate gender wage gaps; the tool can also be used to assess the extent to which observed gender wage gaps correspond to other observable characteristics such as demographics or job characteristics, as well as characteristics which cannot be explained by the model.

TABLE 14.2 Data needed for nonparametric Oaxaca Blinder decomposition analysis to measure gender-earnings gaps

Minimum	Desirable for further analysis
<ul style="list-style-type: none"> • Hourly wage (daily/weekly) • Age • Level of education or literacy • Gender 	<ul style="list-style-type: none"> • Religion • Ethnicity (minority groups) • Marital status • Number of children, children's ages, health of children, gender of firstborn child • Registered employment (contract) • Payment in cash/kind • Benefits • Type of job (specific to the value chain) • Occupation (specific to the value chain) • Temporary work

Source: Authors.

The goal of the Oaxaca Blinder decomposition is to estimate differences in mean wages across two groups. The wage model is assumed to be linear and separable in observable and unobservable characteristics. The estimation for females and for males generates the following counterfactual: “What would the earnings for a male (female) with average individual characteristics be if he (she) is rewarded for his (her) characteristics in the same way that the average female (male) is rewarded?” The difference in average wages between males and females is broken into two additive components: one attributable to differences in the average characteristics of the individuals, and the other attributable to differences in the average rewards for these characteristics. The latter component is thought to contain the effects of both unobservable characteristic gender differences and possible discrimination in the labor market (Blinder 1973; Oaxaca 1973; Oaxaca and Ransom 1994; Ñopo 2008).

The econometric procedure used in this tool is an extension introduced by Ñopo (2008) that uses a nonparametric matching approach. In this extension, Ñopo proposes to account for the fact that females and males do not all possess the same characteristics; he therefore creates matched groups in which it is possible to compare wages across genders and does not assume a linear relationship between variables. Additionally, he suggests a way to address the distribution of these unexplained differences, which is not possible in the standard Oaxaca Blinder decomposition.

In order to create comparable groups, females and males are only matched if they show exactly the same combination of observable characteristics (common support). Nopo (2008) explains that these matching characteristics need to be discrete. This ensures that the match is done perfectly and does away with the need to use propensity scores or any notion of distance among the characteristics. The matching procedure resamples all females without replacement and matches each observation with one synthetic male with the same observable characteristics and with a wage obtained from averaging all males with those same characteristics. This one-to-many matching generates a partition of the dataset. The observations of working males and females are grouped into three sets: (1) males whose observable characteristics cannot be matched to those of any female in the sample, (2) females whose observable characteristics cannot be matched to those of any male in the sample, and (3) matched males and females, such that the distribution of observable characteristics for males is equal to that of females.

In this way, the estimation of the four components is reduced to computations of conditional expectations and empirical probabilities without the need to estimate the nonparametric earnings equations in four separate equations, as in Nopo (2008):

$$\Delta_M = \mu^M (\text{Unmatched}) (E_{M, \text{unmatched}}[Y|M] - E_{M, \text{matched}}[Y|M])$$

$$\Delta_X = E_{M, \text{matched}}[Y|M] - E_{F, \text{matched}}[Y|M]$$

$$\Delta_0 = E_{F, \text{matched}}[Y|M] - E_{F, \text{matched}}[Y|F]$$

$$\Delta_F = \mu^F (\text{Unmatched}) (E_{F, \text{matched}}[Y|F] - E_{F, \text{unmatched}}[Y|F])$$

The wage gap Δ , computed as the difference in average wages between males and females and expressed as a percentage of females' average wages, is then decomposed into four additive elements:

$$\Delta = (\Delta_X + \Delta_M + \Delta_F) + \Delta_0$$

Δ_X is attributed to the differences in observable characteristics between males and females (common support of both characteristics' distribution); Δ_M is the portion of the wage gap that is due to the existence of males with combinations of characteristics that are not matched by any women; Δ_F is the portion of the gap that is due to the existence of females with characteristics that cannot be matched to any male characteristics. The sum of the first three components, $\Delta_X + \Delta_M + \Delta_F$, is the portion of the gap that can be attributed to differences in observable characteristics. Finally, Δ_0 is the portion of the gap that cannot be explained by these characteristics and could be attributable to differences in unobservable characteristics, including discrimination.

The typical interpretation of the wage-gap decomposition applies, but only over the common support: Δ_X is attributable to differences in the average characteristics of the individuals and Δ_0 is attributable to differences in the average rewards for these characteristics. In this new construction, two new additive components have been included, Δ_M and Δ_F (out of common support), resulting in a four-element decomposition.

In a value chain, wage differences between males and females could be calculated for each node and/or at the whole value-chain level. Depending on sample size and available information, one can also compare how results change when controlling for different individual characteristics (age, education, occupation, etc.).

This tool will produce tables and graphs like the ones shown (Table 14.3 and Figure 14.3). Our example uses only age as a control; however, it is possible to add more controls such as education and occupation, and to compare changes in the unexplained part of the wage differential.

The results can be interpreted as follows.

The overall gender gap is 11 percent (Δ). Δ can be decomposed in four elements:

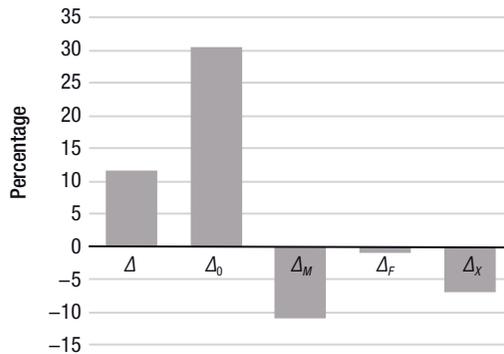
- Δ_0 : Unexplained by the model. Only for the fact of being male wage increased in 30 percent.
- Δ_X : Explained by observable characteristics (common support). The age distribution for women and men in the common support is such it that reduces the gender gap by Δ_X .

TABLE 14.3 Gender wage-gap decomposition results

Gender wage gap decomposition	
Δ	0.11459352
Δ_0	0.30390245
Δ_M	-0.1104065
Δ_F	-0.0097561
Δ_X	-0.06914634

Source: Authors

Notes: Δ = the wage gap computed as the difference in average wages between males and females and expressed as a percentage of females' average wages; Δ_X = the differences in observable characteristics between males and females (common support of both characteristics' distribution); Δ_M = the portion of the wage gap that is due to the existence of males with combinations of characteristics that are not matched by any women; Δ_F = the portion of the gap that is due to the existence of females with characteristics that cannot be matched to any male characteristics; Δ_0 is the portion of the gap that cannot be explained by these characteristics and could be attributable to differences in unobservable characteristics, including discrimination.

FIGURE 14.3 Gender wage-gap decomposition

Source: Authors.

Notes: Δ = the wage gap computed as the difference in average wages between males and females and expressed as a percentage of females' average wages; Δ_X = the differences in observable characteristics between males and females (common support of both characteristics' distribution); Δ_M = the portion of the wage gap that is due to the existence of males with combinations of characteristics that are not matched by any women; Δ_F = the portion of the gap that is due to the existence of females with characteristics that cannot be matched to any male characteristics; Δ_0 is the portion of the gap that cannot be explained by these characteristics and could be attributable to differences in unobservable characteristics, including discrimination.

- Δ_M : Existence of men with ages that cannot be matched by any women reduces the gender wage gap by Δ_M .
- Δ_F : Existence of women with unmatched age reduces the gender wage gap by Δ_F .

The sum of $\Delta_X + \Delta_F + \Delta_M$ is the portion of the gap that can be attributed to observable characteristics, which in this case is 18 percent. For technical details, refer to Nöpo (2008).

To apply this tool, it is important to control for a relevant number of characteristics and to make revisions if the common support is large enough. It is also important to consider the sampling framework and possible selection bias. As presented, the tool is calculated using the sample of employed individuals who have some characteristics that might differ from unemployed people. In this case, it is important not to extend these results to the whole population, but rather only to the employed population. When using a sample in which the entire population is available, it is necessary to correct the selected sample (see Mulligan and Rubinstein 2005; Rubli 2012). This tool could also be used to measure gaps in other individual characteristics, such as ethnicity, poverty, and education. However, further research is needed to consider selection bias using this tool.

Tool: Time-Use Analysis

Time-use data can provide a detailed account of the time devoted to different activities and tasks during a particular period, usually a day. Collecting such information requires individuals to record their time used for each activity performed during the day; this can shed light on the time taken for various tasks within a value chain. This instrument not only describes the time that females and males dedicate to both productive and unproductive activities, it also shows differences in job activities. For example, time-use studies from Africa south of the Sahara reveal that women spend more time at work than men, particularly when their time spent on domestic and care work is included (Blackden and Wodon 2006).

The objective of this tool is to quantitatively estimate the time that women and men spend on different activities during the day, focusing on tasks performed at work. Measuring men's and women's labor burdens could provide interesting insights into how to improve gender balance and labor opportunities for both men and women. Several case studies have shown that women's burdens tend to increase in value chains with higher quality requirements (value-chain upgrading), since women typically perform quality-producing steps; however, this higher burden does not typically translate into higher remuneration. Many of the studies finding increased workload for women have relied mostly on qualitative information (Lyon, Bezary, and Mutersbaugh 2009; Bolwig and Odeke 2007).

In order to obtain time-use data, researchers must ask participants to list all activities undertaken in a typical day, from waking up to going to sleep, emphasizing time spent on different activities while at work. The questionnaire should be adapted to activities relevant to the value chain under analysis and should focus on the productive activities. A properly prepared and conducted interview can yield information on: time spent working as a whole and

TABLE 14.4 Data needed for time-use analysis

Minimum	Desirable for further analysis
<ul style="list-style-type: none"> • Relationship with head of the household • Gender • Occupation • Time wakes up • Time goes to sleep • Activities: preparing food, transportation, working, leisure, and other activities specific to the tasks in the value chain 	<ul style="list-style-type: none"> • Age • Ethnicity (minority groups) • Religion • Marital status • Household size

Source: Authors.

time spent on each separate activity while at work; time spent on household chores; and leisure time. From this information, it is then possible to compare and characterize differences between women's and men's time use using *t*-test analysis or regression analysis.

Depending on the value chain being analyzed, it might be important to capture the time spent on specific work tasks to assess the quality of activities performed by men and women (in other words, the division of labor in skilled and nonskilled activities: who trades, collects, loads, does marketing, sells, etc.).

The tool will produce tables and graphs like the ones shown (Table 14.5 and Figure 14.4).

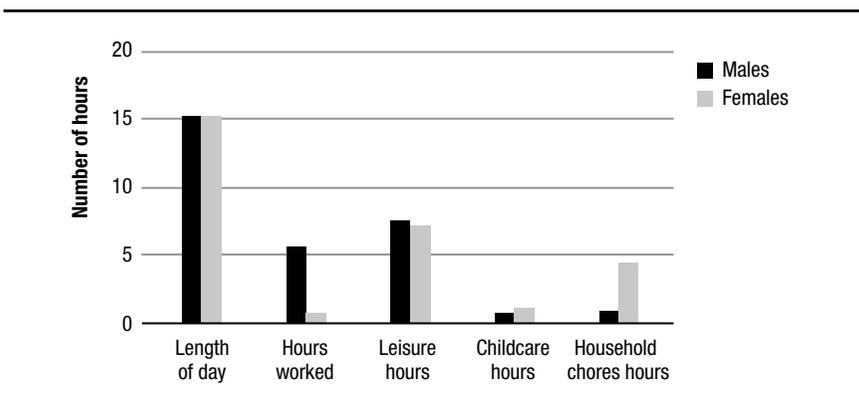
TABLE 14.5 *t*-test for differences between females and males

Differences in time use by gender							
Variable	Males	Females	SD males	SD females	No. males	No. females	P
Wake-up time	5.03	5.26	0.9	0.76	45	53	.18
Sleep time	20.24	20.42	0.88	0.71	45	53	.30
Length of day	15.21	15.15	1.25	1.02	45	53	.80
Hours worked	5.63	0.82	3.98	2.21	45	53	.00
Leisure hours	7.69	7.25	2.6	2.67	45	53	.41
Childcare hours	0.76	1.23	0.38	0.93	9	11	.15
Household-chores hours	1.03	4.42	1.62	2.51	45	53	.00

Source: Authors.

Notes: SD = standard deviation; No. = number of observations; P = probability.

FIGURE 14.4 Differences in time use by gender



Source: Authors.

Judging from these results, there are significant differences in the hours worked (typically outside the household) and the hours spent on household chores (typically performed by women). This distribution implies that women allocate a larger share of their time to activities that do not directly generate income.

Time allocation is a great tool to understand the dynamics of economic change and to model economic behavior. However, it has measurement errors that could complicate the results when people perform more than one activity at the same time. Since time use can also be impacted by seasonality, researchers should be careful to make repeated observations at the same time of year. Moreover, some populations may conceptualize time differently from those in industrialized countries, and illiterate individuals may have a different way of assessing their time use (see Masuda et al. 2012 for two approaches).

Tool: Occupational Segregation Using Duncan Index

Women continue to congregate in sectors and occupations traditionally characterized as “female”—mostly low-paying jobs. According to the World Bank (2012), removing barriers that prevent women from working in certain occupations would reduce the productivity gap between male and female workers by one-third to one-half, and would increase output per worker by 3–25 percent in some countries. This tool estimates gender segregation at each node in the value chain by occupation and can be extended to capture hierarchical segregation by occupation and task (skilled versus nonskilled) depending on available data.

TABLE 14.6 Data needed for occupational segregation using Duncan Index

Minimum	Desirable for further analysis
<ul style="list-style-type: none"> • Employment total • Employment by gender 	<ul style="list-style-type: none"> • Occupation (specific to the value chain) • Type of job (specific to the value chain)

Source: Authors.

The Duncan Index for occupational segregation (Duncan 1955) by gender in each stage of a value chain can be measured by

$$D = \frac{1}{2} \sum_i |m_i - w_i|$$

where m_i is the percentage of males (among total males employed within the value chain) in occupation (or value-chain node) i , and w_i is the similar percentage of females (among total females in the value chain) in value-chain occupation i . The values range from 0 to 100, and measure the relative separation or integration of gender across occupations (or nodes).

If the D value equals 0 percent, it means that occupations are distributed evenly between males and females. If the value is 100 percent, it means that occupations are completely segregated. If the value is 60 percent, it means that 60 percent of workers would have to change occupations to make the gender distribution equal. The benchmark for the Duncan Index for occupational segregation by gender is 25.86 percent. The tool will produce tables similar to Table 14.7.

TABLE 14.7 Duncan Index

Node	Duncan Index (%)
Production	98
Commercialization	85

These percentages show a high level of segregation in the production node of the value chain. Ninety-eight percent of male workers would have to be replaced by female workers in order to have equal gender distribution.

The Duncan Index is a dissimilarity index; it is a measure of the evenness with which two groups are distributed across component groups (in this case, females and males) that make up a larger whole. The index score can be interpreted as the percentage of one group that would have to move to different units in order to produce a distribution that matches that of the whole. The index of dissimilarity can also be used as a measure of inequality.

But the Duncan Index does face some constraints. As highlighted by Iceland, Weinberg, and Steinmetz (2002), the dissimilarity index can be inflated by random factors when the number of minority members is small relative to the number of all potential groups (specifically they refer to the unequal distribution of social groups across aerial units of an urban area). The index is also insensitive to the redistribution of minority members among all potential groups with minority proportions above or below the overall minority proportion. Only transfers of minority members from areas in which these members are overrepresented to areas in which they are underrepresented (below the minority proportion) affect the value of the index.

However, despite its imperfections, the Duncan Index remains the most widely used measure of evenness, and no other index has achieved such widespread acceptance as a summary statistic of segregation (Iceland, Weinberg, and Steinmetz 2002). Further research could extend this segregation measure to different dimensions and could construct a Theil's-type index that could include two or more variables simultaneously.

Tool: Working Conditions / Access to Work Equality Index

Analyzing working conditions and equal access to work can provide information regarding specific barriers to growth within a value chain. The objective of this index is to assess key variables that characterize access to work and working conditions. The index is based on three premises: (1) measurement of gender gaps, (2) ease of computation, and (3) a final value bound between 0 (inequality) and 1 (equality) to facilitate comparisons and interpretation. It has two categories: (1) variables that characterize working conditions, and (2) variables that describe access to work.

TABLE 14.8 Data needed for working conditions / access to work equality index

Minimum	Desirable for further analysis
1. Working conditions <ul style="list-style-type: none"> • Wage (hourly/weekly) 2. Access to work <ul style="list-style-type: none"> • Participation (employment by gender) • Literacy or education level 	1. Working conditions <ul style="list-style-type: none"> • Occupation (job activity) • Category (owner, worker, family worker) • Tenure • Temporary/permanent • Contract • Physical safety / risk of task performed 3. Access to work <ul style="list-style-type: none"> • Education level • Skilled, semiskilled, nonskilled • Requirements for job (experience, abilities, etc.) • Job training

Source: Authors.

This index follows the empirical methodology used by Hausmann, Tyson, and Zahidi (2012), as presented below.

Step 1: Calculate ratios by gender for each variable X_i in each observation. For example, if one is working with the production node (segment) and has information on 100 farmers, a ratio needs to be calculated for each variable x_i in each farm where the variable could be for example: wages, participation, literacy, etc.

$$ratio_i = x_{i_female} / x_{i_male}$$

where x_{i_female} refers to the value of the specific variable for females in the specific farm and x_{i_male} refers to the value of the specific variable for males in the specific farm.

Step 2: Truncate at equality (1) when necessary; this must have bounds between 0 and 1, where 1 means an equal number of women and men.

$$ratio_i = 1 \text{ if } x_{i_female} > x_{i_male}$$

Step 3: Calculate sub-index scores (for each category of variables $j = 1, 2$). To do this, it is necessary to calculate the weighted average of the variables within each category and create two sub-indices (one for working conditions and one for access to work). As mentioned by Hausmann, Tyson, and Zahidi (2012), a simple average would implicitly give more weight to the measure that has more variability; they suggest normalizing the variables by equalizing their standard deviations. Standard deviations over all farm-level data for each variable need to be calculated (var_sd_i); then a 1 percentage point change would be calculated:

$$var_sd_i = 0.01/sd(ratio_i)$$

where var_sd_i is the standard deviation for each variables and $sd(ratio_i)$ is the standard deviation of the ratio for each variable ($ratio_i$).

Sum var_sd_i over each category j :

$$sum_j = \sum_j var_sd_i$$

where var_sd_i is the standard deviation for each variable aggregated over j categories which could be for example wages, and participation (employment by gender and by literacy).

To construct the weight, divide each var_sd_i by sum_j , this will create the variable $weight_i$.

These values should be used as weights to calculate the weighted average of the four variables. In this way, a variable with a small variability of standard deviation gets a larger weight; therefore, when there is a large gender gap in that variable, it would be heavily penalized:

$$\overline{subindex(w)_{category j}} = \frac{\sum_i^n weight_i ratio_i}{\sum weight_i}$$

where the sum is over all variables within each j category.

Step 4: Calculate the final score. An unweighted average for each sub-index is taken to create the overall working conditions / access to work equality index. Sub-indices should include variables that characterize working conditions and variables that describe access to work.

$$Equality\ index = \frac{\sum_i^n \overline{subindex(w)_{category j}}}{n}$$

where the sum is over all j categories (n).

This tool could be applied to separate nodes (segments) or to the entire value chain. It allows for comparisons between nodes and between value chains, since it is based on ratios rather than levels. It will produce a table like Table 14.9.

TABLE 14.9 Working conditions / access to work equality index

Node	Working conditions / access to work equality index (%)
Production	31
Commercialization	55

Source: Authors.

In this production node, the working conditions / access to work equality index is 31 percent, suggesting a large gap between females and males in both working conditions and access to work. This implies that there is a gap of 69 percent. Similarly, for commercialization the index is 55%, which implies 45% inequality in working conditions and access to work.

This index could be more accurate if more variables describing access to work and employment conditions become available. Additionally, better analysis could be drawn if each person was interviewed individually instead of getting their information through third parties (such as the employer). Further work could find a correlation between a country's gender gap in agricultural production and its agricultural competitiveness, because women account for a large proportion of the world's agricultural workforce and thus long-term competitiveness depends significantly on whether women contribute to the sector.

Implementation

Three things are needed to implement these tools: (1) a questionnaire module applied partially or in full; (2) a do-file with additional information on the tool and an explanation of how to construct the indicator; and (3) an Excel file with a table and/or graph produced from the results. Examples of the questionnaire and do-file are given by CRP-PIM (2015), and examples of the Excel file are available at www.tools4valuechains.org.

The questionnaire module can measure either employment or time use. Additionally, a module of unit identification should also be available. Two types of modules are recommended: one for the production node and one for the commercialization node. The questionnaire provided on the website is a general example and should be adapted to the particular value chain and context under study. A list of activities that can be used as a guide to modify

and improve the list of relevant job activities (question Q2.3_L) in the labor module, according to each value-chain node and commodity, can be found in CRP-PIM (2015).

The do-file describes the steps needed to create variables and estimate indicators using the variables in the questionnaires. Additionally, there is a raw dataset with which to perform the example described in the do-file—this dataset is only to illustrate the tool.

The Excel file uses the outcome data to produce a graph and could be used to reproduce similar outputs with specific data. This file can be downloaded from www.tools4valuechains.org.

Data Collection and Sampling

When implementing value-chain surveys to be able to measure the proposed quantitative tools, one of the biggest challenges faced by researchers is gathering appropriate gender-disaggregated data. As mentioned by Doss (2013b), gender-disaggregated data are data that are collected and analyzed separately on males and females. This typically involves asking the “who” questions in an agricultural household survey: who provides labor, who makes the decisions, who owns and controls the land and other resources, in which node of the value chains do they work, and under which conditions and wages.

Who to Survey

When talking about gender-disaggregated data, we are not referring to comparisons of male- and female-headed households. This type of data is already commonly collected, but is problematic because it confounds gender and household structure¹ and we would miss important data on women living in male-headed households—the majority of the world’s women. It is in this sense that data collection for the proposed tools cannot focus solely on female-headed households, but needs to include women living in male-headed households and males living in female-headed households.

1 As mentioned by Doss (2013a, b), male- and female-headed households are not comparable in most cases due to the way in which they are defined. *Male-headed households* generally include all households in which women are married to men, while *female-headed households* are usually those households lacking adult men. Female-headed households are often more labor and resource constrained than male-headed households, but these disparities cannot necessarily be attributed to the sex of the household head.

How to Ask the Questions

A number of empirical studies have proposed using female interviewers to make women more comfortable when responding to surveys; questionnaires designed separately for women and men have also been used to increase accuracy and to improve data collection. Similarly, a clear strategy is needed to interview the males and females in separate environments to assure freedom of response on the part of the females. Other strategies include interviewing the spouse or another member of the household (preferably of the opposite sex) in addition to the household head to capture household composition and behavior (Fisher, Reimer, and Carr 2010). However, if it is not possible to interview multiple individuals within a household, researchers need to at least identify respondents based on their roles and responsibilities. Doss (2013b) also suggests guidelines to improve researchers' ability to capture gender disparities in specific areas such as land tenure, acquisition of land and other assets, and asset ownership.²

Questions to Ask

Once the sampling strategy is developed and appropriate care is taken on who is going to ask the questions, data-collection efforts need to make sure that women's productive activities are considered and that their roles in agricultural value chains are identified (Doss 2013a). Deere (2005) finds that rural women commonly report housework as their principal occupation even when they are actively engaged in agricultural production. This may be due to the fact that many rural women tend to participate in subsistence, household-level activities such as raising livestock, tending kitchen gardens, and agricultural processing. Therefore, it is particularly important to include survey questions about subsistence agriculture in addition to income-generating activities.

For the proposed indicators, the minimum demographic data needed are sex, age, education level, marital status, and relationship to household head or respondent for each of the members involved in the agricultural production process of the value chain under study. In addition, and central to the proposed indicators, it is essential to collect data on labor. Collection of labor data for formal-sector employment is now standard practice and allows the collection of information on hours and days of work, wages, and benefits. The major concern is how to collect this type of information for the nonformal sector. For this purpose, for each indicator we also propose a series

2 For more on data collection issues, see Doss (2013b).

of questions on the agricultural tasks being done disaggregated by age and sex, and important details on their subsistence agriculture activities. Similarly, the use of questionnaires to collect information on time use at the individual level helps substantially in understanding the activities of the female and male of the household. Examples of the questionnaire are given by CRP-PIM (2015), and examples of the Excel file are available at www.tools4valuechains.org.

One additional important issue is to identify the owners of and the people who have access to key resources and production factors. On ownership of land, it is essential that—in addition to the typical question of title or other document for the land ownership—we ask which household member or members own the land and whose names are on the title or other ownership documents to allow for gender analysis, given that it allows us to identify the gender of the owner(s) and not just if the piece of land has a title or not.

In places where the formalization of land ownership is minimal, it will also be important to have data on both the reported ownership and the specific rights over the asset. With respect to other inputs of production, such as livestock and agricultural equipment, it is important to also put the questions of ownership, management, and control to both the female and the male. Another important aspect of quantitative data collection and sampling is repeated individual observations—that is, interviews conducted with the same individuals over a period of time. This process allows researchers to analyze the evolution of quantitative indicators and provides a better understanding of an intervention's possible effects. Conducting follow-up surveys is also important because it allows researchers to control for the impact of omitted variables and thus helps to understand people's behavior as well as any changes seen, including the reasons behind those changes.

Finally, it is important to use appropriate sampling strategies in order to gather data that are statistically representative of the value chain under analysis. In other words, each node or segment of a value chain needs to be sampled so that the complete survey is statistically representative of the value chain as a whole. This can be a challenge because tracking down the people actively involved in each segment of the chain can be difficult and time-consuming, particularly in long and complex value chains. Taking a census of all possible participants in each node of the value chain could be a first step; researchers could then draw a representative sample from this census (for example, all farmers in a particular geographical area). It should

be noted that the sampling methods chosen will have a large impact on the researcher's ability to make inferences from the sample; therefore, it is important to integrate sampling strategies in the analysis.

Depending on the sampling framework chosen, it is important to consider sample selection bias. If participants and nonparticipants are systematically different (as it is typical in the case of women and men in the household), substantive results may be biased in unknown ways, causing their external or internal validity to be compromised. A bias occurring from the use of nonrandomly selected data could distort the results. Additionally, some individuals may be lost over time due to migration, death, or other reasons—known as attrition bias. This attrition bias could bias the final sample if the individuals who are lost differ in some systematic way from the participants who remain.

The problem of bias can be addressed through the use of sample-selection models—these are a well-developed class of econometric models that can be used to detect and correct for selection bias. The use of a sample-selection model, such as the Heckman two-step estimator (Heckman 1976, 1978, 1979), should be considered in any quantitative value-chain analysis.

Conclusion

The tools presented in this chapter are primarily intended to support the integration of gender in agricultural value-chain development through the use of quantitative tools. Identifying gender imbalances through quantitative analysis is the first step in improving the design of policies and interventions that will lead to greater gender equality and increased productivity in developing countries. Quantitative analysis will provide solid indicators that could be used as instruments in monitoring and evaluation processes.

The quantitative tools proposed in this chapter are built on those available in existing gender and labor economics literature and have been adapted for use in a value-chain context. They have the advantage of having already been tested in several previous studies and have proven to be useful indicators of gender differentials. These tools can help researchers and policymakers understand how value chains work, characterize labor distribution, and evaluate working conditions and access to work.

It is important to keep in mind that development interventions in agricultural value chains would benefit from additional gender analysis at different levels—for example, household-level analysis (income and expenditure management) and contextual analysis (institutions, social norms). It is

also important to ensure that female participation leads to greater productivity, not just to an increased number of women in the workforce. This could be achieved by increasing women's bargaining power in relation to other value-chain actors (Riisgard, Escobar Fibla, and Ponte 2010).

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