Mauritius

Earnings Mobility and Inequality of Opportunity in the Labor Market

Additional material relating to this report can be found on the World Bank Mauritius website (www.worldbank.org/mauritius). The material includes a fact sheet.

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Acknowledgments

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Abbreviations and Acronyms

CMPHS	Continuous Multipurpose Household Survey
GDP	gross domestic product
GIC	growth incidence curve
HOI	human opportunity index
IAC	inequality-adjusted coverage
NLFE	not in the labor force or education
OLS	ordinary least squares
SUC	strong unconditional convergence
WUC	weak unconditional convergence

If income mobility were very high,
the degree of inequality in any given year would be unimportant,
because the distribution of lifetime income would be very even. . . .
An increase in income mobility tends to make the distribution of lifetime income more equal.
Paul Krugman (1992, 28)

Higher income inequality would be less of a concern
if low-income earners became high-income earners at some point in their career,
or if children of low-income parents had a good chance
of climbing up the income scales when they grow up.
In other words, if we had a high degree of income mobility
we would be less concerned about the degree of inequality in any given year.
Alan Krueger (2012, 3)

Overview

Over the last decade, steady economic growth has placed Mauritius solidly in the upper middle income group and has contributed to further reducing poverty. Over the last 10 years, the Mauritian economy posted an average annual per capita growth of about 3.6 percent as it continued a process of structural transformation from traditional and low-skill sectors, such as agricultural and textile, towards services. Per capita GDP of $22,309 (measured in current international dollars) in 2017 is the 3rd highest in Africa and places Mauritius solidly in the upper middle income category. Measured against the $5.5 per day 2011 PPP line, poverty is estimated at 18.1 percent in 2012, well below the average of 34.4 percent among upper middle income countries and has declined from 20.3 percent in 2006/07.

Economic growth has been accompanied by an increase in income inequality, despite redistribution efforts by the Mauritian government. As measured by the Gini coefficient, inequality in Mauritius is comparable to the level of inequality in countries at a similar level of economic development (0.41) and moderate compared with the most unequal countries in the world, such as South Africa (0.63), Botswana (0.61) and Namibia (0.59).[1] However, the inequality in Mauritius has widened substantially over the last 15 years. The World Bank (2017a) shows that household income inequality has widened significantly from 0.36 in 2001 to 0.42 in 2015, particularly in the aftermath of the global economic downturn and terms-of-trade shock that hit Mauritius between 2008 and 2015. Rising inequality in household income from labor has been the main culprit behind the growth in overall income inequality, while the government's efforts to redistribute the benefits of growth have helped reduce the pace of the increase.

A divergence in labor incomes due to skills shortages driven by structural transformation has been the single most important contributor to increasing inequality. The economy has experienced a progressive shift from traditional and low-skill sectors to services, notably professional, real estate, and financial services. This transformation has generated a considerable rise in the demand for skilled workers that has not been matched by an equally rapid increase in the supply of skilled workers, notwithstanding the substantial improvement in educational attainment among the population. As a consequence, high-skilled workers benefitted from considerably larger increase in wages compared with low-skilled workers.

This report sheds light on the extent to which earnings mobility and inequality of opportunity in access to the labor market have contributed to the increase in earnings inequality in Mauritius. Among the most important concerns about rising inequality is a situation where people become trapped in low-paying jobs and do not have the opportunity to improve their welfare through their own efforts. For this reason, this report takes a closer look at the extent and nature of earnings mobility and inequality of opportunity in the Mauritian labor market with the objective of addressing the following questions. Do low-paid workers catch up in earnings with high-paid workers who have the same characteristics? Which individual characteristics foster earnings mobility? To what extent do circumstances at birth affect the ability of an individual to access certain good job opportunities? The study finds that there is convergence in earnings' growth over a period of 16 months. In other words, workers <u>initially</u> at the bottom of the earnings distribution enjoy a larger growth in earnings than workers <u>initially</u> at the top. The key to reconciling this finding with the growing inequality in earnings is that workers move along the earnings ladder over time. Workers <u>initially</u> at the bottom are not found at the bottom after one year because they

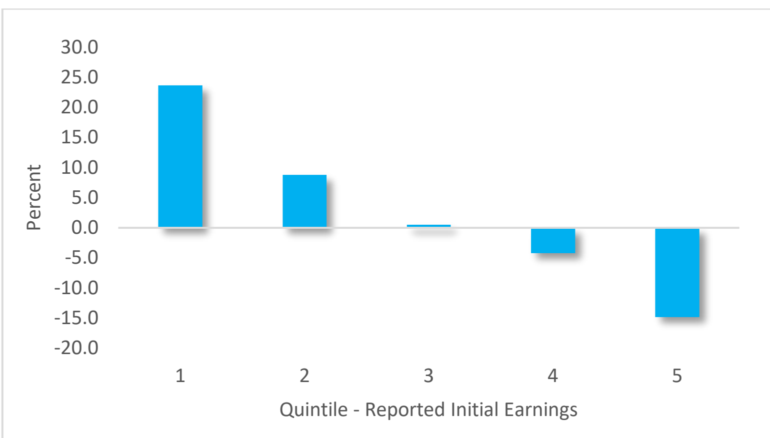
[1] Estimates are based on the latest available surveys from upper-middle-income countries (World Bank, Poverty and Equity database).

move slightly upward and the opposite occurs for workers initially at the top. In addition, and interestingly from a policy perspective, the individual characteristics that are the main driver of the rise in inequality also hinder individual earnings mobility. Women and workers with low educational attainments not only face lower initial earnings, they also face more difficulty in catching up with high-paid workers. On the positive side, unequal access to opportunities in the labor market is moderate and has declined over time, particularly thanks to improvements in educational attainments. For these reasons, the role of inequality of opportunity in explaining the rise in earnings inequality is limited. However, women and youth are still considerably disadvantaged in accessing jobs and full-time jobs, in particular.

Part I – Earnings Mobility

Between 2005 to 2015, earnings' growth of low-paid workers converged towards that of the high-paid, suggesting the presence of earnings mobility. Data from the panel component of the Continuous Multipurpose Household Survey (CMPHS 2005–15) suggest that, between 2005 and 2015, workers at the bottom of the earnings distribution saw their income rise faster than those who started off with higher earnings.[2] Workers starting with earnings in the first quintile of the distribution posted an average growth in earnings of about 24 percent or about Rupees 772 (Figure ES 1). By contrast, workers starting at the top (the 5th quintile) on average faced a reduction in earnings of about −15 percent, which corresponds to a median loss of Rupees 2,200 (Figure ES 1).[3]

Figure ES 1. Percentage Changes in Earnings, by Initial Earnings Quintile, 2005–15



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

[2] The survey consists of an initial interview and three follow-ups: for example, a household interviewed in the first quarter of 2005 is then re-interviewed in the second quarter of 2005 and again in the first and second quarter of 2006. This allows to collect information about individuals over a maximum period of 16 months.

[3] Earnings captured at one point in time might be affected by measurement error or transitory shocks. For this reason, the study also makes use of more permanent measures of earnings. First, an average of the earnings of individuals using information reported during the last three interviews is used instead of earnings reported in the first interview only. Second, predicted earnings are obtained taking advantage of variables that are predictors of a permanent advantage—such as age, educational attainment, gender, and household consumption—as a proxy for welfare. Estimates based on this adjusted measure of earnings indicate a median gain of about Rupees 473 for workers in the first quintile compared with a median loss of Rupees 515 for workers at the top. This corresponds to a change in earnings of about 9 percent at the bottom (the 1st quintile) and of -2 percent at the top (the 5th quintile).

Catching up with the earnings of high-paid workers is more difficult for women. Among the individual characteristics for which data is available, gender and educational attainment are the most important drivers of earnings mobility for Mauritian workers.[4] Conditional on the initial level of earnings, women experience less mobility than men with similar characteristics (Figure ES 2, panel a). This could be ascribable to unequal treatment but might also be the result of traditional models of housework and family care where women bear more of these responsibilities. According to data collected by AfroBarometer in 2017, over 7 in 10 Mauritians report that it is better for a family if a woman has the main responsibility of home and children care. Family-related activities compete with the labor market for women's time and may lead women to seek less competitive and less remunerative career paths in exchange for greater employment flexibility. On average, working women devote three times more of their day than working men to household chores and childcare: 3.8 hours per day among working women compared with 1.2 hours per day among working men (CSO 2005).

Lower education also results in lower mobility. Conditional on the initial level of earnings, workers with lower educational attainments are found to catch up less with the earnings of better educated workers with similar characteristics (Figure ES 2, panel b). For example, workers with post-secondary or tertiary education have a larger percentage change in earnings (+26 percent) than identical workers with up to completed primary education.

Figure ES 2. Percentage Changes in Earnings by Gender and Educational Attainment, 2005–15

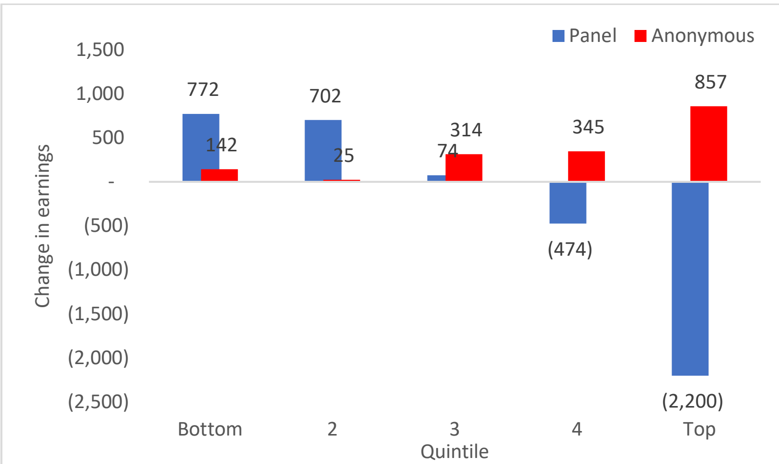
Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.
Note: Columns represent the predicted percentage change in earnings among men and women with tertiary education (panel a) and among workers at different educational levels (panel b) assuming that they have average characteristics in terms of initial earnings, age, district of residence, initial employment category, sector, occupation, and transitions across sectors between the initial and final period.

Despite the convergence in earnings' growth, inequality in earnings has continued to increase. The rise in earnings' inequality observed over the last decade suggests that earnings at the bottom of the distribution have grown less than earnings at the top (Figure ES 3, red columns). At the same time, tracking workers over a period of 16 months shows that workers initially at the bottom of the distribution have experienced a larger increase in earnings than those initially at the top (Figure ES 3, blue columns). The

[4] The analysis controls for a number of individual characteristics, including initial earnings, age, gender, educational attainment, district of residence, initial employment category, sector, occupation, and transitions across sectors between the initial and final period.

key to understand the difference between these two findings is that workers at different points of the earnings distribution change over time, as workers move along the distribution. Workers <u>initially</u> at the bottom are not the same workers that are found at the bottom at the end of the period (16 months later) because they have moved slightly upward. The opposite is observed in the case of workers <u>initially</u> at the top. Therefore, inequality, which is a comparative static measure of the earnings gap between high and low-paid workers observed at each point in time, might be widening, while tracking individuals over time indicates that <u>initially</u> low-paid workers earn larger gains in earnings relative to the <u>initially</u> high-paid.

Figure ES 3. Median Changes in Earnings by Quintile: Anonymous and Panel Workers, 2005–15



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.
Note: Earnings are expressed in 2015 prices.

The development of skills in line with the changing economic landscape can further enhance mobility while reversing the increase in inequality. Workers with skills that are most demanded in the labor market not only start off with higher earnings, but they also experience faster earnings growth. Therefore, policies targeted at developing skills that are in high demand have the potential to mitigate the increase in inequality and promote mobility. As a first step, a comprehensive assessment of current and future needs of firms in terms of skills is needed and can help inform education curricula for the coming generation of workers. Training systems can help those who are already working adapt to the new demands of the labor market.

Family-friendly social policies are also key. While Mauritius has made remarkable progress in terms of closing gender education gaps, the returns to human capital investments will not materialize unless progress can be made in closing the gender pay gap in the labor market. This starts with helping women access the labor market and re-enter once they have children. Affordable childcare and eldercare as well as working-time regulations that promote flexibility can help in this regard. Awareness campaigns can help to shift norms on the employment of women in high-paying positions. Investing in career promotion and leadership development programs for women could help them prepare for private sector jobs. Tackling wage discrimination is another priority. Currently, the Mauritian public sector – where a modest wage discrimination plays in favor of women – is most successful in attracting qualified women. If the private sector wants to attract a greater share of the growing number of well educated women, it needs to address wage discrimination.

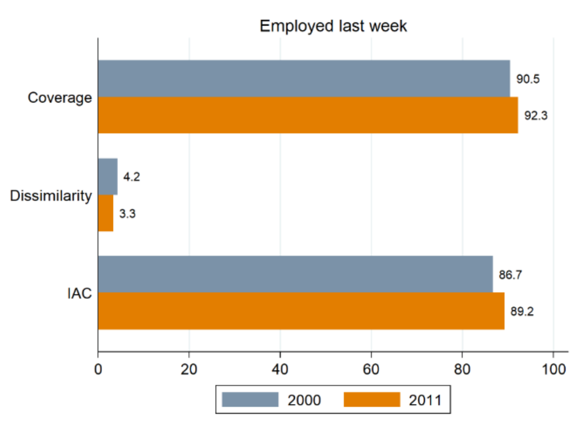
Part II – Inequality of Opportunity in the Labor Market

Employment rates do not always tell the full story on the availability of labor market opportunities in a country. Individuals might have a job but no labor market opportunities. For example, some individuals are willing to take any job even if the job profile does not match their skills because they cannot afford to be without one. Such individuals are recorded as employed in labor statistics, yet, in reality their labor market opportunities could be more constrained relative to individuals who are voluntarily unemployed. For example, individuals may choose to stay unemployed because they wait for better job opportunities to come along. They may do so because they can rely on other income sources and are not under pressure to find a job today. However, standard labor force surveys do not allow to identify voluntarily unemployment. In addition to a general employment indicator, based whether or not someone worked for at least 1 hour in the seven days preceding the interview, this study identifies the following labor market opportunities: employment full time (whether someone worked in the previous seven days for at least 40 hours), and wage employment (whether someone worked in the previous seven days for a wage or salary). The unemployed and those employed in jobs that do not have the desired characteristics are without a labor market opportunity. Inequality in access to labor market opportunities is measured by the extent to which such opportunities are available primarily to those born in privileged circumstances rather than being allocated to individuals based on skills and effort. This part of the study is based on data from the 2000 and 2011 Population Census because the census best captures variables that can be used as circumstances at birth.

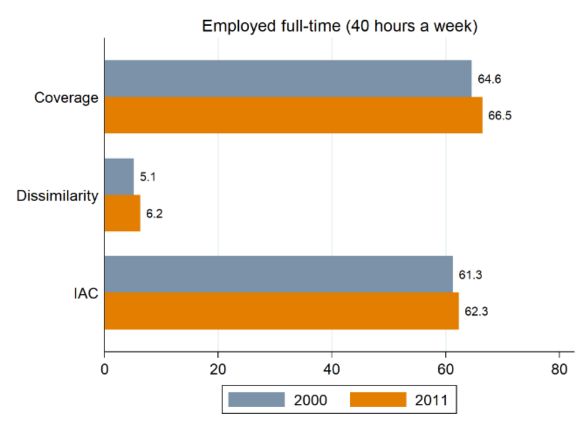
Equality in access to labor market opportunities improved over time, largely thanks to better educational attainments across the population. Between 2000 and 2011, inequality in access to job opportunities declined for overall employment and wage employment (Figure ES 4, panel a and c). By contrast, such inequality increased moderately in the access to full-time employment from 5.1 to 6.2 (Figure ES 4, panel b). Such improvements are ascribable to a growing proportion of society entering the retirement age and important investments in education that have created greater equality of opportunity for the next generation. These improvements in access to labor market opportunities are to be welcomed.

Figure ES 4. Inequality in Access to Labor Market Opportunities, 2000 and 2011

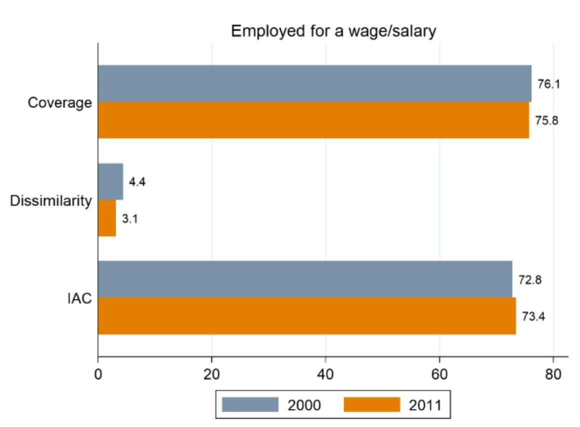
a. Employed in the previous week



b. Employed full time



c. Employed for a wage or salary

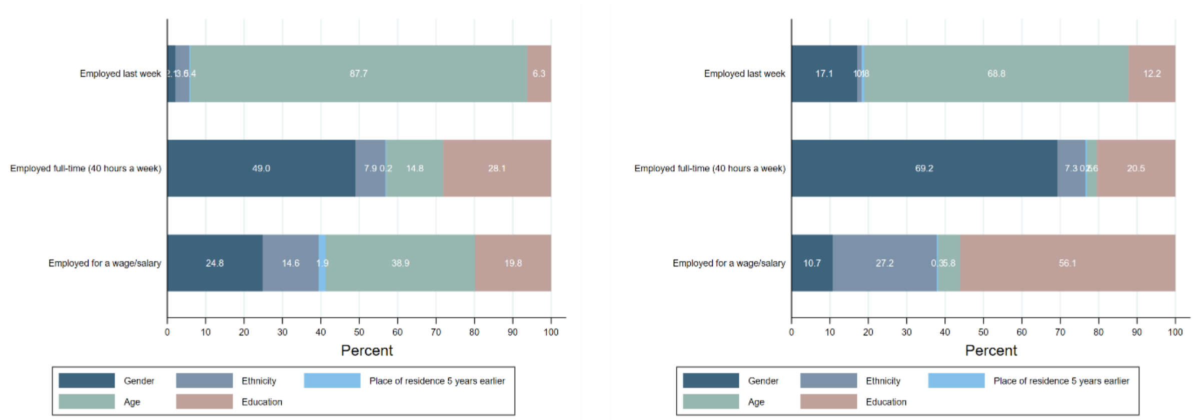


Source: Based on data of the Housing and Population Census, Statistics Mauritius.

However, women and youth continue to suffer disproportionally from less access to jobs and to full-time jobs in particular. Age and education explain the largest share of inequality in the access to job opportunities (Figure ES 5). Men are more likely to access employment in general and full-time employment in particular (Figure ES 5). In 2016, the participation rate for men was as high as 89 percent versus 56 percent among women. Age is key to explaining differences in access to employment in general. This is in line with the high unemployment rates observed among youth. At about 13 percent in 2016, youth unemployment (ages 16–34) is about twice as high as the average unemployment rate, and it reaches a peak of 20 percent among young women. Finally, educational attainment is extremely important to access wage employment because it is correlated with skills and employability, and it is an important factor affecting access to good-quality jobs. However, these have not been sufficient to mark a change in the upward trend in earnings inequality as some workers, particularly women, still suffer substantial gaps in earnings once they have access to the labor market.

Figure ES 5. Contributors to Inequality: Circumstances and Characteristics, 2000 and 2011

a. 2000 **b. 2011**



Source: Based on data of the Housing and Population Census, Statistics Mauritius.

Youth unemployment is a complex phenomenon that requires a two-pronged strategy. As explained in World Bank (2017a), in Mauritius youth unemployment is the by-product of two main factors. It is ascribable to a reluctance among low skilled youth to take up jobs in certain sectors, particularly agriculture and export-oriented enterprises, because of the working conditions as well as the social status associated with being employed in these sectors. Based on a series of surveys conducted by the Mauritian Human Resources Development Council, employers report lack of adequate attitudes toward work, unfavorable conditions with respect to other sectors, unavailability to work in shifts or overtime or use flexible time arrangements, insufficient job security, or low wages as common attitudes among their younger employees. As a result, an increasing share of work permits is issued every year to attract foreign labor, which is then overwhelmingly employed in low-skilled occupations. Employers also report difficulties in finding people with proficiency in technical skills, suggesting that the Mauritian education system does not meet labor market demands.

Evaluating and forecasting areas of growth and improving communication channels between education and workplace actors is key to promoting human resource development in line with the country's economic transformation. The capacity of evaluating and forecasting areas of growth is key to better prepare the work force of the future to changing labor demand needs. For example, the development of the ocean economy can be an expanding source of jobs and income, and, in the context of an aging population, health care and social care are areas that will continue growing in the years ahead. The provision of health care and care services is labor intensive and has therefore the potential to create jobs on a large scale that are less likely to be completely automatized as the technological revolution unfolds. Improving the communication between the education and training system and the labor market is also essential to develop human resources that possess the skills required in the economy in the future. This can help provide employers with the skills they look for and youth with what they need to take informed schooling decisions. For example, dual training systems have proved successful in facilitating the transition from school to work and in reducing youth unemployment in other countries. Such systems tend to be most successful when they involve an active cooperation between public institutions and the private sector.

Going forward a consolidation of employment programs and better integration with education policies will be required. Current youth employment programs are fragmented and in the absence of a central registry it is difficult to track if participants benefit from more than one scheme. This is most likely as some interventions overlap: there are, for example, several entrepreneurship schemes with similar target groups. In addition, the interventions are often disconnected from the demand. Many programs offer on-the-job or short class room training, yet they lack integration with job placement services. This calls for greater emphasis on comprehensive programming that combines on-the-job training, short classroom training, life-skills training, and labor market intermediation services and career guidance for participants.

Introduction

Over the last decade, growing earnings inequality has been the driving force behind the rise in inequality in Mauritius. The World Bank (2017a) shows that, over the past 15 years, household income inequality has widened significantly, particularly in the aftermath of the global economic downturn and terms-of-trade shock that hit Mauritius between 2008 and 2015. Rising inequality in household income from labor has been the main culprit behind the growth in overall inequality, while the government's efforts to redistribute the benefits of growth through the social protection system have helped reduce the pace of the increase. The single most important contributor to this trend is the growing inequality of individual earnings that can be attributed to the skills shortage created by structural changes that have occurred in Mauritius over the last decade. The economy has experienced a progressive shift from traditional and low-skill sectors to services, notably professional, real estate, and financial services. This transformation has generated a considerable rise in the demand for skilled workers that has not been matched by an equally rapid increase in the supply of skilled workers, notwithstanding the substantial improvement in educational attainment among the population.

The concern is that the recent inequality trends may have long-term negative effects on the country's economic prospects and eventually lead to a breakdown of the social contract that has been a key element of Mauritius' economic success. More inequality could reduce growth if (1) it reduces the incentives to invest or, in extreme cases, generate political instability and social unrest; (2) it leads to suboptimal investment in education, for example among low-income households in the presence of financial market imperfections; and (3) the adoption of advanced technologies depends on a minimum critical amount of domestic demand. Recent studies have introduced a distinction between the effect of inequality of opportunity and residual inequality. The intuition behind this approach is that inequality of opportunity, which captures inequality attributable to circumstances at birth, is expected to be harmful to growth, while other inequalities that are the result of differences in effort might operate in the opposite direction. There are indications from country studies that inequality of opportunity might be bad for growth.[5]

The extent to which the increase in inequality is a serious concern is linked to several issues. Among the most important concerns about rising inequality is a situation where people are becoming trapped in low-paying jobs and do not have the opportunity to improve their condition through their own efforts. The following quotations from the work of two great scholars help explaining why and how mobility and inequality of opportunity matter. Krueger (2012, 3) explains that

> higher income inequality would be less of a concern if low-income earners became high-income earners at some point in their career, or if children of low-income parents had a good chance of climbing up the income scales when they grow up. In other words, if we had a high degree of income mobility we would be less concerned about the degree of inequality in any given year.

Friedman (1962, 171) brilliantly argues how income mobility in the within-generation context is desirable as a force supporting the reduction in the inequality of longer-term incomes:

> A major problem in interpreting evidence on the distribution of income is the need to distinguish two basically different kinds of inequality; temporary, short-run differences in income, and differences in long-run income status. Consider two societies that have the same annual distribution of income. In one

[5] See, among others, Marrero and Rodriguez (2013); Van der Weide and Milanović (2014); Marrero, Rodriguez, and van der Weide (2016); Teyssier (2015).

> there is great mobility and change so that the position of particular families in the income hierarchy varies widely from year to year. In the other there is great rigidity so that each family stays in the same position year after year. The one kind of inequality is a sign of dynamic change, social mobility, equality of opportunity; the other, of a status society.

Building on the findings of the World Bank (2017a), this report takes a deep dive into assessing the extent to which the increase in inequality is a severe concern in Mauritius by analyzing earnings mobility and inequality in access to job opportunities. It aims at providing answers to the following questions: Do low-paid workers eventually catch up in earnings with high-paid workers (un)conditionally on their characteristics? Which individual characteristics foster earnings mobility? To what extent do circumstances at birth affect the ability of an individual to access a labor market opportunity?

The first part of the report is devoted to the analysis of earnings mobility. It starts off with an overview of the main stylized facts regarding individual earnings overall and by initial worker characteristics; it then explores the magnitude and the direction of changes in earnings overall and by initial individual characteristics; and it investigates the role of initial earnings and of other characteristics on earnings mobility. the first part concludes reconciling observed patterns in earnings mobility with the increase in income inequality occurred over the last decade. The second part of the report studies the extent of inequality of opportunity in the labor market among individuals of working age. It measures the degree of the inequality of opportunity in the labor market and describes how this has changed over time; it investigates the factors that contribute to this type of inequality; and it concludes with an analysis of the main drivers of the changes observed in the inequality of opportunity in the labor market over time.

A set of 4 Annexes are available to the reader at the end of the study with the goal of providing additional information. Precisely, Annex A illustrates additional statistics; Annex B introduces the issue of attrition and discusses its relevance in the case of the CMPHS as well as the sample selection criteria adopted in the analysis; Annex C describes transitions across labor market statuses among workers who are not part of the main sample, that is, youth (ages 16–29) and people ages 55–64; Annex D illustrates further the methodologies adopted to correct for measurement error and transitory earnings shocks in the analysis of earnings mobility.

The analysis has required the use of a number of different empirical approaches. Table O 1 summarizes the main definitions, methodologies and data sources adopted in the study. The first part uses data from the Continuous Multipurpose Household Survey (CMPHS 2005–15) and its rotating panel component. The second part is based on data from the 2000 and 2011 Population Census because the census best captures variables that can be used as circumstances at birth.

Table O 1. List of Definitions, Methodologies, and Data Used in the Analysis

PART I	
EARNINGS MOBILITY	Throughout this report, earnings mobility for an individual is defined as either the change in earnings or the change in log earnings for an individual from one period to another. Additional measures of central tendency, such as mean or median changes for all workers, or some subset of workers, are also used to identify a typical earnings mobility experience. Analyses exploring how mobility experiences differ across individuals to understand more about how the labor market is changing and what groups have been excluded from gains or positively or adversely affected by such changes are considered micromobility studies because they focus on changes for individuals or groups. In contrast, macromobility studies seek to identify the amount of the earnings mobility in the economy as a whole. There are multiple concepts of earnings mobility that might be studied. The New Palgrave Dictionary of Economics provides a description of six mobility concepts for income mobility (Fields 2008). Besides directional movement, there is time-independence, that is, the extent to which today's level of earnings (or recent changes in earnings) affects tomorrow's level of earnings; positional movement, that is, the change in the relative position of an individual in relation to other earners; share movement, that is, the change in the relative share of earnings; flux (or nondirectional movement), which captures the amount of variation in earnings that an individual experiences over time; and mobility as an equalizer of longer-term incomes, which highlights the ability of mobility to lower the variance of longer-term (or average) earnings relative to earnings at a given point in time. Micromobility studies start by asking who has more economic mobility and who has less. Let Y1 denote the reported value of the economic variable of interest in the initial period (quarter 1 in the case of the Continuous Multipurpose Household Survey [CMPHS]) and let Y2 denote the reported value of the economic variable of interest in the final period (after six quarters in the case of the CMPHS). Define economic mobility for income recipient i as $\Delta\mathrm{Y}_{\mathrm{i,t}} \equiv Y_{i,2} - Y_{i,1}$. Throughout the micromobility literature, the dependent variable is invariably the change in the reported value of Y. It is useful to separate out two types of micromobility studies. Both examine such correlates of earnings change as initial earnings, gender, education, and geographic location. Unconditional micromobility studies examine these correlates one variable at a time, for example, to determine who has more economic mobility, men or women or more well educated vs. less well educated workers. The purpose of these studies is explicitly not to hold other things equal; their purpose is to see who is doing better, period. On the other hand, conditional micromobility studies gauge the effect of one correlate controlling for the role of others, for example, to determine whether men have more economic mobility than women after controlling for gender differences in education, geographic location, and so on. Both sets of issues—identifying which are the important unconditional correlates of economic mobility and which are the important conditional correlates—are of interest and are taken up in turn in the following sections. Earnings mobility for worker i as $\Delta\mathrm{Y}_{\mathrm{i,t}} \equiv Y_{i,2} - Y_{i,1}$. The focus here is on individual changes in earnings, and changes are measured as changes in income in real currency units, changes in log-income (in real value terms), and, briefly, changes in position within the earnings distribution (quintiles, deciles, or centiles).
UNCONDITIONAL MICROMOBILITY	This decomposition It is possible to distinguish two types of micromobility analyses. The first, unconditional micromobility, investigates the correlation between earnings changes and initial earnings overall and separately for different groups defined by individual characteristics, including gender, education, and so on. The analysis does not explicitly hold other things equal; its purpose is to see who is doing better. The regression to be estimated is of the following form: $$\Delta\mathrm{Y}_{\mathrm{i,t}} = \alpha + \beta\mathrm{Y}_{\mathrm{i,1}} + \varepsilon_{\mathrm{i,t}}, \quad (1)$$ although nonparametric regressions have occasionally been estimated as well. The error term in (BI.1.1) is usually assumed to be independent and identically distributed. Unconditional convergence comes in two flavors. The weak form of unconditional convergence is that the largest percentage changes in income or earnings are experienced by those who have the lowest reported incomes or earnings to begin with. This is obtained by using the logarithm of earnings in the specification above. Strong unconditional convergence (SUC) implies that those with the lowest reported incomes or earnings to begin with have experienced the most positive or least negative changes in dollars. The estimated coefficient $\hat{\beta}$ provides information about the relationship between the change in earnings and initial earnings. If the estimated coefficient is negative, $\beta < 0$, earnings changes are negatively related to initial earnings, and therefore earnings are said to be convergent, which indicates that workers who start with lower earnings experience larger gains (or smaller losses). On the other hand, if it is positive, $\beta > 0$, earnings are said to be divergent, and the opposite is true. When the estimated parameter is not significantly different from zero, the dynamics of earnings changes are not dependent on initial earnings. If $Y_{i,1}$ is measured with error, the mismeasured variable appears both on the left-hand side and on the right-hand side of the regression, producing an attenuation bias, which, in this

context, means that apparent convergent mobility can be spurious rather than real.[a] A negative coefficient may this be the product of reversion to the mean, whereby, in the short-run, earnings converge over time merely because workers who reported having initially low (or high) earnings were hit by a transitory shock, and the observed convergence (or divergence) is simply an adjustment to their permanent earnings level, even in the case their longer-term earnings do not converge (or diverge). A direct way of remedying the measurement error in survey data is to use administrative data such as employer reports to the tax authorities. Lacking administrative data, the study addresses the measurement error issue by replacing $Y_{i,1}$ on the right-hand side of (BI.1.1) by a measure of predicted or long-term income or earnings, $\hat{Y}_{i,1}$:

$$\Delta \mathrm{Y}_{\mathrm{i,t}} = \alpha + \beta \hat{Y}_{i,1} + \varepsilon_{\mathrm{i,t}} \quad (2)$$

As explained in detail in annex C, a measure of longer-term or permanent individual earnings is derived by (a) regressing initial earnings on variables that are good predictors of the permanent earnings of an individual, including consumption level, and (b) by averaging individual earnings using information from other quarters. This is supposed to retrieve a parameter indicating convergence or divergence not affected by transitory shocks reverting to the mean that is a better measure of how earnings mobility is related to a permanent measure of initial advantage. Moreover, measurement error that typically affects the reporting of individual earnings does not bias the estimated coefficient estimated using the first measure of permanent initial advantage (Duval-Hernández 2006).

CONDITIONAL MICROMOBILITY

The second type, conditional micromobility, gauges the effect of one correlate controlling for the role of others, for example, to determine whether men have more economic mobility than women after controlling for gender differences in education, geographic location, and so on. The regression to be estimated is of the following form:

$$\Delta \mathrm{Y}_{\mathrm{i,t}} = \alpha + \beta \mathrm{Y}_{\mathrm{i,1}} + \gamma Z_i + \delta X_{i,t} + \theta X_{i,1} + \varepsilon_{\mathrm{i,t}} \qquad (3)$$

In (BI.1.3), the earnings change and initial earnings are the same as defined above; on the right-hand side, Z_i denotes time-invariant individual characteristics, such as age, gender, and education. $X_{i,1}$ and $X_{i,t}$ denote time-varying individual characteristics, such as occupation and sector of employment in quarter 1 and t, respectively. The coefficient β estimates whether mobility is strongly conditionally convergent. If $\beta < 0$, there is strong conditional convergence; if $\beta > 0$, there is strong conditional divergence; and if $\beta = 0$ or is not significantly different from zero, the pattern of earnings change is neutral with respect to initial earnings; thus, recipients in different parts of the initial earnings distribution gain the same amount in currency units (and, hence, those who report low initial earnings gain more in percentage terms than those with higher reported initial earnings). The concept of conditional convergence can be articulated in two ways, either as weak conditional convergence (WUC) or strong conditional convergence (SUC) as in the case of unconditional mobility. As in the case of unconditional convergence, a measure of longer-term or permanent individual earnings is used.

a. Whenever the right-hand-side variable is measured with error in a regression, an attenuation bias results (Deaton 1997). However, the presence of the same mismeasured Y1 variable as a regressor on the right-hand side and in Y2 – Y1 on the left-hand side produces a further attenuation bias. See Bound, Brown, and Mathiowetz (2001) for details.

DIRECTIONAL MOBILITY INDEXES

Denoting with y the monthly initial earnings of individual i at time t, the two main indexes of directional mobility discussed in this section are the average earnings change:

$$\overline{\Delta y_s} = \frac{1}{N_s}\sum_{i=1}^{N_s}\left(y_{it} - y_{i,t-1}\right), \qquad (1)$$

and the average log-earnings change:

$$\overline{m_s} = \frac{1}{N_s}\sum_{i=1}^{N_s}\left(\ln y_{it} - \ln y_{i,t-1}\right), \qquad (2)$$

where $i \in s$, and s is a subgroup of the population of size N_s. In addition, the share of workers who posted positive earnings changes may also be illustrated:

$$\overline{p_s} = \frac{1}{N_s}\sum_{i=1}^{N_s} I\left(y_{it} - y_{i,t-1} > 0\right), \qquad (3)$$

where I is an indicator function taking value 1 if $\left(y_{it} - y_{i,t-1} > 0\right)$ is strictly positive. It is clear that the average earnings change measures the change in earnings levels on average in the reference group over a period of 16 months. The average log-earnings change is analyzed for one main reason. Log-earnings change weights more earnings mobility among individuals at the bottom of the earnings distribution, and it approximates proportional changes in earnings.

DATA

The main dataset employed in this analysis is derived from the Continuous Multi-Purpose Household Survey (CMPHS). The CMPHS was launched by Statistics Mauritius in April 1999.

[a] Whenever the right-hand-side variable is measured with error in a regression, an attenuation bias results (Deaton, 1997). However, the presence of the same mismeasured Y_1 variable as a regressor on the right-hand-side and in $Y_2 – Y_1$ on the left-hand-side produces a further attenuation bias. See Bound, Brown, and Mathiowetz (2001) for details.

Since then it has been conducted monthly with the exception of 2000 when the survey was suspended to avoid overlapping with the Housing and Population Census and in 2004 when it was carried out on a quarterly basis. Starting with 2005, Statistics Mauritius has introduced a rotating panel for the island of Mauritius (excluding Rodrigues): 50 percent of the households sampled in a quarter are re-interviewed in the following quarter, rotated out of the sample for two quarters and then re-introduced for two additional quarters. For example, 50 percent of the households sampled in the first quarter of 2005 have been re-interviewed in the second quarter of 2005 and again in the first and second quarter of 2006. In other words, the rotating scheme allows to follow households and individuals therein over a maximum period of 16 months.

To maintain an updated list of residential households, a complete listing exercise has been performed in 2008, 2013, and 2016. While the 2008 new households list was used once the four panel interviews of each household were completed, the households that did not complete the four interviews by the end of 2012 were dropped out of the sample because the 2013 round of the CMPHS was based on a new list of Primary Sampling Units (PSUs) derived from the 2011 census. This means the panel rotation was interrupted in 2012 and started fresh in 2013.

Since 2005 sample size for each annual cross-section has been increased to 11,280 overall (10,560 for the island of Mauritius). In other words, each year 5,280 unique households are interviewed twice. A Stratified two-stage sampling design is used. At the first stage, PSUs are selected with probability proportional to size and at the second stage, a fixed number of households is selected from each selected PSU. A Relative Development Index (RDI) is used as spatial stratification factor. This index is based on 12 variables encompassing housing and living conditions, literacy and education, and employment derived from the 2000 Housing and Population Census to rank PSUs. The second stage stratification criteria are community, household size and average monthly expenditure of the household.

Each household that is not found is replaced with a different household from a list of replacement households. Replacement households do not become part of the panel rotation.

Details about the construction of the panel sample as well as attrition are discussed in Annex B.

PART II

INEQUALITY OF OPPORTUNITY IN THE LABOR MARKET

The analysis builds on the HOI framework which is widely used as an intuitive measure of a society's progress toward equitable provision of opportunities for children (de Barros et al., 2009). The index measures the extent to which circumstances for which a child cannot be held accountable – for example, location, gender, race, parental wealth – affect his probability of accessing basic services that are necessary to succeed in life such as timely education, vaccination, running water, electricity or connection to internet.

The index summarizes two elements in a composite indicator: (1) the set of available opportunities is the coverage rate, and (2) how equitably those opportunities are distributed, whether the distribution of that coverage is related to exogenous circumstances. The first component of the index is the average coverage rate for a given opportunity. The second is a dissimilarity index that measures differences in access to a given opportunity for groups defined by circumstances, compared to the average access rate to the same opportunity for the children population as a whole.

The choice of the Opportunity index is motivated by the fact that it is suitable to measures inequality of opportunities of discrete outcomes (among others, see Abras et al. 2013; Foguel and Veloso 2014; Krishnan et al. 2016). Formally, the index for a specific opportunity is given by:

$$O \equiv \bar{C}(1-D), \qquad (1),$$

where O is the Opportunity index, $\bar{C}$ is the average coverage rate of access to a given opportunity, and D is the Dissimilarity index that equals zero if access to opportunity is independent of circumstances, in which case the O index is equal to the average coverage rate. The Dissimilarity index is constructed as follow:

$$D = \frac{1}{2\bar{C}} \sum_{k=1}^{m} \alpha_k \left|\overline{C} - C_k\right|, \qquad (2)$$

Where k indicates a circumstance-group; C_k the coverage rate of group k; α_k the share of group k in the population; and k the number of disjoint circumstance groups. The dissimilarity index equals zero when $\overline{C} = C_k$ for all k types and the Opportunity index takes its maximum value, which is the coverage rate $\overline{C}$.

Empirically, calculating the Opportunity index consists of running a logistic regression model to estimate the relationship between access to a specific opportunity Y and circumstances X, which are exogeneous to the individual.

$$P(Y=1) = \frac{\exp(\beta`X)}{1+\exp(\beta`X)} = \Lambda(\beta`X) \qquad (3)$$

The estimated coefficients $\hat{\beta}$ are used to obtain for each individual the predicted probability of access to that specific opportunity, which is then used to calculate the average coverage rate, the dissimilarity index, and the opportunity index.

$$\widehat{p_i} = \frac{\exp(x_i\hat{\beta})}{1+\exp(x_i\hat{\beta})} \qquad (4)$$

The dissimilarity index is calculated as a function of the set of circumstances selected for the analysis. The fact that it is typically impossible to observe all relevant circumstances has raised the questions as to the extent to which the measure is able to capture true inequality of opportunity. This concern is mitigated by one important property: adding circumstances to a given predetermined set on which the dissimilarity index is calculated can only increase the value of the index. In other words, the calculated dissimilarity index can be considered a lower bound of the actual inequality that could be calculated if all circumstances of interest could be observed.[b]

In addition to standard circumstances, the analysis includes individual characteristics, such as education and age. Education and age are proxies for skills and experience, two important correlates of any labor market variable. The exercise then is to determine the role of circumstances on labor market opportunities, net of age and experience. This method captures the direct contribution of circumstances to inequalities in the labor market. It misses the role of circumstances through their effect on earlier human capital accumulation, or the indirect channel. The direct effect can be interpreted as inequality produced by distortions in the labor market, distinct from those produced in earlier stages of life, that is, prior to the individual's entry into the labor market.

In a second step, to assess the relative contribution of circumstances and characteristics to inequality, the dissimilarity index is decomposed by applying the decomposition proposed by Shorrocks (2012). The decomposition is aimed at measuring how much the dissimilarity index would change when a circumstance or characteristics is added to the existing set of circumstances and characteristics. The change in inequality as a result of adding a circumstance or a characteristic is an indicator of the contribution of that variable to inequality of opportunities. To identify the impact of a certain circumstance or characteristic, all the changes that occur when the variable of interest is added to all possible sets of existing variables need to be considered and an average of all the possible changes must be calculated (Hoyos and Narayan 2011).

The share of inequality attributable to circumstances is interpreted as the part of inequality that is unfair. This part represents barriers to equitable access to employment for certain types for workers. This is likely to underestimate the true extent of inequality caused by circumstances because of both the limited number of circumstance controlled for in the analysis and of the effect those same circumstances have on individuals' educational attainment. From a policy-making standpoint, this analysis provides relevant information as to the extent to which the labor market might be unfair, but also inefficient in the allocation of employment opportunities. More precisely, it indicates whether and the degree to which signals for skills (as proxied by education and experience) are dominated by the effect of factors are less likely to be correlated with the individual productivity.

OPPORTUNITIES AND CIRCUMSTANCES IN THE LABOR MARKET

Category	Definition
Opportunity	
Employed	Individual worked the previous week at least 1 hour
Employed full time	Individual worked the previous week at least 40 hours
Employed for a wage	Individual worked the previous week at least 1 hour for a wage
Circumstance	
Basic	
Gender	Binary variable to identify male individuals
Ethnicity	Series of binary variables to identify the individual's ethnicity
Place of residence five years earlier	Series of binary variables to identify the individual's district of birth
Additional circumstance	
Father's education	Series of binary variables to identify different levels of educational attainment of individual's father
Mother's education	Series of binary variables to identify different levels of educational attainment of individual's mother
Father's occupation	Series of binary variables to identify different levels of occupation of individual's father
Characteristic	

[b] However, in the case of working-age individuals, the omitted variables could include circumstances that do not affect labor market status as well as other characteristics, such as how hard the person worked to get a job of that kind. Distinguishing between the two different types of variables and how they interact with the circumstances included in the analysis is not possible with the available data sets.

	Age	Individual’s age
	Educational attainment	Series of binary variables to identify the maximum educational level attained by the individual
DATA	The main dataset used in the second part of the study is derived from the 2000 and 2011 Population Census (1 percent sample). At about 10-year intervals, Statistics Mauritius conducts a population census that covers the entire population in the Republic of Mauritius. In addition to demographic characteristics of the population such age, gender, location of residence, educational attainment, the census captured labor market information including status in employment, industry, occupation, number of weekly working hours, absence from work, availability to work, and job search. A similar analysis is performed using post-census data from the CMPHS rounds conducted between 2012 and 2015.	

Part I – Earnings Mobility and Inequality

Each class of the [distribution of income] resembles a hotel . . . ,
always full, but always of different people.
Schumpeter (1955, 126)

Economic mobility studies provide information
about changes of people among rooms and changes in the rooms themselves.
Fields (2010, 409–10)

Different countries experience different growth patterns. The traditional way to examine the distributional consequences of economic growth is thus to take advantage of data collected at two points in time and derive a range of poverty and inequality indicators. Thanks to rapid improvements in the capacity to collect microdata in developing countries, a new approach has found space in the development literature over the last 25 years. It relies on using data for the same individuals at two or more points in time to understand changes in income or welfare in general. This type of data, known as panel or longitudinal data, typically require a baseline interview and one or more follow-up interviews or a single interview with retrospective questions.

Overall, the studies of earnings mobility in developing countries have found that, unconditionally, initial low earners are those who gain the most over time, with the exception of China in 1998–2002 where weak unconditional divergence is found. Conditionally on other individual characteristics, the literature has found that earnings or incomes converge to their conditional mean. Strong conditional convergence has been found in income mobility in Côte d'Ivoire (Grootaert, Kanbur, and Oh 1997), India (Coondoo and Dutta 1990), and Indonesia, South Africa, and Venezuela (Fields et al. 2003b) and in earnings mobility in Argentina, Mexico, and Venezuela (Fields et al. 2015) and in South Africa (Cichello, Fields, and Leibbrandt 2005).[8]

This first part of the study takes advantage of the panel component of the Continuous Multipurpose Household Survey (CMPHS) data collected by Statistics Mauritius with the scope of investigating the patterns of earnings mobility in the short run, precisely over a time period of 16 months, and how mobility in the earnings of individuals relates to changes in income inequality. The main questions addressed in this first part are the following: Are earnings mobility patterns similar across different population groups? How do initial earnings affect mobility? Are the initially least advantaged individuals gaining more (or losing less) in terms of earnings changes (un)conditionally on their characteristics? What is the effect of socioeconomic characteristics on earnings mobility? Does mobility equalize earnings over time? How does earnings mobility affect our understanding of changes in inequality?

The structure of this first part is as follows. Section 1 provides an overview of the main stylized facts regarding individual earnings overall and by initial worker characteristics using the panel component of the CMPHS. Section 2 explores the magnitude and the direction of changes in earnings overall and by initial individual characteristics. Section 3 is the core of the first part of the study and looks at the role of initial

[8] Recently, mobility studies have become available for a number of developing countries, including Argentina (Fields et al. 2015), China (Jalan and Ravallion 2000; Khor and Pencavel 2006; Nee 1996; Ying, Li, and Deng 2006), Hungary (Galasi 1998), India (Coondoo and Dutta 1990; Gaiha 1988), Indonesia (Fields et al. 2003a), Mexico (Duval-Hernández, Fields, and Jakubson 2017), Peru (Grimm 2007; Herrera 1999), South Africa (Cichello, Fields, and Leibbrandt 2005; Fields et al. 2003a, 2003b), Tanzania (Quinn and Teal 2008), Venezuela (Freije 2001), and Zimbabwe (Gunning et al. 2000).

earnings as well as of other characteristics on mobility. Section 4 reconciles mobility patterns with the increase in income inequality observed over the last decade and assesses how such patterns can affect our understanding of the changes in inequality.

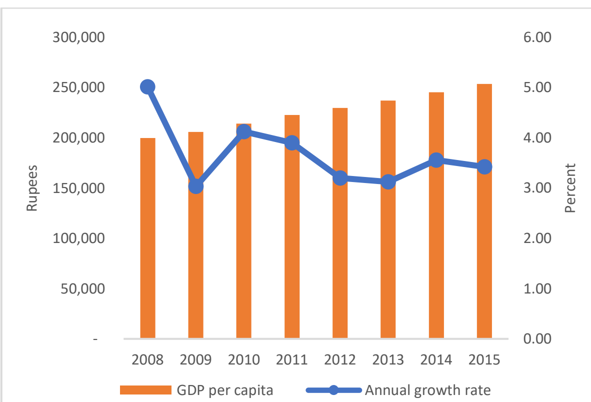
1. Growth, inequality and earnings: stylized facts

This section starts with a description of trends and patterns of economic growth over the last decade, one of the three concepts, together with inequality and mobility, key to understanding changes in inequality. Then the section presents evidence on subgroups of workers to identify those that experience higher initial earnings, which can be considered a measure of initial advantage among panel individuals.

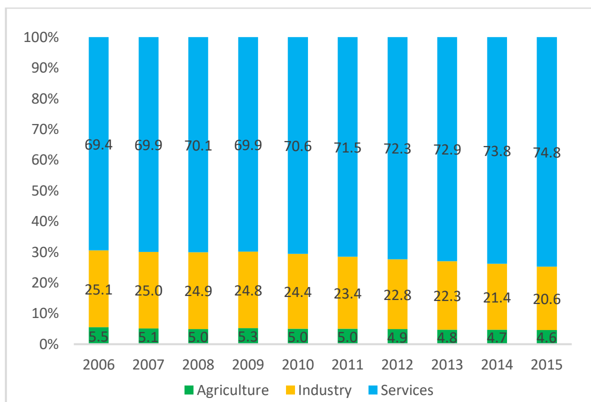
Between 2005 and 2015, the Mauritian economy posted an average annual per capita growth of about 3.7 percent (Figure 1.1, panel a) as it continued a process of structural transformation from traditional and low-skill sectors, such as agricultural and textile, to services, notably professional, real estate, and financial services (Figure 1.1, panel b). Per capita GDP of $22,278 (measured in purchasing power parity) in 2017 is the 3rd highest in Africa and places Mauritius solidly in the upper middle income category.

Figure 1.1. Economic growth and structural transformation, 2006-15

a. GDP per capita level and annual growth rate, 2008-15



b. Sectoral breakdown of gross value added, 2006-15

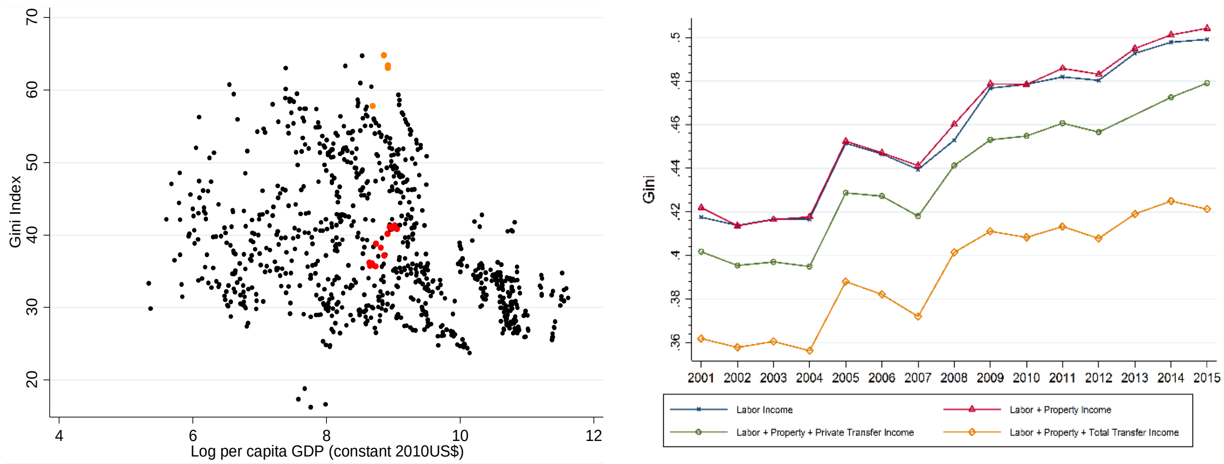


Source: Based on national accounts data, Statistics Mauritius.
Note: GDP is measured in 2006 prices.

Economic growth and structural transformation were accompanied by rising income inequality. Inequality, as measured by the Gini coefficient, in Mauritius is moderate compared with countries at a similar level of economic development and compared with the most unequal countries in the world such as South Africa (Figure 1.2, panel a). Although 40 percent of the countries on which data are available are more unequal than Mauritius, the inequality in Mauritius has widened substantially over the last 15 years. The Gini coefficient increased from 0.36 in 2001 to 0.42 in 2015 (Figure 1.2, panel b).

Figure 1.2. Inequality in Mauritius and in the Rest of the World

a. Gini coefficient in Mauritius and in the Rest of the World, 2000–12 **b. Gini coefficient – different income sources, 2001-15**

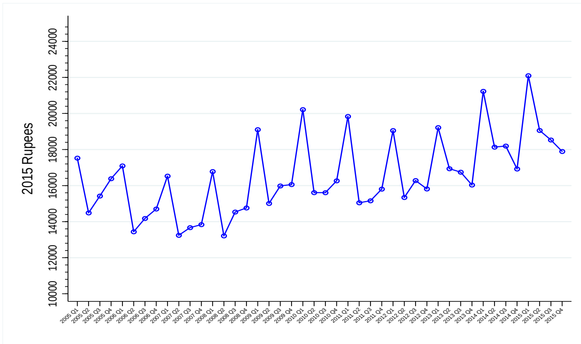


Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius; WDI.
Note: Red dots indicate Mauritius; orange dots indicate South Africa.

The World Bank (2017a) shows that, over the past 15 years the rise in inequality is mostly attributable to growing inequality in individual earnings that has widened particularly in the aftermath of the global economic downturn and terms-of-trade shock that hit Mauritius between 2008 and 2015 (Figure 1.2, panel b). Rising inequality in household income from labor has been the main culprit behind the growth in overall inequality, while the government's efforts to redistribute the benefits of growth through the social protection system have helped reduce the pace of the increase. The single most important contributor to this trend is the growing inequality of individual earnings that can be attributed to the skills shortage created by structural changes that have occurred in Mauritius over the last decade. This transformation has generated a considerable rise in the demand for skilled workers that has not been matched by an equally rapid increase in the supply of skilled workers, notwithstanding the substantial improvement in educational attainment among the population (World Bank 2017a).

Economic growth is, to some extent, reflected in the changes observed between 2005 and 2015 in average earnings for the employed population (ages 16–64) that is part of the CMPHS panel (Figure 1.3). Average monthly earnings increased by about 1.8 percent per year on average, from about MUR 16,000 in 2005 to about MUR 19,400 in 2015.

Figure 1.3. Average Earnings, Full Sample, 2005–15



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

However, as illustrated in World Bank (2017a), growth in earnings was not uniform across workers with different characteristics, particularly between men and women and between high- and low-skilled. Three key facts emerge about trends in hourly wages (World Bank 2017a). First, hourly wages increase more rapidly among women (29.5 percent over 2004–15) compared with men (22.6 percent); second, the rise in the wage premium among workers with upper-secondary or higher education is attributable to the large increase in hourly wages among these workers relative to low-educated workers (over 2004–15, 31 percent as opposed to 22.2 percent and 15.8 percent); third, young workers experience larger wage increases with respect to middle-age and older workers.

Such different growth patterns are the main culprit behind the rising income inequality that accompanied economic growth and structural transformation. For this reason, it is of interest to check whether workers in the panel component show considerable differences in their initial level of earnings along the main dimensions discussed above. Initial earnings can be considered a measure of initial advantage and therefore identifying group of workers that experience higher initial earnings is important for the analysis of mobility in earnings (Figure 1.4).

- Quintiles of the initial earnings distribution: Figure 1.4 (panel a) shows that workers in the richest quintile have higher initial earnings relative to workers in the poorest quintile by construction. The figure also illustrates how large the differences in earnings are across quintiles. There are large differentials in initial earnings between workers in the top quintile and the rest of the employed population. Earnings in the first four quintiles are between MUR 5,000 and MUR 20,000 a month; earnings of workers in the highest quintile average above MUR 40,000 a month, that is, between two and eight times higher.
- Gender: Men have a large initial advantage in terms of earnings with respect to women (Figure 1.4, panel b). However, the difference has modestly shrunk over time. In the first quarter of 2005, the average gender difference in initial earnings was about MUR 8,623, and this declined to MUR 5,676 by the first quarter of 2011.
- Age: Figure 1.4 (panel c) illustrates that initial earnings among youth are, on average, the lowest relative to the initial earnings of workers ages 50–54. Clearly, mid- and old-age workers have an initial advantage with respect to younger ones.
- Educational attainment: Figure 1.4 (panel d) shows a clear ranking among workers, whereby workers with higher education have higher initial earnings. Workers with postsecondary or tertiary

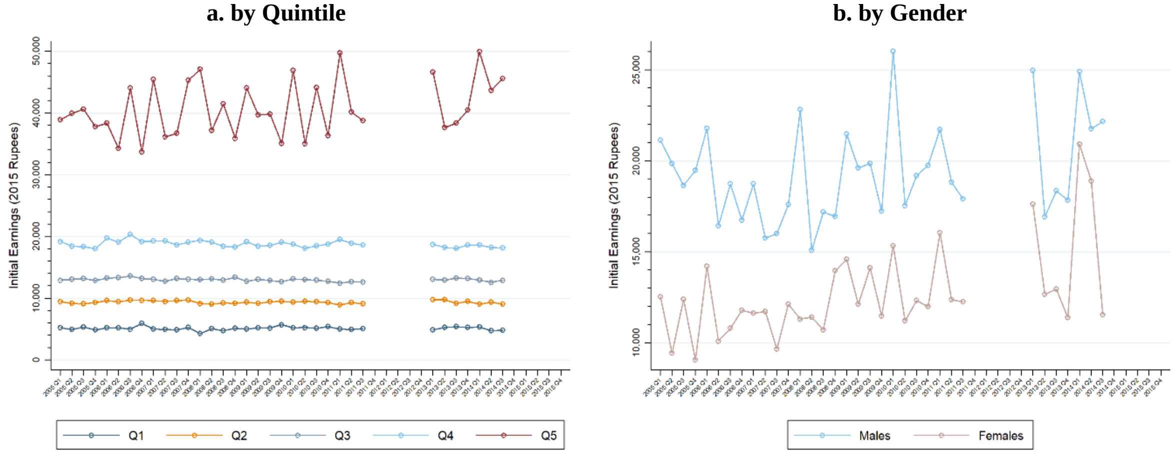
education earn initially between about two and four times as much as workers with upper-secondary education and up to completed primary education, respectively.

- Industry: workers employed in different industrial sectors also have different initial earnings. Agriculture and manufacturing sector workers earn, on average, lower initial earnings compared with workers employed in services, both trade and other services (Figure 1.4, panel e).
- Occupation: Even larger are the difference in initial earnings and therefore the initial advantage of workers in certain occupations. Figure 1.4 (panel f) illustrates that professionals, managers, and technicians earn initially over three times as much as craft, production, and elementary occupation workers and almost twice as much as clerical, sales, and service workers.

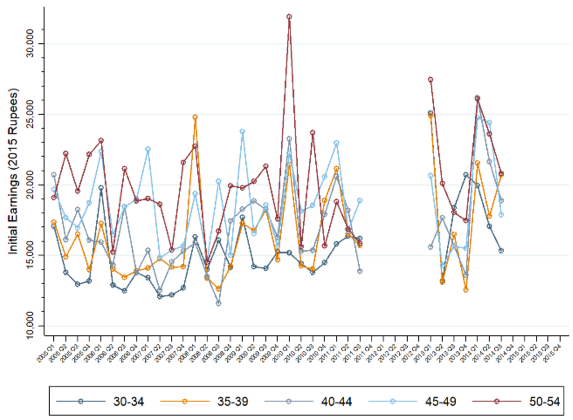
To conclude, Figure 1.3 and Figure 1.4 illustrate considerable variation in earnings, possibly linked to seasonality. This could lead to observe negative coefficients if for example workers are subject to transitory earnings shocks over time. In other words, one could observe that earnings are convergent simply because workers who start with a positive earnings shock are then adjusting back to their lower permanent level of earnings, even if long term earnings do not converge. To investigate whether convergence in earnings is occurring in a more permanent sense, this study adopts two approaches to derive a more permanent measure of initial earnings. First, an average of the earnings of individuals using information reported during the last three interviews is used instead of earnings reported in the first interview only. Average earnings over repeated periods of time average out the ups and downs in earnings and should therefore be less affected by transitory shocks. Second, predicted earnings are obtained taking advantage of variables that are predictors of a permanent advantage—such as age, educational attainment, gender, and household consumption—as a proxy for welfare.

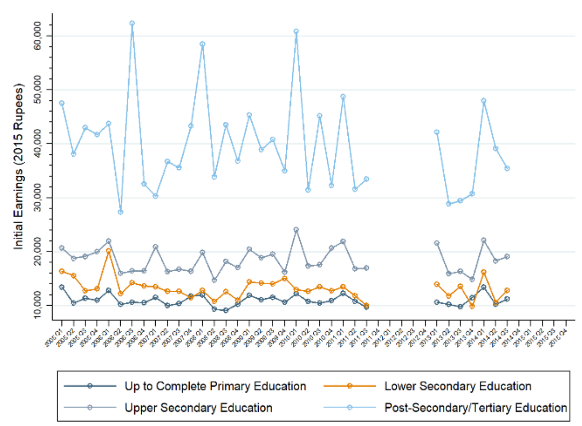
Figure 1.4. Average Earnings, by Characteristics, 2005–15

a. by Quintile **b. by Gender**

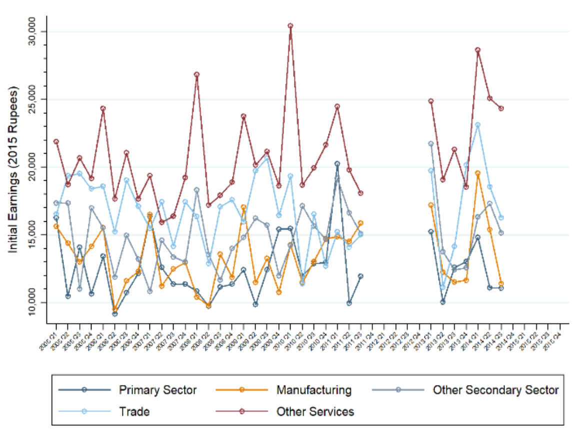


c. by Age-Group **d. by Educational Attainment**

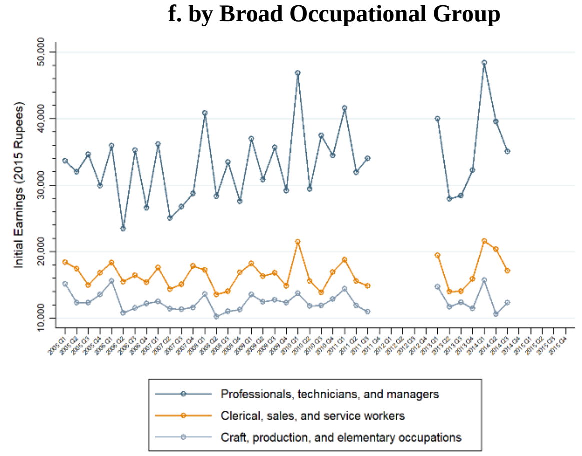




e. by Industrial Sector



f. by Broad Occupational Group



Source: Based on data of the Continuous Multi-Purpose Household Survey (CMPHS), Statistics Mauritius.

2. The Patterns in the Changes in Earnings

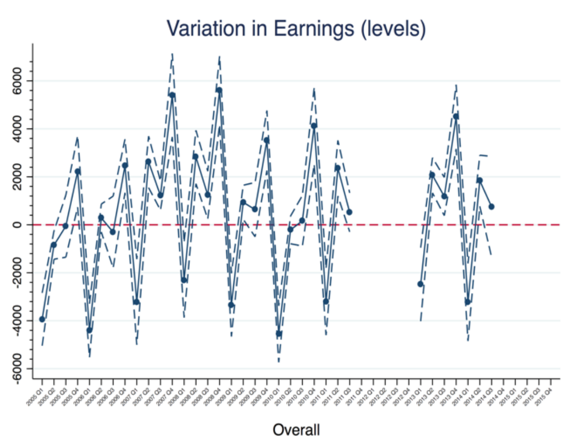
This section explores the magnitude and the direction of the changes in earnings overall and by initial individual characteristics. The goal is to understand who has larger earnings gains and smaller earnings losses over a series of repeated 16-month time spans between 2005 and 2015: individuals whose earnings were relatively high or those whose earnings were relatively low?

The "hypothesis of divergent mobility" explains that individuals with the initially highest earnings experience the largest earnings gains and the smallest earnings losses (Boudon 1973; Huber 1998; Merton 1968). A number of theories have advanced economic explanations of such hypothesis. According to the theory of cumulative advantage, one of the factors that may contribute to such larger gains among the initially more well off is the labor market twist. The idea is that globalization and skill-biased technological change generate an increase in the demand for skills that outpaces the supply of these same skills. This induces much larger earnings gains for the skilled and possibly a decline in the relative earnings of the unskilled (Gottschalk 1997; Johnson 1997; Topel 1997). An alternative explanation posits that better-off individuals own physical and human capital, have access to social and political connections, and have greater ability to borrow and save, could all contribute to cumulative advantage. In addition, poverty traps can make individuals who lack a minimum level of human, physical, and social assets more likely to be trapped in poverty from which they cannot escape.

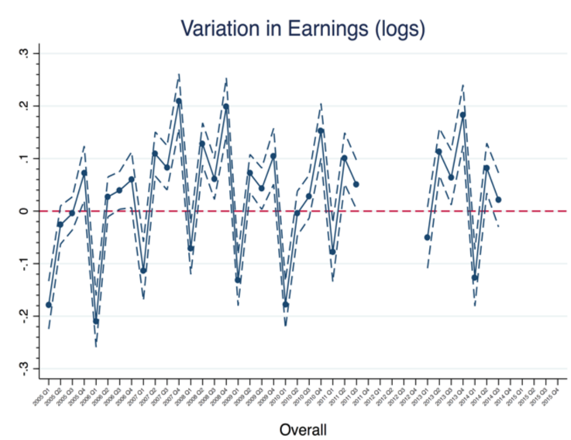
By contrast, individuals who start with the highest earnings gain the least, according to the theory of the convergence to the grand mean (Galton 1889). Workers starting above the grand mean converge downward relatively, while workers starting below the grand mean converge upward relatively.

Figure 2.1. Average Earnings Change, Log-Earnings Change, and Share of Workers Exhibiting Positive Earnings Change, 2005–15

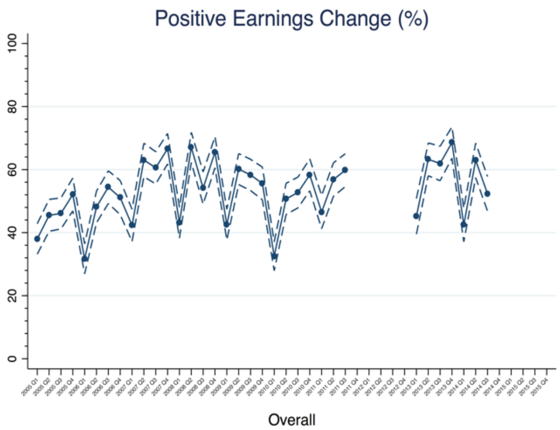
a. Earnings change (levels)



b. Earnings change (logs)



c. Share with positive earnings change



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.
Note: Dotted lines indicate confidence intervals (95 percent).

The average mobility among all individuals ages 30–54 in levels and logs is illustrated in Figure 2.1. Average changes in earnings are largely positive, although there are occasionally negative changes. The average change in 2005–15 was MUR 336; the corresponding proportionate change was 2 percent; and some 53 percent of workers experienced a positive change. The share of workers recording a positive change modestly increased, starting off at about 40 percent and ending at an average of about 60 percent. The most recent time period is therefore characterized by smaller negative changes, on average.

Figure 2.2 illustrates the magnitude and the direction of the changes in earnings by initial characteristics along 5 dimensions:

- Quintile: workers initially at the bottom of the distribution are expected to experience the smallest earnings gains, which is not expected to be the case of the initially more well off. Figure 2.2 (panel a) plots the average earnings change in levels and logs by initial earnings quintile to validate this hypothesis. The evidence points in a different direction: workers initially at the bottom of the distribution posted the largest gains in earnings (an average of MUR 1,658 over 2005–15); workers at the top of the distribution experienced a sizable decline in earnings (an average drop of MUR 3,388 over the same period). In other words, there is evidence of a reversion to the mean in individual earnings, which suggests the existence of convergence in earnings. The average percentage change is +21 percent among workers in the lowest quintile, +8 percent in the second quintile, +1 percent in the middle of the distribution, and −4 and −16 percent among workers in the fourth and highest quintile, respectively. It is also evident that the average percentage increase in earnings and the share of workers experiencing positive earnings changes become larger over time. The picture is even clearer if average earnings changes are estimated according to a ranking based on the low-earnings line (Figure A 1).
- Age-Group: There are no large differences across age-groups in terms of average changes in earnings (Figure 2.2, panel b). The average change over 2005–15 is larger among workers in the 50–54 age-group, at MUR 734, whereas the average change in log-earnings is larger among workers in the 30–34 and 35–39 age-groups. This is likely attributable to the fact that these workers may be gaining initially lower wages relative to older workers.

- Gender: Women exhibit moderately larger average changes in levels and in logs because they start off with lower initial earnings, and, among them, some 55 percent of workers experience positive changes, compared with 52 percent among men (Figure 2.2, panel c).
- Educational attainment: Highly educated workers, namely, those with upper-secondary and, even more distinctly, those with postsecondary or tertiary education experience larger average earnings changes (Figure 2.2, panel d). Over 2005–15, workers with postsecondary or tertiary education posted an average gain of about MUR 1,373, which is over 20 times the gain estimated among those with up to completed primary education (MUR 63) and about 6 times as large as the gain observed among workers with lower-secondary education (MUR 237). The average log-earnings change is estimated at about 3 percent among workers in the top two education groups, at 2 percent among workers with lower-secondary education and at 1 percent among workers with completed primary or lower secondary education. As illustrated by the World Bank (2017a), structural transformation is certainly one of the main factors that have created different earnings growth paths among skilled and unskilled workers and therefore contributed to increasing inequality in the long term.
- Industry: the average changes in earnings are largest among workers initially employed in the tertiary sector, followed by workers in the primary sector (Figure 2.2, panel e). Within the tertiary sector, there are no large differentials between trade and other subsectors. However, in the manufacturing subsector, workers experience an average decline in average earnings (a loss of MUR 146 over 2005–15).

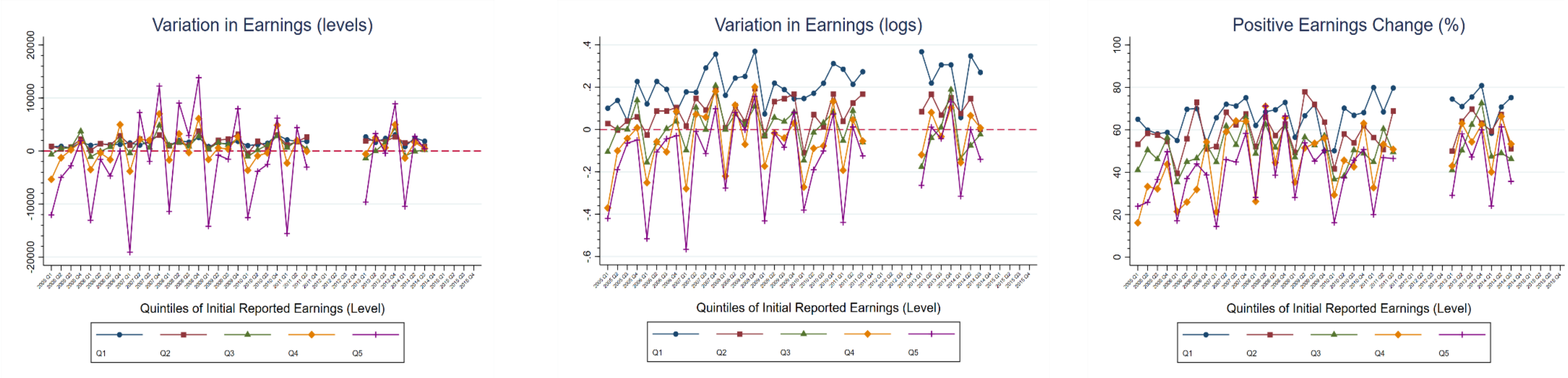
Because earnings observed over a short time are likely subject to transitory shocks, and earnings in general are affected by measurement error (see Annex C for more details), the average changes in earnings estimated by the initial predicted earnings quintile and average earnings quintile are considered. The evidence confirms the existence of mean reversion in earnings in the short run; workers starting above the grand mean tend to converge downward relatively, and vice versa. Using both predicted and average earnings as a measure of more permanent initial earnings, the estimates indicate a larger increase—although mitigated relative to estimates based on initially reported earnings—among workers at the bottom of the distribution and earnings declines among workers at the top (Figure A 6 and Figure A 7). Workers with initial earnings more than four times the low-earnings line experienced an average decline in earnings (a drop of MUR 3,719 over 2005–15) as opposed to workers with initial earnings below the line or between one and two times the line; these workers gained an average of MUR 1,751 and MUR 1,163, respectively. The differences in the average percentage change are also considerable: the initially poorest workers posted a 27 percent increase on average (and 70 percent of them had a positive earnings change); workers in the middle posted an average increase of 2 percent (53 percent with positive earnings change); and the richest workers experienced a decline of 17 percent on average (and only 38 percent of them showed a positive earnings change).[9]

[9] Estimates based on a ranking according to initial predicted and average earnings do not change the main findings, although the magnitude of the average change is mitigated.

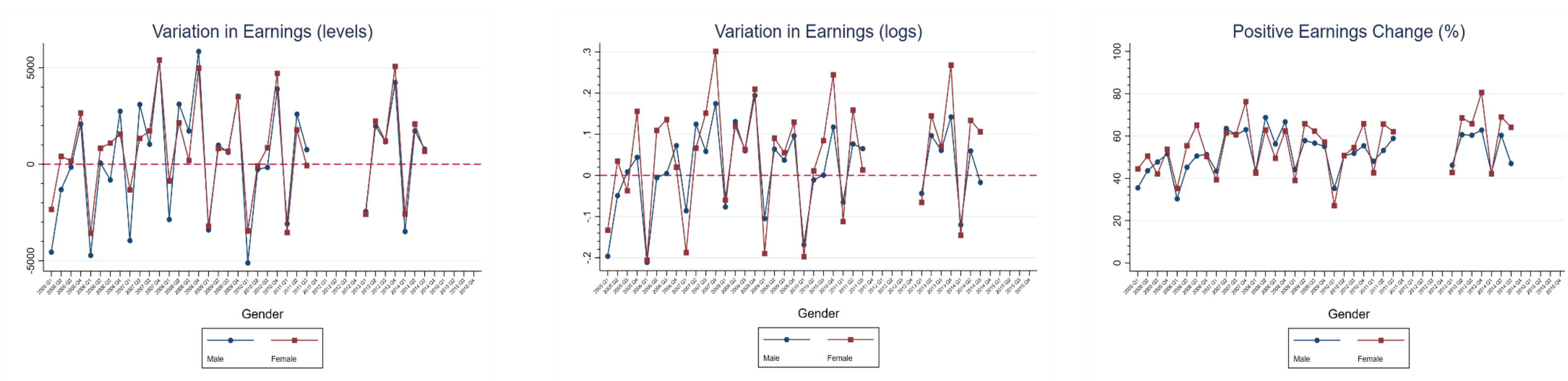
Figure 2.2. Average Earnings Change, Log-Earnings Change, and Share with Positive Earnings Change, by Initial Characteristics, 2005–15

Earnings change (levels)	Earnings change (logs)	Share with positive earnings change

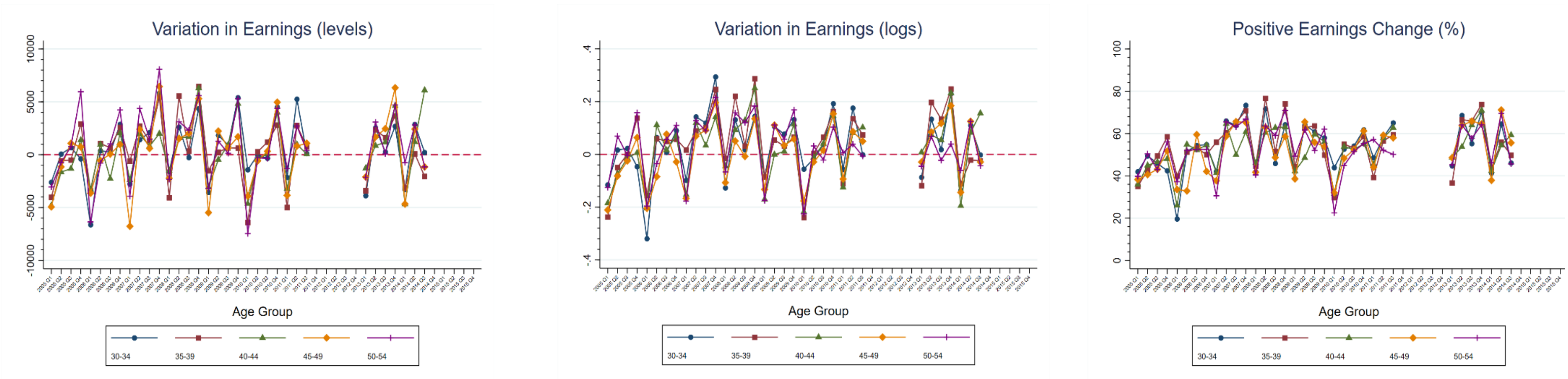
a. By Initial Earnings Quintile



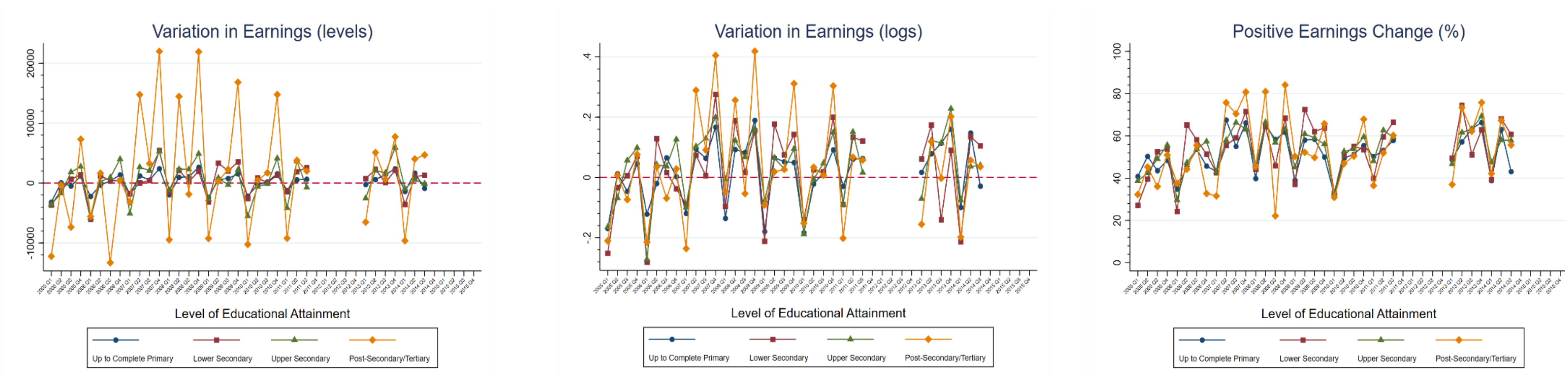
b. By Gender



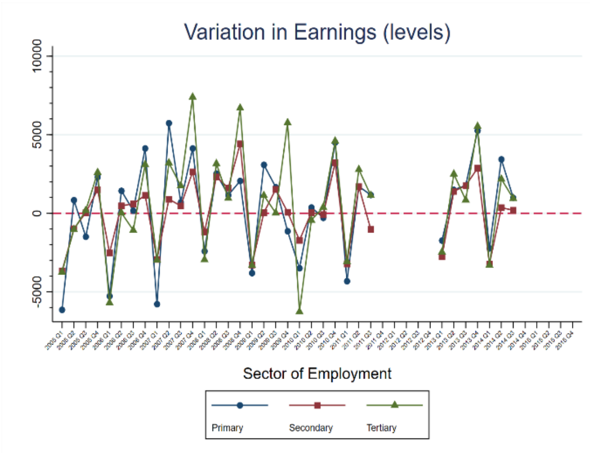
c. By Age-Group

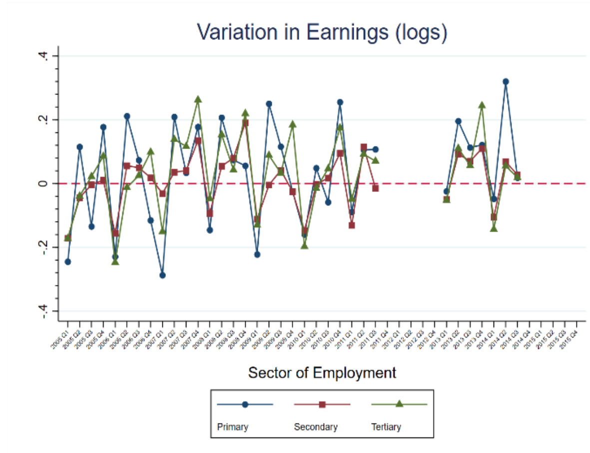


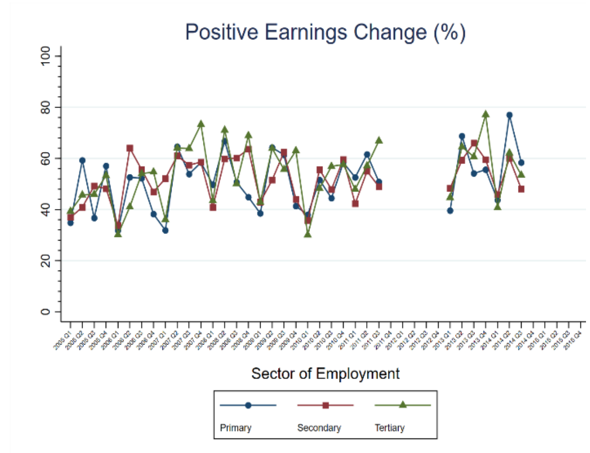
d. By Educational Attainment



e. By Initial Sector of Employment







Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Finally, earnings change can be informative if estimated by sector transitions because this can reveal whether there are specific sectoral transitions that come with sizable earnings gains. Because most sectoral transitions have few (and, in some quarters, zero) observations, the analysis is conducted over the pooled 2005–15 period. Most workers do not change their sector of employment over the short run observed in the data (Table 2.1). Persistence in the initial sector of employment is, on average, over 80 percent, indicating that more than 8 workers in 10 do not change sector over a period of 16 months. Persistence is particularly high among workers employed in services other than trade services. Some transitions are observed from the primary sector to manufacturing (6.3 percent), to other secondary sectors (4.1 percent), and to other services (8.2 percent). About 11 percent of the workers initially employed in construction move to other services, and 10.5 percent of the workers initially in trade move to other services.

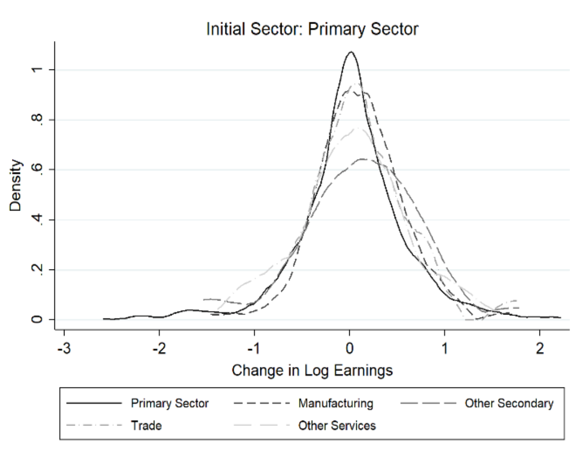
Table 2.1. Sectoral Transitions of Individuals Ages 30–54, Q1–Q4, 2005–15

			t=4			
t=1	*Primary sector*	*Manufacturing*	*Other secondary*	*Trade*	*Other services*	*Total*
Primary sector	79.6	6.3	4.1	1.9	8.2	100
Manufacturing	3.1	84.6	3.6	3.5	5.2	100
Other secondary	2.6	4.0	80.7	1.9	10.8	100
Trade	1.9	8.2	3.3	76.0	10.6	100
Other services	1.1	1.9	2.7	2.5	91.8	100
Total	8.4	19.6	13.3	11.3	47.4	100

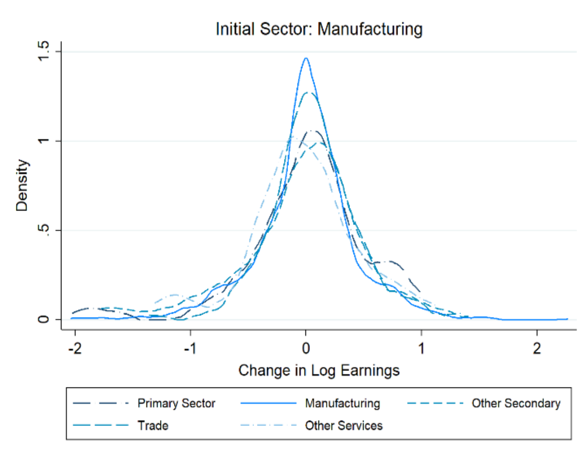
Despite such sparse transitions across sectors, it is possible to identify some transitions that generate large positive percentage changes in earnings (Figure 2.3). Workers moving away from the primary sector experience positive earnings changes both in levels and percentages that are larger relative to stayers (except for workers moving into other secondary sectors that post a decline in earnings levels). Among the workers initially employed in manufacturing, only those moving to trade experienced an increase in average earnings; all the others, including those who remained employed in manufacturing, experienced a decline. Workers employed in trade at the baseline experienced the largest gain in earnings if they moved to services other than trade and a large decline if they moved to the primary sector. By contrast, workers initially working in the service sector, other than trade, who moved to trade exhibited a decline in earnings. Overall, transiting out of the primary sector always leads to sizable average increases in earnings. Manufacturing is characterized by a decline in earnings among stayers, and only workers who moved from manufacturing to trade on average showed earnings gains. Transitions to services other than trade bring about positive changes, whereas exiting the service sector, excluding transitions out of trade, does not lead workers to higher average earnings relative to stayers.

Figure 2.3. Average Log-Earnings Change, by Sectoral Transitions, Pooled, 2005–15

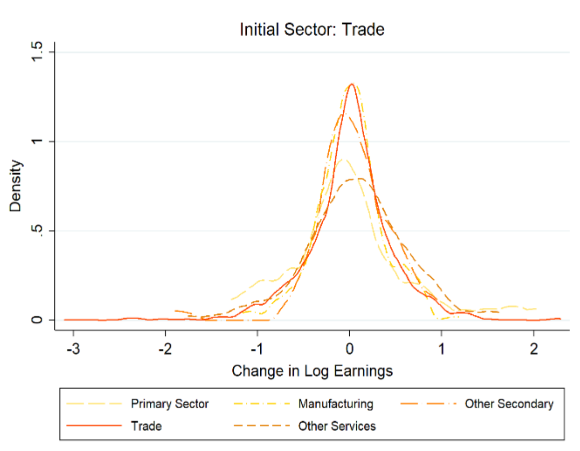
a. From the primary sector



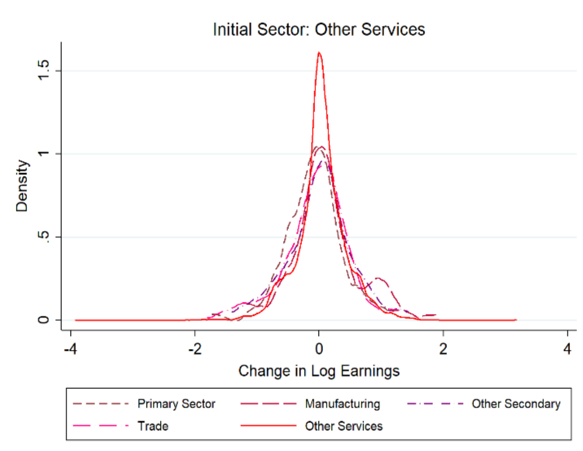
b. From manufacturing



c. From trade



c. From other services

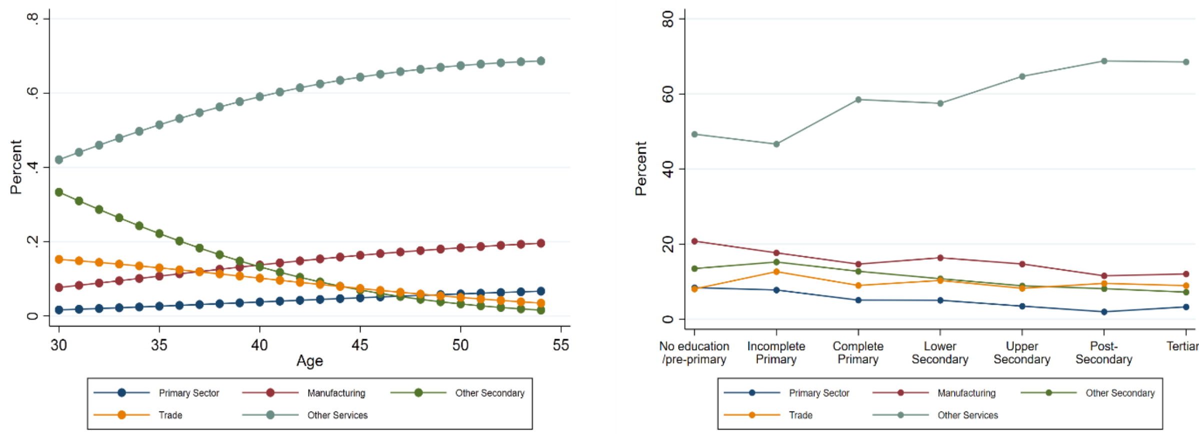


Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Which individual characteristics make it more likely that people are working in certain sectors and accomplishing certain transitions? The results of a multinomial probit regression on the probability of working in each of the five sectors at the end of the 16-month panel on a set of controls that include initial sector of employment, initial earnings level, demographics, and other labor market characteristics are shown in terms of the predicted probability of being employed in each sector at the end of the 16-month period. The likelihood of working in services other than trade monotonically increases with age starting from about 40 percent at age 30 and rising up to about 70 percent by age 54. By contrast, the likelihood of working in other sectors is much lower at any age and also declines as workers become old, as in the case of trade and construction (Figure 2.4, panel a). Education is a strong correlate of the probability of working in different sectors. Working in services (other than trade), which include finance, real estate, and professional activities, rises strongly with individual educational attainment from about 50 percent among workers with less than primary up to about 70 percent among workers with upper-secondary or postsecondary-tertiary education (Figure 2.4, panel b).

Figure 2.4. Predicted Probability of Working in a Certain Sector, by Age and Educational Level, Pooled, 2005–15

a. Age **b. Educational level**

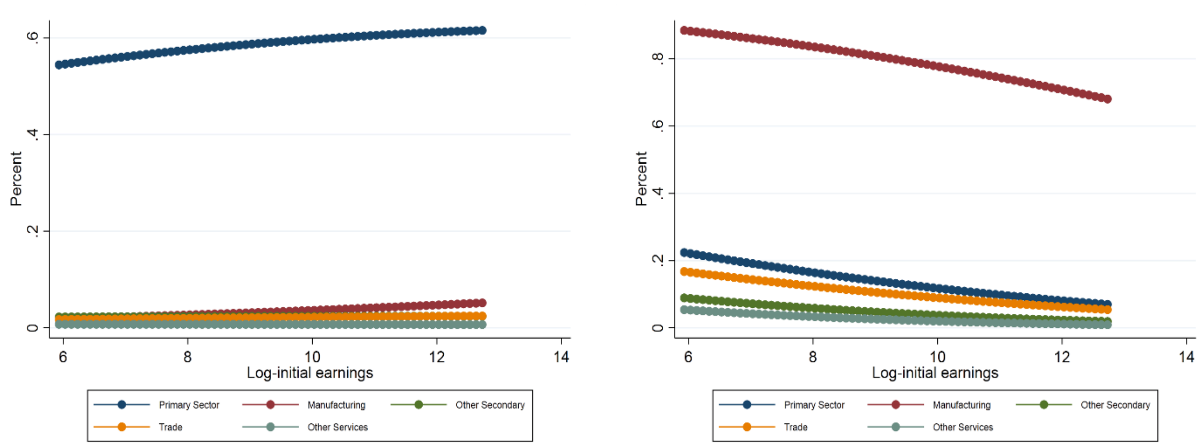


Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.
Note: A multinomial probit regression is estimated by regressing categorical variables taking values from 1 to 5—one for each of the five selected sectors—upon a set of controls, including initial log-earnings, a dummy for being female, a second-degree polynomial in age, dummies for year of birth cohort, dummies for residence in each of the districts of Mauritius, a dummy for being married, dummies for each educational level, dummies for each of the five industrial sectors, a dummy for full-time workers, a dummy for working in the public sector, a dummy for being a wage worker, a dummy for each occupational category, and a set of dummies for panel-specific effects. Estimated coefficients are then used to generate a prediction of the probability of individuals working in each of the five sectors by age and educational level by assuming all other covariates take mean values in the sample.

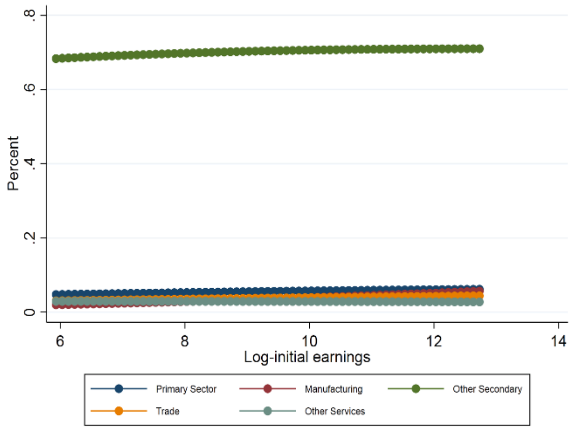
Irrespective of the initial sector of employment, the probability of working in the same sector is always much higher than the probability of changing sectors as reflected in the low transition rates across sectors (Figure 2.5). In addition, the probability of moving into the primary sector is the highest at a low initial earnings level. Together with the evidence that transitions into agriculture are associated, on average, with lower earnings gains or, more frequently, earnings losses, this points to the low quality and last resort feature of jobs in agriculture.

Figure 2.5. Predicted Probability of Working in a Certain Sector, by Initial Sector of Employment and Initial Earnings, Pooled, 2005–15

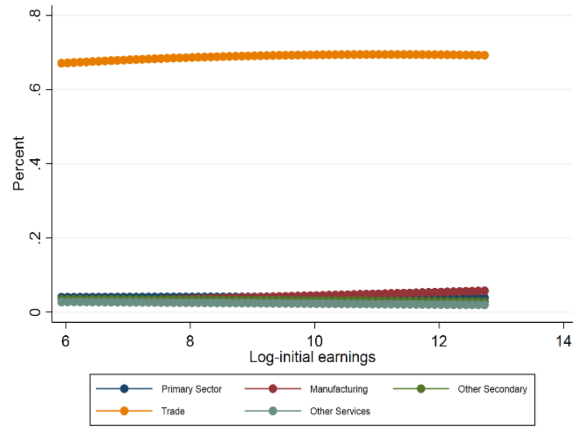
a. From the primary sector **b. From manufacturing**



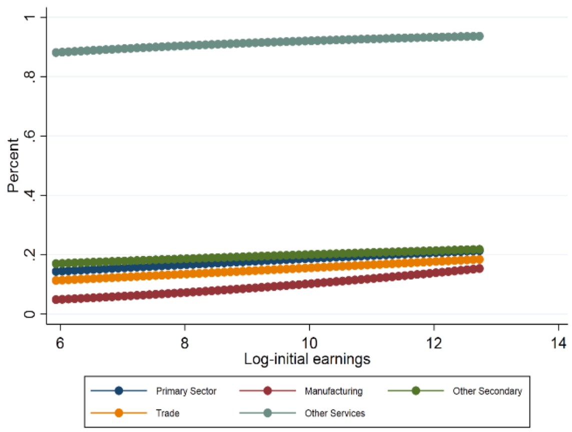
c. From other secondary sectors



d. From trade



e. From other services



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.
Note: A multinomial probit regression is estimated by regressing categorical variables taking values from 1 to 5—one for each of the five selected sectors—upon a set of controls, including initial log-earnings, a dummy for being female, a second-degree polynomial in age, dummies for year of birth cohort, dummies for residing in each of the districts of Mauritius, dummy for being married, dummies for each educational level, dummies for each of the five industrial sectors, a dummy for full-time workers, a dummy for working in the public sector, a dummy for being a wage worker, a dummy for each occupational category, and a set of dummies for panel-specific effects. Estimated coefficients are then used to generate a prediction of the probability of individuals working in each of the five sectors by initial earnings level and by assuming all other covariates take mean values in the sample.

3. Who Experiences the Highest Earnings Mobility?

Section 3 studies aggregate mobility and looks at earnings gains and losses in the economy (directional mobility) as well as the changes in positions in the income distribution experienced by various groups of workers (positional mobility). Between 2005 and 2015, average changes in earnings are positive. The period-average change is estimated at MUR 336, or about 2 percent, and around 53 percent of workers experienced a positive change. The evidence seems to support the existence of a labor market twist, whereby skilled workers experienced the largest earnings gains. Globalization, skill-biased technological change, and structural transformation were generating an increase in the demand for skills that outpaced the supply of the same skills and influenced the different earnings growth paths among skilled and unskilled workers. The evidence also points to reversion to the mean in individual earnings, whereby workers initially at the bottom of the distribution posted the largest gains in earnings, which suggests the existence of a convergence in earnings. Finally, transiting out of the primary sector always leads to sizable average increases in earnings. Manufacturing is characterized by declines in earnings among stayers, and only workers who moved from manufacturing to trade on average show earnings gains. Transitions to services other than trade bring about positive changes, whereas exiting the service sector, excluding transitions out of trade, does not lead workers to higher average earnings relative to stayers. The likelihood of working in services, including finance, real estate, and professional activities, is strongly positively associated with higher educational levels.

This section investigates the correlates of earnings mobility, which is defined as the change in individual earnings over a 16-month period. Several correlates of earnings changes are considered, and the relationship between earnings mobility and initial earnings is spotlighted. In addition, a host of other factors are taken into account, including gender, age, educational attainment, geographical location, initial labor market conditions (such as employment type, sector of activity, and occupation), and labor market transitions.

The analysis is divided into two parts. The first part assesses *unconditional earnings mobility*, which essentially involves evaluating the extent of earnings mobility experienced within each initial-characteristics group with the aim of determining who fared better. This is done by means of bivariate regressions of the earnings change on initial earnings for all individuals and separately by group. The second part examines *conditional earnings mobility*: the idea is to assess the extent of mobility, while controlling for a number of initial characteristics and transitions over time. This includes implementing a decomposition aimed at determining which groups of factors contribute more to explaining earnings mobility.

3.1 How Is Earnings Mobility Related to Initial Earnings?

Estimates of the effect of changes in log earnings on log initial earnings (or weak unconditional convergence, WUC) and changes in the level of earnings on initial earnings levels (or strong unconditional convergence, SUC) are reported in Table 4.1. A negative coefficient could mean that individuals at the bottom are faring better by experiencing gains that will continue in the future. Yet, it could also be the product of a reversion to the mean resulting from adjustments in earnings to a temporary shock. For example, individuals who report low (high) initial earnings might have been temporarily unlucky (lucky), and the positive (negative) mobility observed among them is merely an adjustment back to their permanent earnings level. For this reason, for each of these two types of regressions, three specifications are adopted, which, respectively, use reported, longer-term predicted, and longer-term average earnings as right-hand variables.[10]

Table 3.1. Weak and Strong Unconditional Convergence Estimates at the Mean, Pooled, Q1–Q4, 2005–15

WUC (reported)	*WUC (predicted)*	*WUC (average)*
−0.199***	−0.107***	−0.0693***

SUC (reported)	*SUC (predicted)*	*SUC (average)*
−0.253***	−0.132***	−0.100***

Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.
Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

Coefficients displayed in the top panel of Table 4.1 refer to WUC estimates for all individuals in the sample. The negative signs indicate the presence of significant WUC in earnings. During the 16-month period, individuals who started off at low-earnings experienced larger *percentage* earnings changes than the initially high-earners, thereby contributing to the reduction in overall earnings differentials.

Evidence is also found in support of SUC, as shown in the bottom panel of Table 4.1. Individuals initially in low-earnings groups reaped higher gains in terms of rupees than those starting in high-earnings groups.

The last two columns of Table 4.1 show coefficients obtained using predicted and average earnings instead of reported earnings. Notice a slight decrease in the value of the coefficient, but an unchanged statistical significance in both WUC and SUC estimates. This confirms that the results are robust to measurement error and transitory earnings shocks and provides a lower bound to WUC and SUC.

As an additional robustness check, Table 3.2 shows unconditional quantile regression estimates at the median. The estimated parameters appear moderately lower for WUC, but more considerably so for SUC, which indicates that the former hypothesis might be more robust than the latter. Taking all individuals together, it therefore seems more likely that those starting off in the lower part of the earnings distribution experienced a larger change with respect to those who were initially in the higher part in percentage terms rather than in levels.

[10] Details on the derivation of predicted and long-term earnings are provided in Annex C. Moreover, in developing countries, available evidence indicates that measurement error in earnings arises because of the underreporting of transitory earnings fluctuations. Without validation data for the measurement of earnings in developing countries, it is possible only to speculate about whether a similar pattern would hold for the data at hand. However, it is reassuring to know that, if measurement error in CMPHS data follows the patterns found in the literature for the developing world, Fields et al. (2005) show that measurement error would have no effects on the estimated parameter as long as this error is uncorrelated with the observed permanent characteristics included in the vector z (see Annex C).

Table 3.2. Weak and Strong Unconditional Convergence Estimates (at the Median), Pooled, Q1–Q4, 2005–15

WUC (reported)	*WUC (predicted)*	*WUC (average)*
−0.106***	−0.0617***	−0.0360***

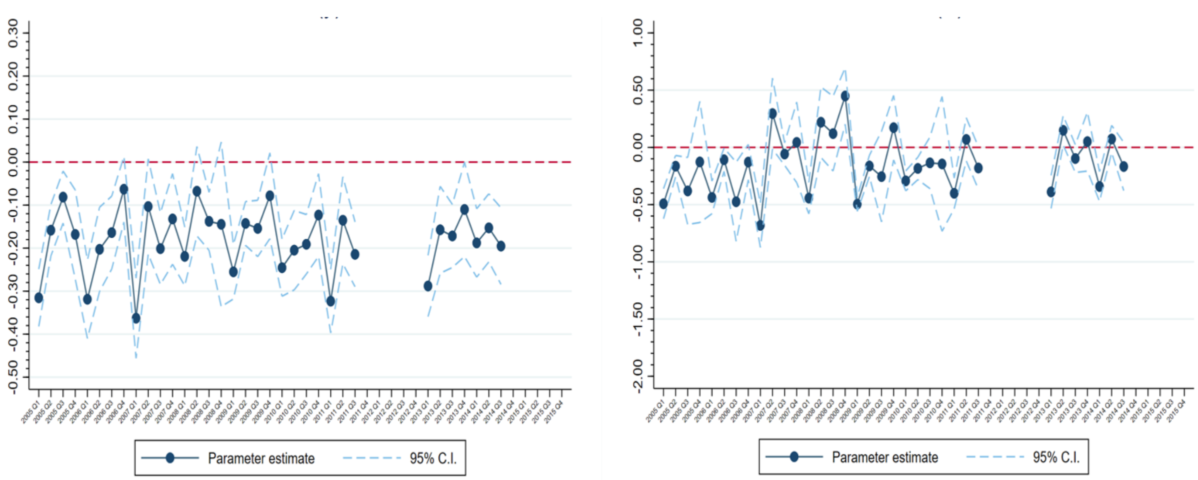
SUC (reported)	*SUC (predicted)*	*SUC (average)*
−0.0356***	−0.0204***	−0.0102***

Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.
Statistical significance: *** p<0.01, ** p<0.05, * p<0.1.

While the numbers illustrated so far pool all the short-term panels over which individuals are observed between 2005 and 2015, it might be the case that the extent of earnings mobility has changed over time. Figure 3.1 displays estimates of earnings mobility regressions in each of 44 quarters using initial reported earnings. The top two panels show parameters from ordinary least squares (OLS) regressions at the mean, while the bottom two illustrate estimates at the median from unconditional quantile regressions. WUC estimates at the mean wander in a stable fashion around −0.2 and feature a progressively slightly smaller volatility in more recent quarters. A similar but less volatile trend can be observed in estimates at the median, which cluster at a marginally higher level (−0.1).[11]

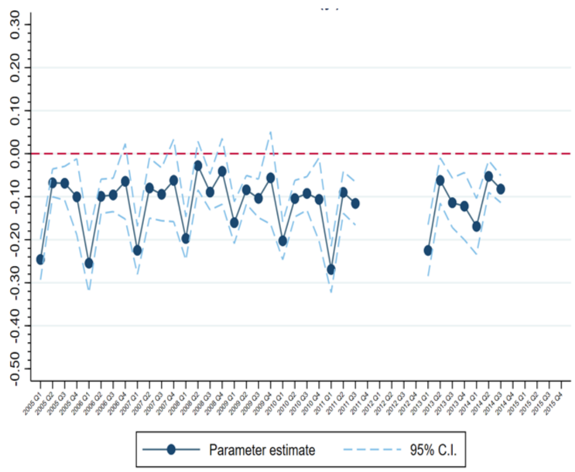
Figure 3.1. Weak and Strong Unconditional Convergence Estimates Using Reported Earnings, 2005–15

a. WUC, at the mean **b. SUC, at the mean**

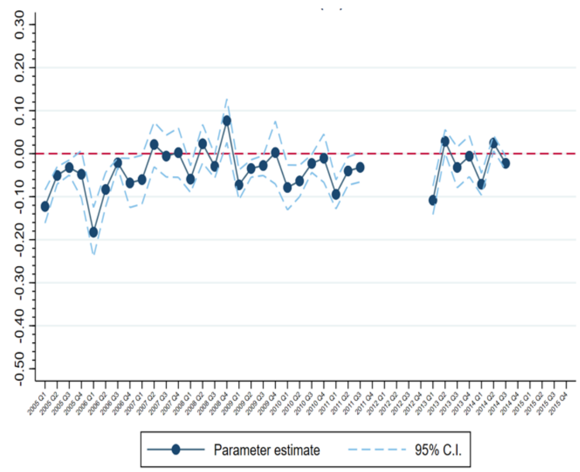


[11] Figure A1 in annex illustrates estimated coefficients of weak and strong unconditional mobility on a sample that excludes outliers in earnings changes (smaller than the 5th and larger than the 95th percentile of earnings changes). Results confirm the existence of WUC and SUC in earnings.

c. WUC, at the median



d. SUC, at the median



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.
Note: Estimates have been obtained using reported earnings as the explanatory variable. Panels a and b show parameters from OLS regressions at the mean, while panels c and d illustrate estimates from unconditional quantile regressions at the median.

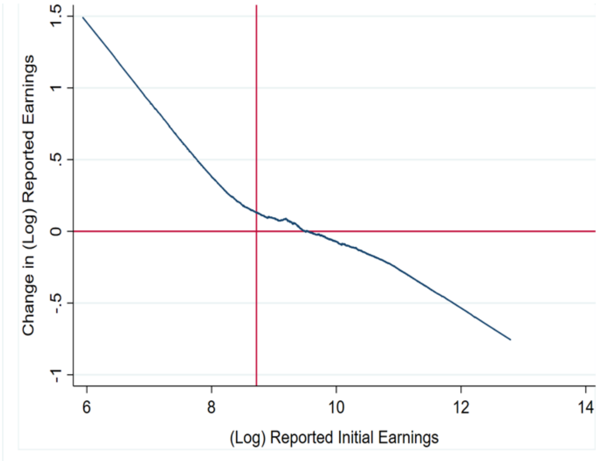
The coefficients of the SUC regressions are smaller in absolute value. This is typical of earnings mobility, whereby earnings are more likely to converge in terms of growth rates than in levels and exhibit a slight upward trend, that is, the magnitude of the estimated coefficients diminishes over time in both specifications, and here, too, estimates at the median exhibit less variability. Notice also that, although in some instances the SUC coefficient becomes positive, it is not statistically significant. Moreover, in accordance with results from the pooled regressions, a small gap can be observed between the WUC estimates at the mean and at the median, while a larger gap is observed between the two sets of estimates in the case of changes in earning levels.

The corresponding estimates over time obtained using predicted and average earnings indicate weak earnings convergence in most cases and no convergence or divergence in a few quarters (Annex A, Figure A 1). The results obtained using average earnings point to the absence of SUC or divergence in most cases; only in a few cases is there evidence of strong convergence in earnings (Annex A, Figure A2).

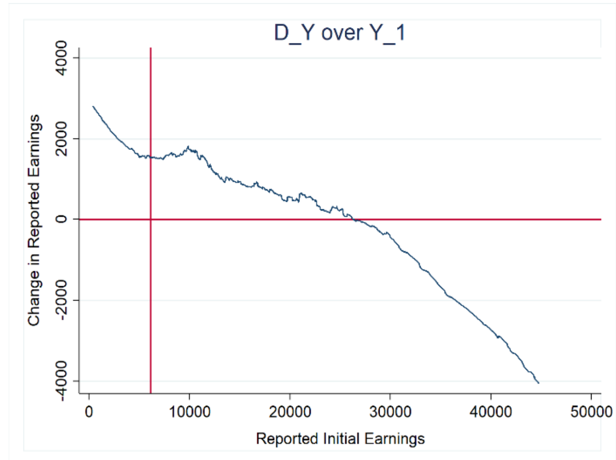
Delving deeper, Figure 3.2 shows estimates of nonparametric regression to test for the existence of a nonlinear relation between earnings changes and initial earnings and of poverty traps, whereby individuals who lack a minimum level of human, physical, or social capital become trapped in a condition of low earnings from which they cannot escape. The red vertical line indicates the poverty line (measured in 2015 prices). The estimates for WUC, displayed in panel a, reveal a nearly linear relation between log-earnings change and initial log-earnings; individuals who started off in the lower half of the initial earnings distribution experience significant positive percentage gains in earnings, while those in the upper half post a decline in earnings, which is consistent with the WUC hypothesis. Evidence for SUC is illustrated in Figure 4.2, panel b. Estimates obtained using longer-term predicted and average earnings, shown in Annex A, Figure A 3, confirm the roughly linear relation.

Figure 3.2. Weak and Strong Unconditional Convergence Nonparametric Estimates Using Reported Earnings, Pooled 2005–15

a. WUC



b. SUC



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.
Note: Estimates are obtained using reported earnings as explanatory variables. The red vertical line represents the poverty line. In the case of strong earnings convergence (panel b), initial earnings are trimmed at the 95th percentile.

How is unconditional earnings mobility related to initial characteristics? Figure 3.3 and Annex A, Table A 3, illustrate WUC and SUC estimates from OLS regressions on subsamples of individuals defined by initial characteristics.[12] WUC is higher among men, workers the 30–34 and 35–39 age-groups, unmarried workers, and workers with up to completed primary and lower-secondary education. Using a measure of permanent initial earnings, although weakening the extent of convergence, does not wear off the statistical significance. Estimates for SUC confirm higher convergence among men and individuals between 35 and 39 years of age as well as among the least well educated. SUC disappears in a few cases if predicted and average measures of earnings are employed, including women, youngsters, and unmarried individuals.

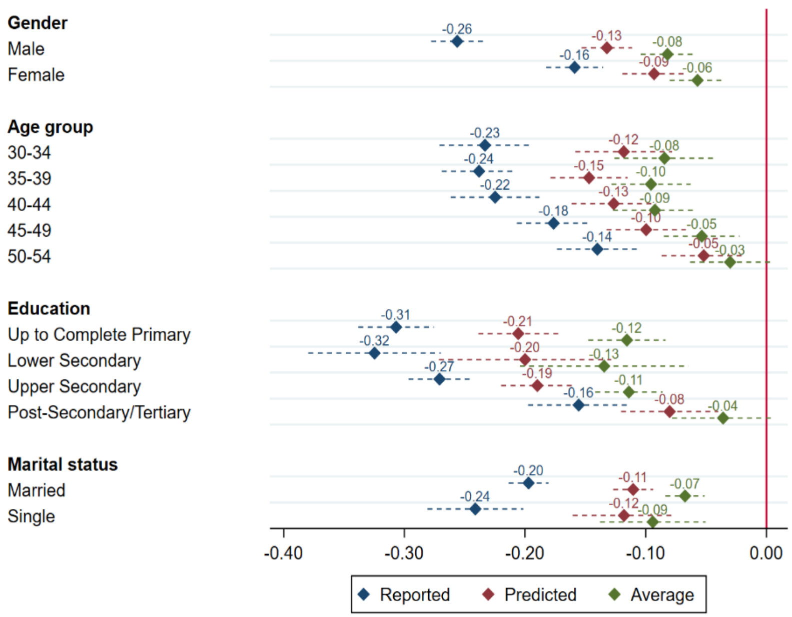
Looking at the breakdown by initial labor market characteristics, weak and strong conditional convergence are found among initially nonwage workers, individuals carrying out elementary occupations, machine operators, and skilled agricultural and craft workers, as well as those working in the primary sector. Mixed results are found regarding the public vs the private sector, but the overall differences seem negligible.

[12] Estimates by group derived by means of unconditional quantile regressions are displayed in Annex A, Table A 3.

Figure 3.3. Weak and Strong Unconditional Convergence Estimates (at the Mean), by Initial Characteristics, Pooled 2005–15

Weak unconditional convergence

a. By demographic characteristics

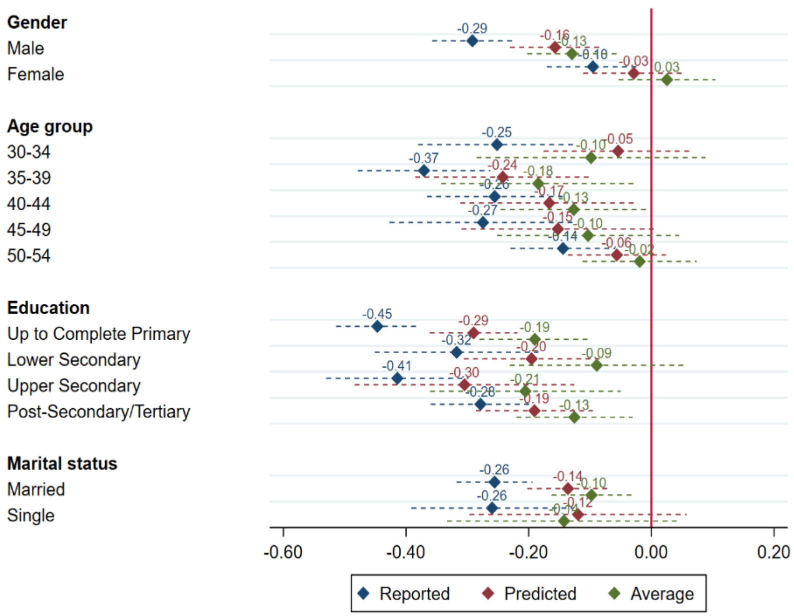


b. By job characteristics (sector and industry)

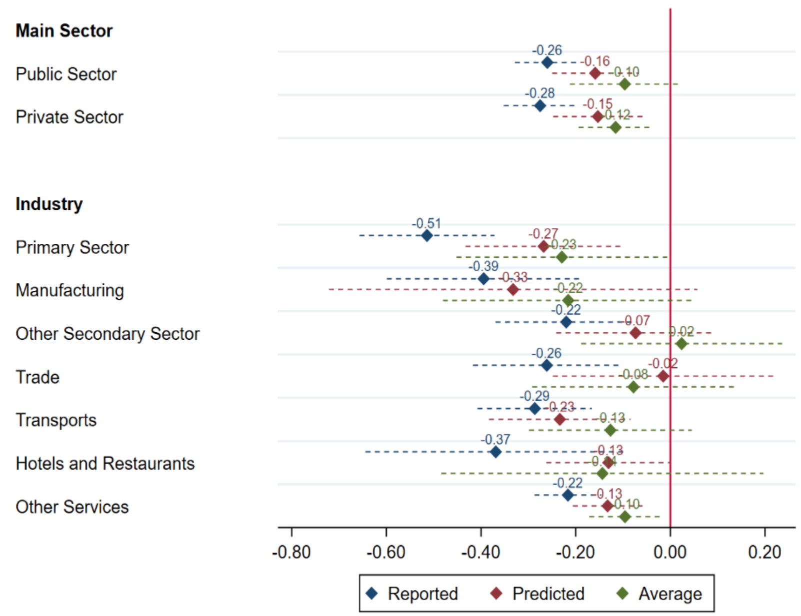
c. By job characteristics (category and occupation)

Strong unconditional convergence

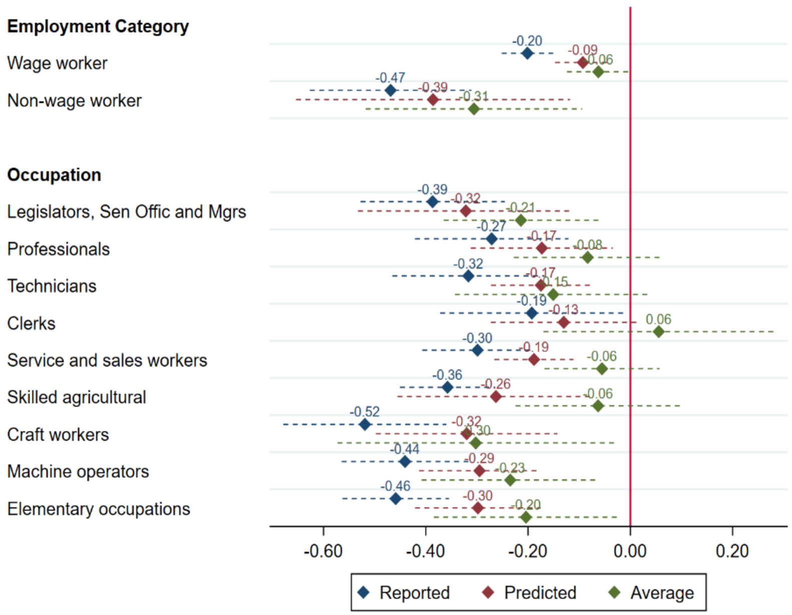
d. By demographic characteristics



d. By job characteristics (sector and industry)



e. by job characteristics (category and occupation)



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.
Note: The red vertical lines indicate the zero value.

3.2 How Is Earnings Mobility Related to Initial Earnings and Other Characteristics?

Unconditional analysis answers the question regarding who is gaining more (or losing less) in terms of earnings among the employed population: are the rich becoming richer (and the poor poorer)? The conditional approach involves estimating the relationship between earnings changes and initial earnings while controlling for additional individual characteristics. Two separate sets of estimates for weak and strong *conditional* convergence are shown in Table 3.3 and Table 3.4, respectively.

Table 3.3. Weak Conditional Convergence Estimates Using Reported Earnings, Pooled, 2005–15

Dependent variable: log-earnings changes	*(1)*	*(2)*	*(3)*
Log initial (reported) earnings	−0.337***	−0.402***	−0.403***
Observations	12,168	12,168	12,168
R-squared	0.172	0.205	0.207

Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.
Note: Model (1) includes initial earnings, demographic characteristics, and geographical location. Model (2) controls for initial job characteristics, such as employment category, sector, and occupation. Model (3) adds to the variables included in Model 2 a set of controls for sectoral transitions.
Statistical significance *** p<0.01, ** p<0.05, * p<0.1.

Table 3.4. Strong Conditional Convergence Estimates Using Reported Earnings, Pooled, 2005–15

Dependent variable: earnings change (level)	*(1)*	*(2)*	*(3)*
Initial (reported) earnings	−0.375***	−0.431***	−0.431***
Observations	12,168	12,168	12,168
R-squared	0.202	0.232	0.232

Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.
Note: Model (1) includes initial earnings, demographic characteristics, and geographical location. Model (2) controls for initial job characteristics, such as employment category, sector, and occupation. Model (3) adds to the variables included in Model 2 a set of controls for sectoral transitions.
Statistical significance *** p<0.01, ** p<0.05, * p<0.1.

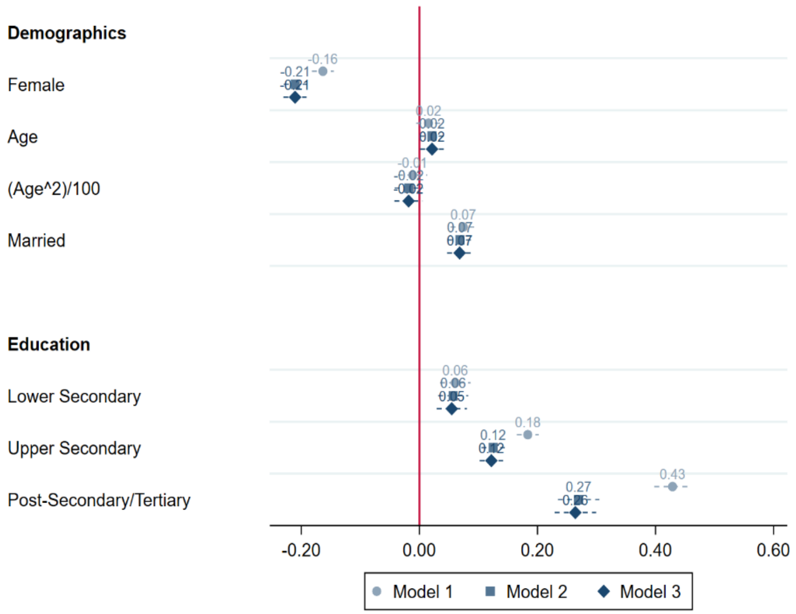
Three different models are estimated both for weak and strong convergence. The first model controls for socioeconomic characteristics, including age, gender, educational level, and district. The second model adds employment category (wage vs. nonwage worker), sector of employment (public vs private sector), and occupational level. Model 3 includes sectoral transition dummies to capture the effect on earnings convergence of the sectoral mobility experienced by workers between the first and the last interview. Both weak and strong convergence hold if controlling for individual characteristics at baseline. Estimates indicate that earnings convergence becomes stronger and maintains statistical significance after including initial year labor market characteristics and labor market transitions, in addition to initial demographic characteristics (columns 2 and 3 as opposed to column 1 in Table 3.3 and Table 3.4). This means that the overall effect of additional controls is to generate divergence in earnings and, after accounting for the effects of this variable, convergence in earnings is therefore even stronger.

What is the effect of individual characteristics on earnings mobility? Estimates illustrated in Figure 3.4 show that being a woman decreases earnings mobility, while age and geographical location do not have a large statistically significant effect. Age exerts a positive effect, at a decreasing rate, on earnings changes, and residing in districts other than Port Louis also contributes positively to earnings mobility. Education plays a key role and increases mobility conditional on initial earnings. Compared with workers with no or up to complete primary education, workers with secondary or higher education have a sizable and positive effect on earnings change, and the effect increases monotonically with educational attainment. For example, attaining postsecondary or tertiary education increases earnings growth by 26 percentage points with respect to the least well educated workers.

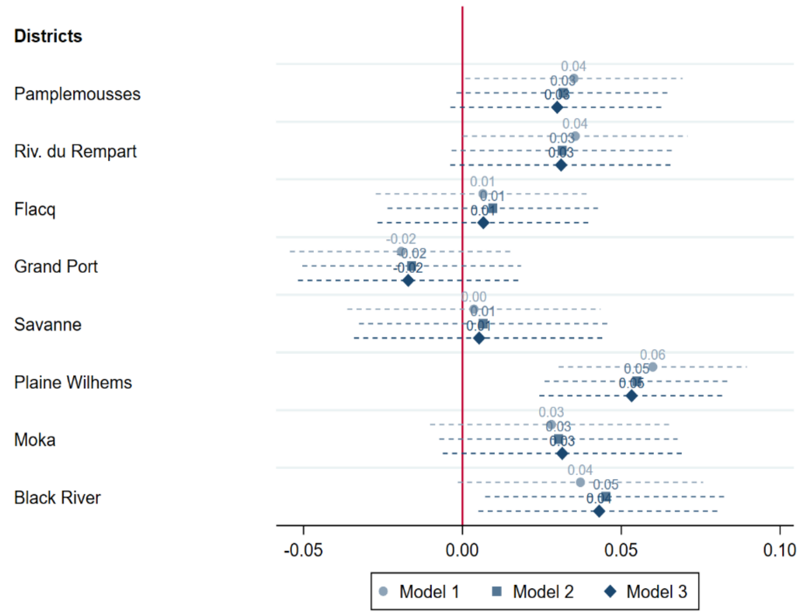
Figure 3.4. Weak and Strong Conditional Convergence Estimates of Covariates Using Reported Earnings, Pooled 2005–15

Weak conditional convergence

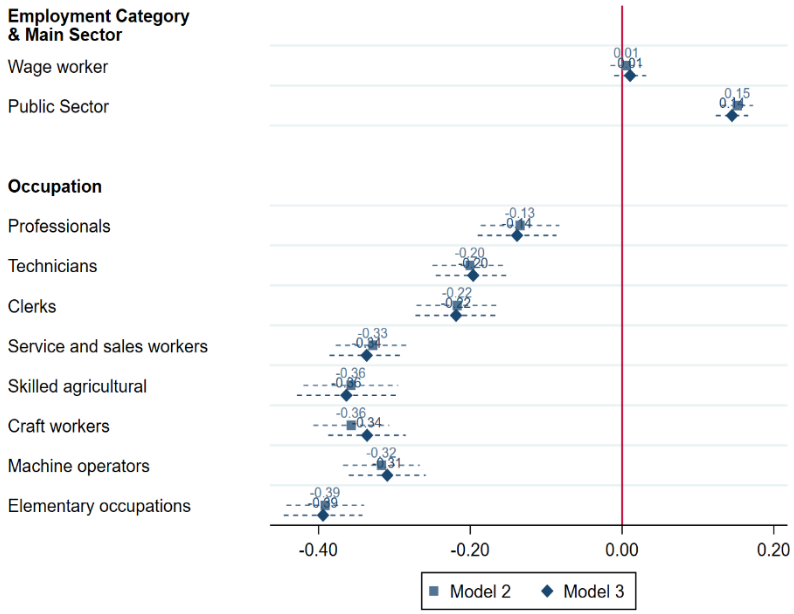
a. Demographic characteristics



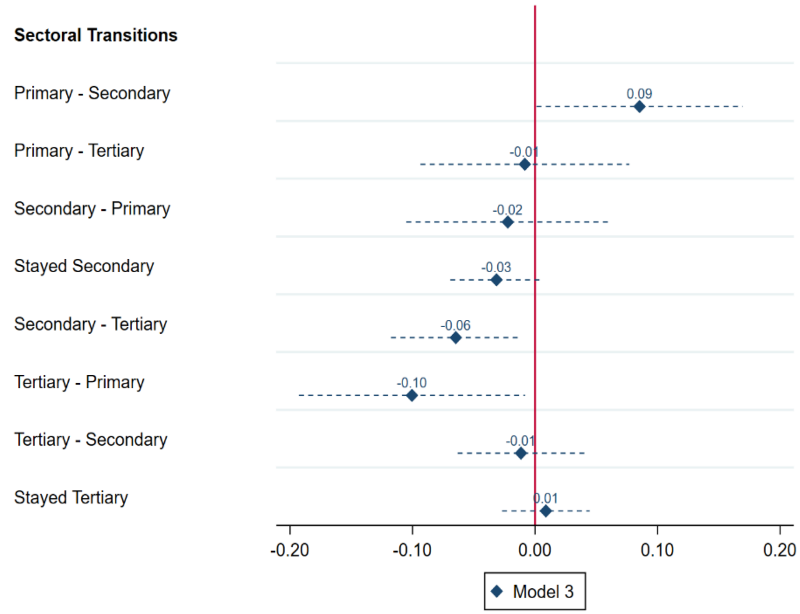
b. Geographical location



c. Job characteristics

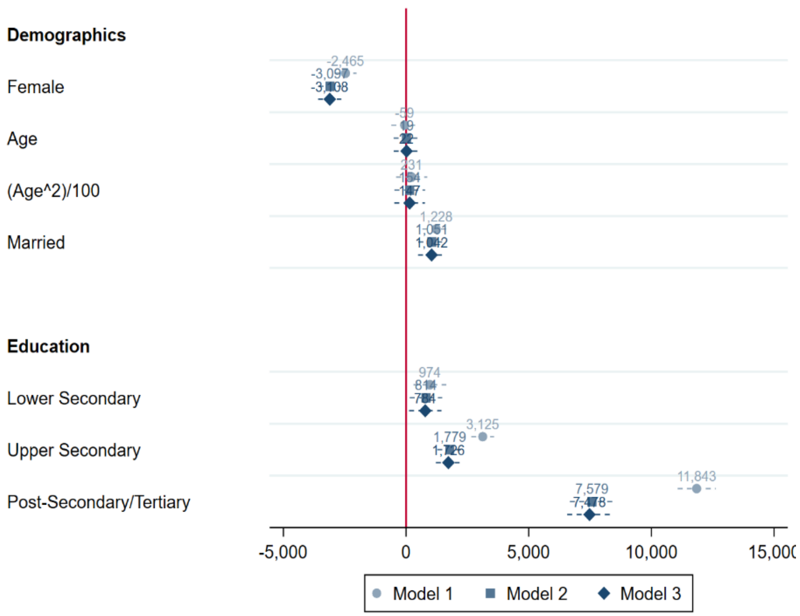


d. Sectoral transition

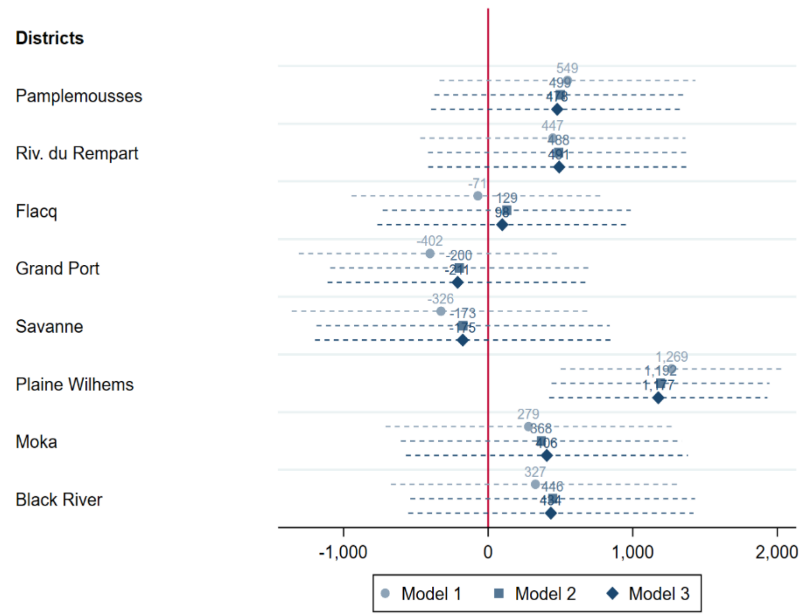


Strong conditional convergence

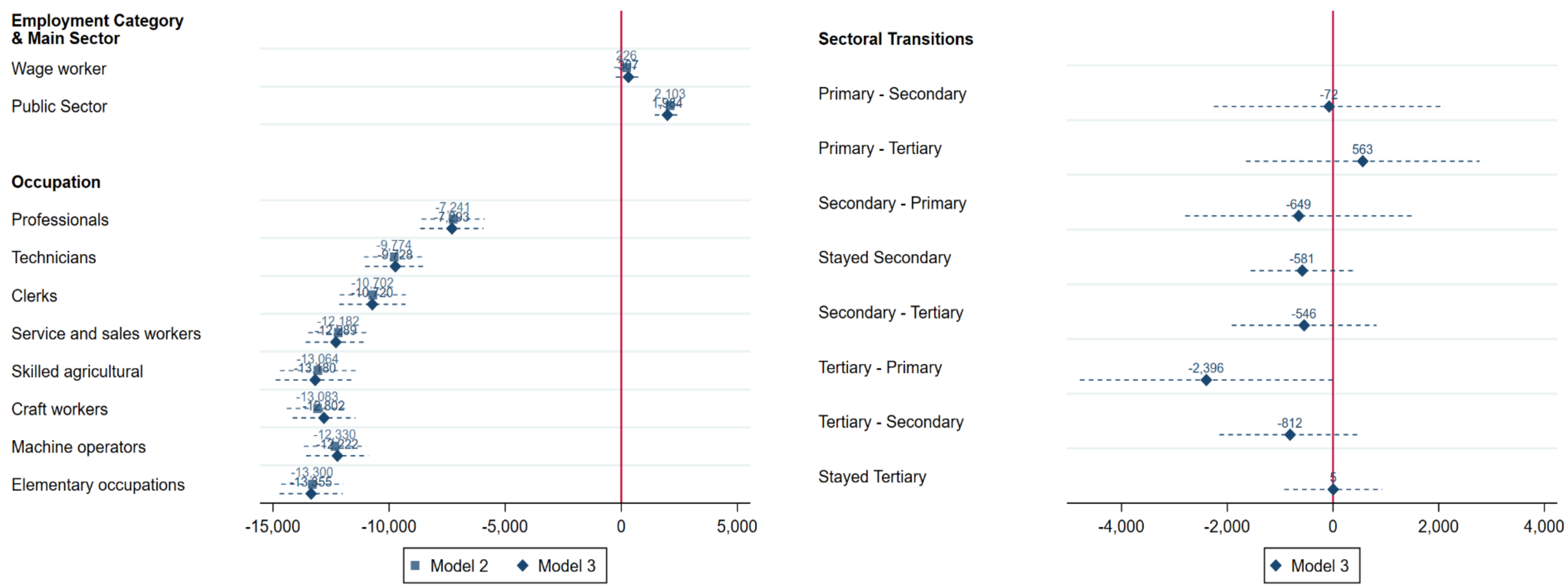
f. Demographic characteristics



g. Geographical location



h. Job characteristics **i. Sectoral transition**



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Note: Conditional convergence regressions are run using three specifications. Model 1 includes initial earnings, demographic characteristics, and geographical location. Model 2 controls for initial job characteristics such as employment category, sector, and occupation. Model 3 adds to the variables included in Model 2 a set of controls for sectoral transitions. Reference categories are as follows: gender = men; educational level = up to completed primary education; district = Port Louis; employment category = nonwage worker; sector = private sector; occupation = manager; sectoral transition = primary-primary.

In terms of initial labor market characteristics, working in the public sector has a positive effect on earnings mobility, whereas employment in low-end occupations relative to management positions reduces earnings mobility. Among the sectoral transitions between initial and last quarter, transiting from primary to secondary sectors has a positive effect on mobility compared with staying in the primary sector, while transiting from secondary to tertiary and moving from tertiary to primary reduces conditional earnings mobility.

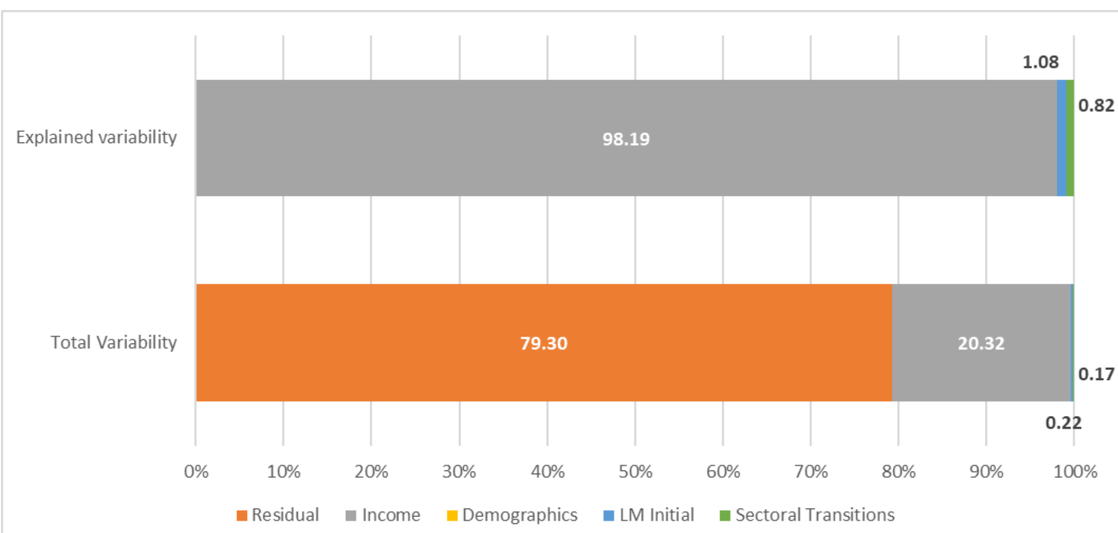
Similar results are obtained if estimating conditional earnings mobility with predicted and average initial earnings to correct for measurement error and transitory earnings shocks. To sum up, the most important factors related to earnings mobility are initial earnings, gender, educational level, and initial labor market conditions, particularly working in the public as opposed to the private sector, and initial occupational level. By contrast, labor market transitions, with few exceptions, do not play an important role.

To obtain a better understanding about which factors contribute the most to explaining changes in earnings, a decomposition exercise, which allows one to gauge the extent of the contribution of given groups of factors to the variability of the dependent variable, is implemented (Fields 2003).

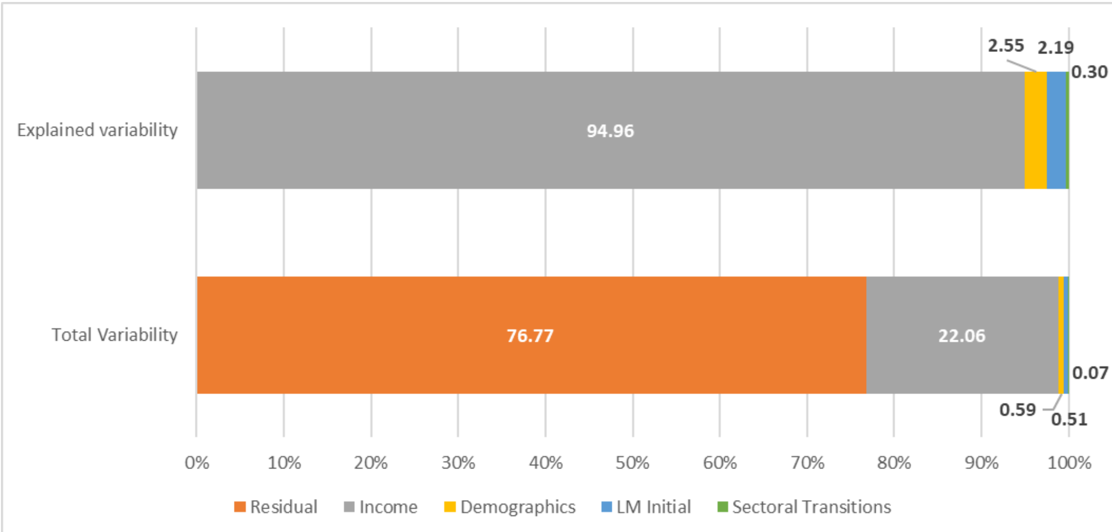
There are two ways of carrying out this decomposition. The first method decomposes the overall variation observed in earnings changes and includes among the contributing factors a residual term, which captures the magnitude of the variability that is not explained by the earnings regression. The second decomposes the variation observed in earnings changes net of what remains unexplained in the earnings regression. Given the large component that remains unexplained by observable characteristics, the second approach provides a cleaner way to illustrate graphically the contribution of the observable factors.

Figure 3.5. Decomposition of Factors Group Contributions to Weak and Strong Conditional Convergence, Pooled, 2005–15

a. Weak



b. Strong



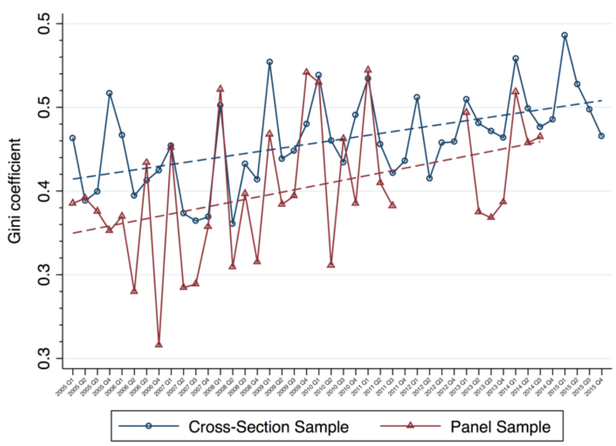
Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Adopting the first method, the decomposition reveals that most of the variability in earnings change is unexplained, which is almost 80 percent in the case of weak conditional convergence (Figure 3.5, panel a). Nonetheless, it also unveils a sizable effect of initial earnings, which alone explain some 20 percent of the overall variability observed in earnings, and a second-order role for initial labor market conditions and sectoral transitions. A similar result emerges from the decomposition of strong conditional convergence. The second approach, which looks at the variation in earnings changes explained by the model, shows that initial earnings account for about 98 percent of the explained earnings change variation, while initial labor market conditions contribute some 1 percent, and sectoral transitions less than 1 percent.

4. Earnings Convergence and Rising Inequality: Are They at Odds?

The earnings mobility findings illustrated so far indicate that the mobility patterns, observed using CMPHS longitudinal data over the period 2005–15, are nearly always convergent; workers initially at the bottom of the earnings distribution posted the largest gains in both levels and growth terms. In parallel, the World Bank (2017a) estimates that inequality in individual earnings increased between 2001 and 2015, but considerably since 2008. Figure 4.1 confirms that earnings inequality among individuals in the 30–54 age-group, calculated using cross-sectional and panel data, increased between 2005 and 2015.

Figure 4.1. Inequality of Initial Earnings Using Data from Cross-Section and Panel Samples, Q1: Q4, 2005–15



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

While rising earnings inequality and convergent mobility might seem at odds, they are not. Convergent mobility does not necessarily imply declining inequality. First, measures of inequality are typically constructed by making use of a series of annual survey data; inequality indicators therefore treat individuals observed over several periods anonymously. Such measures show that workers at the top of the earnings distribution gained at least as much as individuals at the lower tail of the earnings distribution. By contrast, evidence from earnings mobility analyses, which exploit information about the same individuals, who are followed over time, suggest that individuals who started as low-earners posted earnings gains at least as large as individuals who started at the upper end of the distribution.

Duval-Hernández, Fields, and Jakubson (2017) argue that different combinations of changes in inequality and mobility patterns can coexist, as follows: (1) falling inequality and divergent mobility, (2) rising inequality and convergent mobility, (3) falling inequality and divergent mobility, and (4) falling inequality and convergent mobility. While the first and the last combinations are more easily appreciated, all combinations are viable. The key to understanding the two intermediate possibilities, which are, at first sight, the most contradictory (and the second case mirrors the case of Mauritius), lies in the difference between earnings patterns observed by considering individuals anonymously and nonanonymously (or as panel individuals). Duval-Hernández, Fields, and Jakubson (2017) show that one possible occurrence, which combines inequality increases and convergence mobility, is that anonymous high (low) earners are not the same as the initial high (low) earners. The authors provide an illustrative example of many possible scenarios with rising inequality and convergent mobility that is reported here to clarify the difference between imposing anonymity and nonanonymity. Consider an economy composed of five persons with the following level of initial earnings in ascending order:

$$y_0 = [20,41,45,49,70] \qquad (5.1)$$

After one year, the earnings levels of the same five persons is, in ascending order of initial earnings, the following:

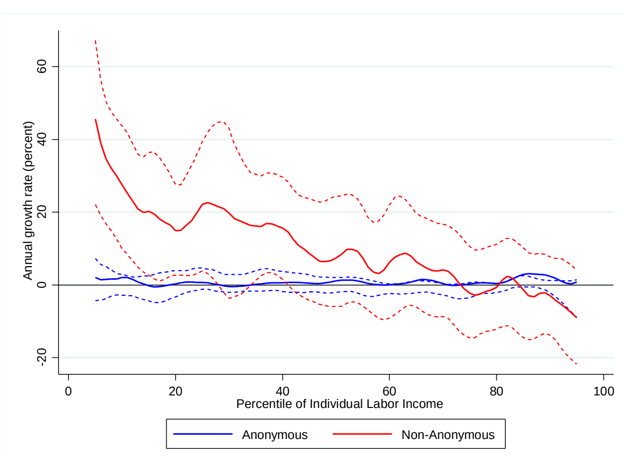
$$y_1 = [100,41,45,49,10] \qquad (5.2)$$

In this economy, inequality clearly increased between time *0* and time *1* as the earnings gap between the anonymous low earners and anonymous high earners widened, and, yet, earnings mobility is convergent because the initial low earners and initial high earners swapped positions.

A commonly used measure of pro-poor growth, the growth incidence curve (GIC), can serve the purpose of illustrating the difference in earnings growth across percentiles if data are treated anonymously and nonanonymously. The GIC shows the rate of growth in income at each percentile of the income distribution between two points in time. If individuals are treated anonymously, mean income is calculated independently for each percentile of the initial and final distribution, and an income growth rate is calculated for each percentile. If the anonymity assumption is removed and individuals are treated as panel observations, they can be sorted in ascending order according to the initial income percentile. Percentile-specific mean incomes and income growth rates, where each percentile is composed of the same individuals at time *0* and time *1*, are then constructed (Grimm 2007).

Figure 4.2 shows both the anonymous and the nonanonymous GIC constructed using individual earnings of workers in the CMPHS panel data. Workers who are followed over time are first treated as if they were different workers, and they are then treated as panel observations. The anonymous GIC does not point to considerable differences in earnings growth rates across percentiles. By contrast, the nonanonymous GIC clearly shows that individuals initially at the bottom of the earnings distribution gained the most over a period of 16 months and that individuals at the top in fact posted a loss in mean earnings. The nonanonymous GIC thus confirms the existence of the convergence of earnings.

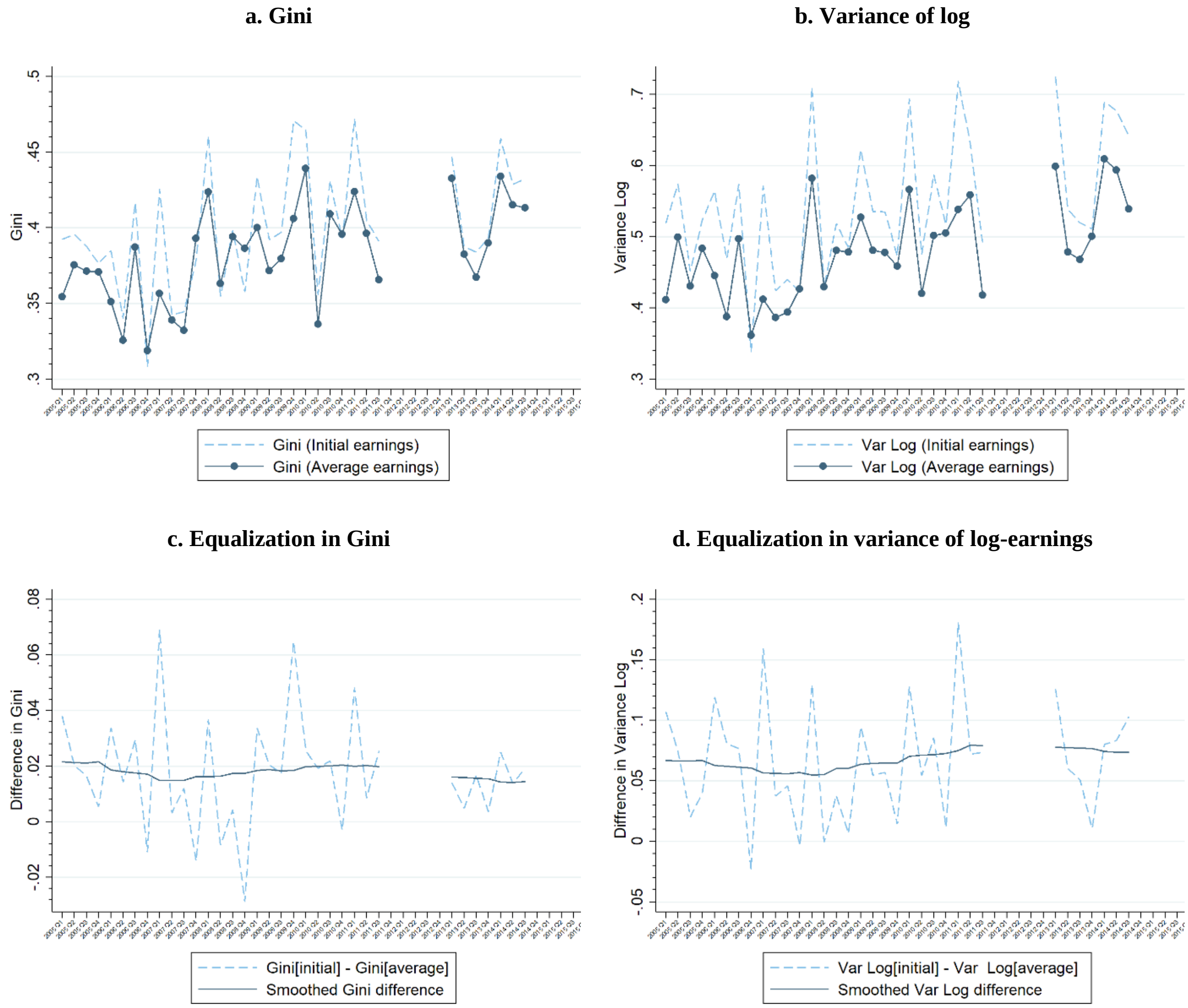
Figure 4.2. Growth Incidence Curves: Anonymous and Nonanonymous, Average Q1–Q4 Change, 2005–15



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.
Note: Both curves are truncated at the 5th and 95th percentile.

It is clear that expanding inequality does not imply that, on average, *initial* high earners are getting higher earnings at a more rapid rate than *initial* low earners. The GIC has shown that the opposite is true: convergent mobility implies that the initial low earners post larger gains in both levels and percentage terms than the initial high earners. However, earnings convergence is not sufficient to make the majority of the initial high earners poorer than the initial low earners over a period of 16 months.

Figure 4.3. Inequality of Initial and Average Earnings, Q1:Q4, 2005–15



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Among others, Fields et al. (2015) show that some of the observed earnings changes might be transitory. It is therefore important to investigate the extent to which such changes affect a measure of inequality purged of transitory earnings components. Given the availability of repeated rounds of earnings information for the same individuals, one commonly adopted measure of this type of inequality is calculated by averaging individual earnings over time. This way earnings are less affected by transitory shocks.

By comparing inequality measures in initial and average earnings, one can ascertain whether individual earnings changes make average earnings more equally distributed relative to a situation without changes in earnings.[13] The difference between inequality measures in initial and average earnings takes positive values if earnings changes equalize average earnings relative to initial earnings, and it takes negative values if it makes them more unequal. Figure 4.3 illustrates the trends in inequality in initial and average earnings as captured by the Gini coefficient (panel a) and by the variance in log-earnings (panel b). While inequality in average earnings largely mirrors the time trend of inequality in initial earnings, in the case of both the Gini coefficient and the variance, the levels of inequality in average earnings are lower than the levels in initial earnings. This is best illustrated in Figure 4.3, panels c and d, which plot the difference between inequality measures in initial earnings and inequality measures in average earnings. Both the differences calculated using the Gini coefficient and the variance are nearly always positive, indicating that average earnings are more equally distributed, and the trends are roughly flat over time, pointing to no considerable changes in the relation between the two measures over time.

[13] The reader should not be misled and think that inequality in average earnings is necessarily lower than inequality in single-period earnings. Fields (2010) offers a simple example whereby changes in inequality in single-period earnings does not reveal anything about whether longer-term earnings are more equally distributed than initial earnings or not.

Part II – Inequality of Opportunity in the Labor Market

> Greater mobility in the sense of less association between origins and destinations has long been linked with having a more open society; if where you end up does not depend on where you started from, there is greater equality of opportunity.
> —Jäntti and Jenkins (2015, 814)

What is inequality of opportunity? The degree of inequality of a society is typically the by-product of a multiplicity of factors. The level of inequality reflects the choices, efforts, and pure luck of individuals. Inequality attributable to such factors is certainly less objectionable and might even be necessary to create and maintain economic incentives that drive individual enterprise and effort. Inequality of opportunity is the part of inequality that can be ascribed to individual circumstances, that is, factors that are exogenous to the individual, such as gender, race, family background, or place of birth. This part of inequality—the part that can be attributed to unequal opportunities—is regarded as unjust and unfair and could also exert a negative effect on individuals who lack exactly these circumstances.

The key assumption of the literature on inequality of opportunity is that inequality in outcomes can be divided into inequalities deriving from justifiable sources, that is, factors that are under the control of the individual, including choice and effort, and inequalities attributable to circumstances, which are beyond the control of the individual (Ferreira et al. 2014; Marrero and Rodriguez 2013; Roemer 1998; World Bank 2005). The idea is that the first type of inequalities may be related to the misallocation of resources, and this can lead to low economic growth. For this reason, such inequalities should be eliminated or at least minimized. By contrast, inequalities ascribable to individual effort, ability, and preferences are considered essential to maintaining economic incentives, including, for example, investments in human capital, and to spur economic growth. This argument suggests that investigating the two dimensions of inequality is of paramount importance on both equity and efficiency grounds. Reducing and, in the long run, removing inequalities ascribable to circumstances might improve the allocation of resources, allow everyone to participate in economic activity, and increase the economic potential of a country.

The scope of this second part of the report is to investigate the extent of inequality of opportunity in the labor market among individuals of working age. The ability of individuals to access labor markets and jobs that match the human capital they possess regardless of their socioeconomic background is key to their future income and, more generally, to economic mobility, equality, and long-term growth. The crucial question is to what extent is the ability of an individual to access a labor market opportunity a function of circumstances the individual has no control over, such as gender, ethnicity, parental background, and place of birth.

Inequality of opportunity is potentially an important contributor to overall inequality in light of the recent challenges Mauritius has faced. The long-lasting economic success that followed the declaration of independence in Mauritius has now failed to meet the expectations of economic growth and shared prosperity. The growth of gross domestic product (GDP) and employment creation have lost steam, and rising inequality has been eroding the living standards of the poor (World Bank 2017b).

"The public-private dialogue that worked so well in the past is having less impact," argues the World Bank (2015, x). "What is more worrisome, it is becoming increasingly difficult to deliver on the social contract as signs of a strained middle class show."

In addition to the problem in the overall availability of labor market opportunities, recent trends clearly bring to the forefront the issue of the allocation of such opportunities. If economic growth creates a large number of good jobs, the normal functioning of demand and supply makes the distributive side less relevant. By contrast, whenever economic growth slows, and labor markets are strained in contexts characterized by considerable inequality of opportunity, then the scarce number of good job opportunities may become available primarily to individuals born in privileged circumstances.

In addition to objective measures of inequality, perceptions can also matter on development grounds (Krishnan et al. 2016). Perceived inequality can affect the motivations and aspirations of individuals and thereby affect the degree of effort people are willing to exert to achieve their objectives and change their conditions if they think such conditions are unchangeable. Perceptions about the distribution of income and wealth can affect social cohesion and trust in public institutions and therefore in the ability of such institutions and society at large to come up with solutions that can be widely shared. Perceptions of inequality can raise the demand for redistribution, and this may influence economic growth whenever the effect is the implementation of distortionary and consensus-building economic policies.

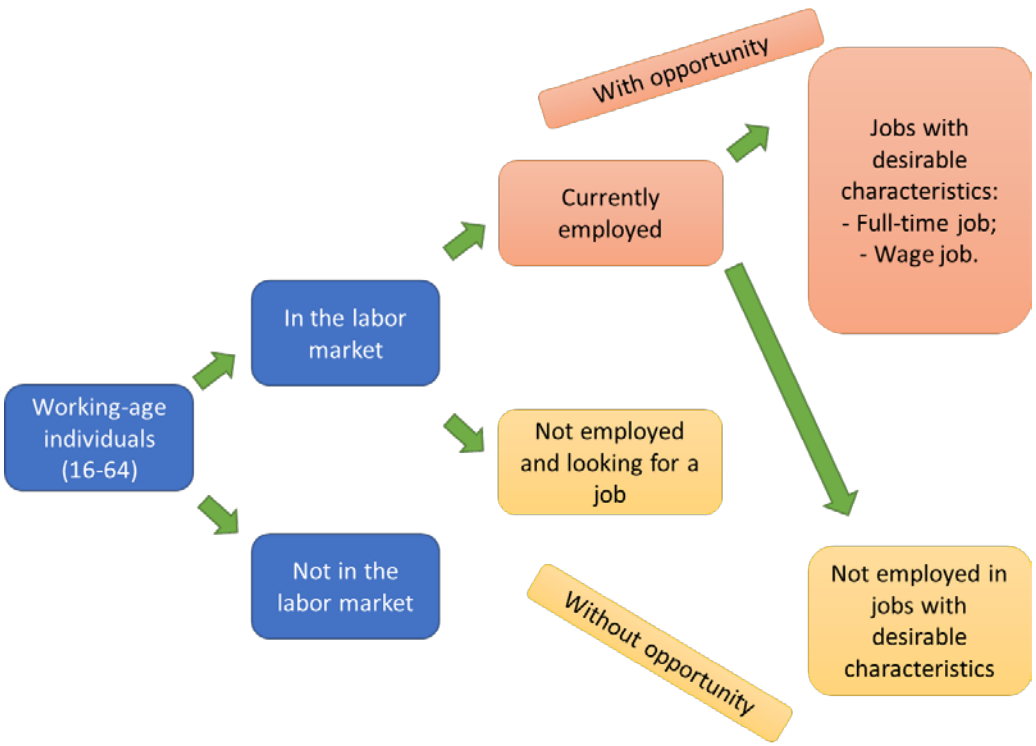
What drives the gap between perceptions and reality? Krishnan et al. (2016) argue that important elements are (1) the preferences, values, and beliefs systems of individuals; (2) the rank of individuals in the distribution of income and wealth at a point in time relative to a point in the past and how that mobility compares with mobility among others in the individual's own reference group; (3) processes behind observed inequality and the extent to which these are considered fair. Because perceptions about inequality might also hinge on the underlying process that generates inequality and on the extent to which it is perceived as fair, this second part of the report is aimed at identifying how much of the inequality in labor market opportunities can be considered unfair and the factors (or circumstances) that most contribute to this component. The hypothesis is that inequality generated by principles of meritocracy, reward, effort, talent is less likely to be viewed as objectionable by most people because this type of inequality is necessary to create and maintain economic incentives. By contrast, inequalities ascribable to circumstances that are exogenous to the control of the individual are likely to be deemed unfair and to be opposed, at least by some.

5. How Can Inequality of Opportunity in the Labor Market Be Measured?

This section identifies what constitutes an opportunity in the labor market, explains how to interpret the human opportunity index (HOI) in the case of labor market opportunities, and provides a brief overview of the Mauritian labor market with the aim of identifying the most rewarding opportunities. It then presents the results of the analysis of equality of opportunities starting with a description of coverage and the inequality-adjusted coverage (IAC) rate (the equivalent of the HOI in the case of labor market analysis), the contributions made by characteristics and circumstances to inequality of opportunity, and, exploiting data from the 2000 and 2011 population census, how they have changed over time.

What is meant by labor market opportunity? Many would agree that every person with a similar combination of skills and experience and desiring to have a certain type of job should enjoy an equal probability of obtaining this type of job (Krishnan et al. 2016). This seems to imply that being employed is somewhat superior to other states of being. Well, this might not always be true. Individuals who are waiting for a better job and therefore have a high reservation wage—the lowest wage the worker will accept—and strong preferences for certain types of jobs. Such individuals, who are voluntarily unemployed, are better off than others who are without a job because no job is available. The first might also be in a better situation relative to individuals who are employed but are engaged in low-pay activity because there is no better alternative and they cannot afford to be unemployed.

Figure 5.1: What Is an Opportunity in the Labor Market?



Source: Adapted from Krishnan et al. 2016.

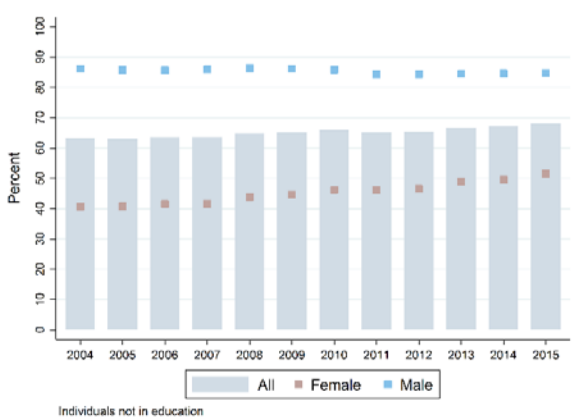
Defining opportunities as some sort of universal good in the case of children is not straightforward in the case of jobs. Moreover, being employed is an outcome, the result of choices, motivations, decisions within and outside the control of individuals. Employability is likely to be the most appropriate “opportunity” in the labor market, and the effect of circumstances on employability would be a good topic of investigation. However, employability is difficult to observe and measure in typical household and labor force surveys (Abras et al. 2013; Krishnan et al. 2016). Therefore, the simplest indicator of labor market opportunity one can think of is the state of being employed (Figure 6.1). However, for the reasons explained above, being employed is not necessarily an opportunity. The analysis therefore starts by using the basic state of having a job as the relevant metric and also considers additional, finer categories. Individuals with a labor market opportunity are those who have jobs that have desirable characteristics, while individuals without such an opportunity are those without jobs with the desired characteristics, including those who are unemployed. The motivation is to keep the focus on labor market opportunities that are generally desirable: having them is unambiguously better than not having them. Compared with being employed, the state of being employed in a job with certain characteristics is arguably more desirable (Figure 5.1). So, individuals with an opportunity are those employed or employed in jobs with certain characteristics. By contrast, individuals without an opportunity are those not employed, but and participating in the labor market (unemployed) or those employed in jobs that do not have the desired characteristics.[14]

The set of labor market opportunities includes the following variables: employed (whether someone worked in the previous seven days for at least 1 hour), employed full time (whether someone worked in the previous seven days for at least 40 hours), and employed as wage worker (whether someone worked in the previous seven days for a wage or salary). In addition, using postcensus data from the CMPHS, an additional opportunity is considered, namely, employment in a job that pays above the poverty line.

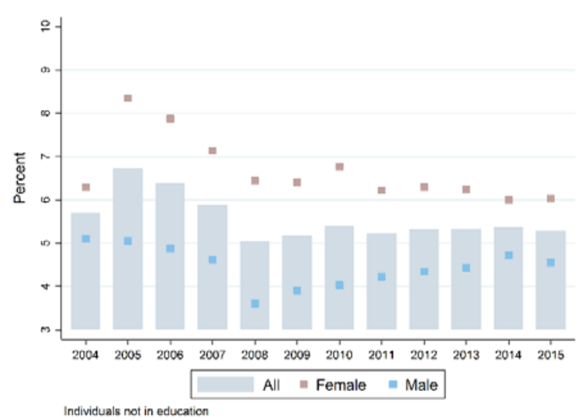
As extensively discussed in World Bank (2017a), Mauritius features an overall labor market participation rate at around 70 percent measured over the last decade. This is in line with the participation rates among the countries of the Organisation for Economic Co-operation and Development (71.3 percent in 2015). Although women's labor force participation rose steadily over the decade and had reached 57 percent by 2015, women are still severely disadvantaged in accessing the Mauritian labor market. The employment-to-population ratio has increased over the last decade and reached on average 68 percent in 2015. Among men, the rate was as high as 85.0 percent, whereas women still lag, at a rate of 51.5 percent (Figure 5.2, panel a).

Figure 5.2. Employment Ratio and Unemployment Rate, by Gender and Age, 2004–15

a. Employment-to-population ratio, by gender

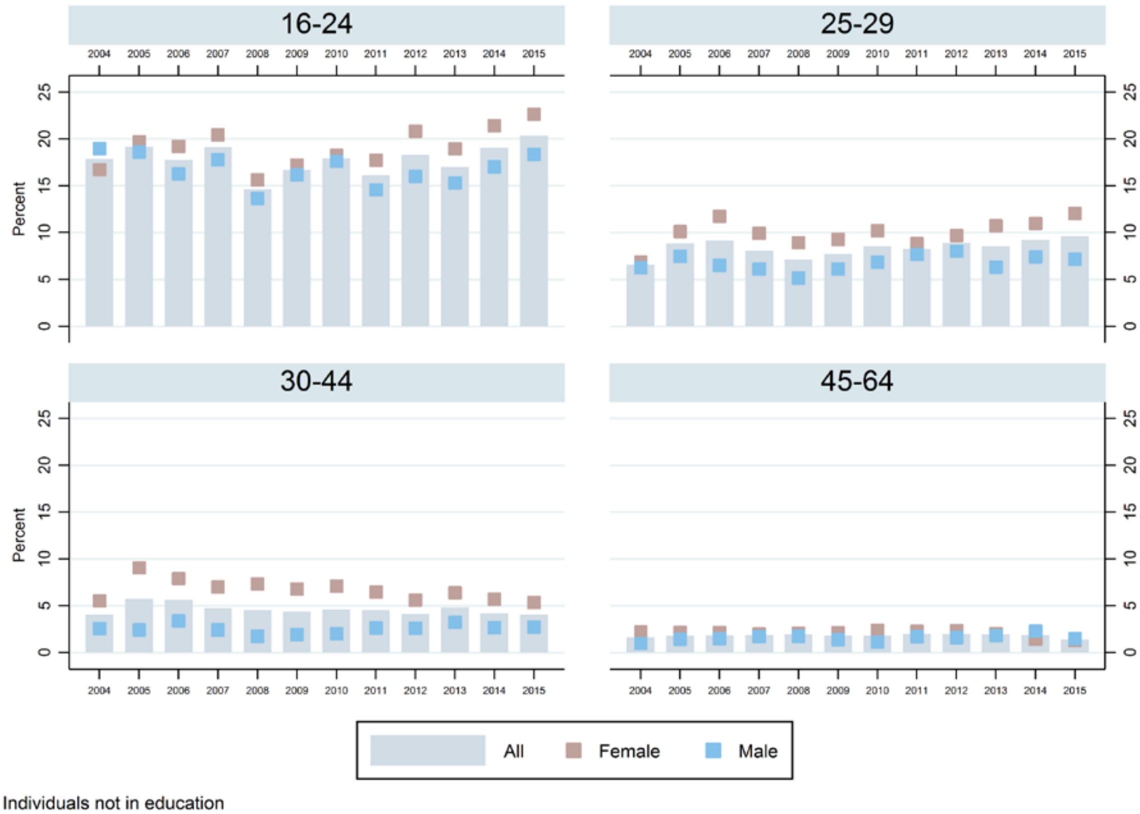


b. Unemployment rate, by gender



c. Unemployment rate, by gender and age-group

[14] The inactive are excluded from the analysis because they are not willing to have access to a labor market opportunity and exert no effort in that respect. Certainly, the degree of effort individuals exert to gain access to employment or to a certain type of job varies greatly among individuals, and this is unobservable in the available data sources.



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

The unemployment rate has hovered at around 5 percent over the last decade and has been regularly higher among women (Figure 5.2, panel b). Access to jobs seems particularly difficult among youth. Figure 5.2, panel c, shows that unemployment among youth ages 15–24 has consistently been three times the overall unemployment rate and significantly higher compared with the rate among individuals in the 25–29 age-group. The unemployment rate among the younger age-group rose from about 19 percent in 2008 to 25 percent in 2015. The unemployment rate among youth increased from about 19 percent in 2008 to 25 percent in 2015. The latter compares with about 11 percent among the 25–29 age-group, 5 percent among the 30–44 age-group, and less than 2.5 percent among the oldest age-group (45–64). The unemployment rate is consistently higher among women across all age-groups. The World Bank (2017a) also shows how unemployed youth are becoming typically more highly educated.

How to measure inequality of opportunity in the labor market? The report adopts the HOI methodology introduced by the World Bank (2005) and Barros et al. (2009). The first step foresees the classification of individuals into groups or types based on their circumstances, in addition to age and educational attainment, which are important factors and proxy for skill and experience and for access to a labor market opportunity. The between-group inequality in access to each labor market opportunity is defined by the dissimilarity index. The share of inequality attributable to circumstances is interpreted as the part of inequality that is unfair. This part accounts for barriers to equitable access to employment among certain types of workers. This is likely to underestimate the true extent of inequality caused by circumstances because of both the limited number of circumstances controlled for in the analysis and the effect these circumstances have on the educational attainment of individuals. From a policy-making standpoint, this analysis can provide relevant information on the extent to which the labor market might be unfair, but also on inefficiencies in the allocation of employment opportunities. The analysis thus indicates (whether and) the degree to which signals for skills (proxied by education and experience) are dominated by the effect of factors that are less likely to be correlated with the productivity of individuals.

The analysis therefore identifies the effect of circumstances on inequality of opportunity net of age and experience. This method captures the *direct* contribution of circumstances to inequality of opportunities in the labor market, and it neglects the role that the same set of circumstances plays in human capital accumulation earlier in life, which can be defined as the *indirect* effect. The direct effect can be interpreted as inequality produced by distortions in the labor market, distinct from those produced in earlier stages of life, that is, prior to an individual's entry into the labor market.

As Krishnan et al. (2016) note, as opposed to the case of children where every omitted characteristic can be considered as a circumstance, in the case of adults in the labor market there can be important characteristics that are omitted and influence the opportunity under study such as the degree of effort exerted to look for a (certain type of) job. Since separating out the two types of characteristics and how they interplay with observed circumstances is not possible with the available data sources, the interpretation of the output is adjusted following Krishnan et al. (2016). The dissimilarity index, which in the case of children is interpreted as the inequality of opportunity index, is an index of inequality in the labor market and the HOI becomes the IAC rate.

The analysis includes religion among circumstances as a proxy for ethnic origin, in addition to gender, and place of residence five years earlier is taken as a proxy for place of birth, given the limited internal mobility in Mauritius. The inequality of opportunity literature typically encompasses additional circumstances aimed at capturing the role of parental background such as the educational attainment and occupations of parents. This information is not available on individuals who no longer live with their parents. To gauge the extent to which the degree of inequality in access to labor market opportunities and the contribution of the restricted set of circumstances is affected by the exclusion of parental background variables, a sensitivity test is performed (see Box II.1). The test consists of running the same exercise on a subset of the working-age population on which the information on parental characteristics, namely, educational attainment and occupation, is available in the data. This sample includes all coresident youth ages 16–25, that is, young individuals who still reside with their parents.

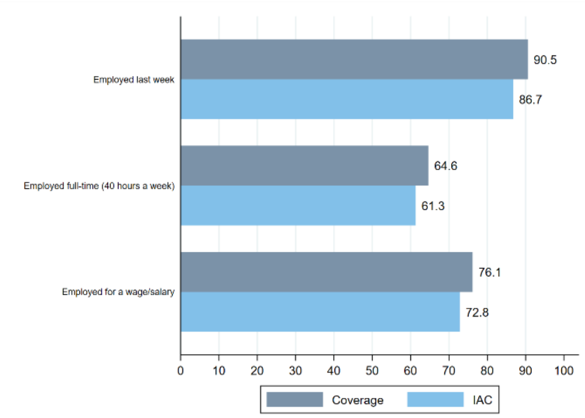
6. How Much Inequality of Opportunity Is There in the Labor Market?

The starting point of the analysis of equality of opportunities is the calculation of the coverage rate and the IAC. The gap between coverage and adjusted-coverage represents the penalty arising because of an unequal distribution of outcomes across groups defined by circumstances (and characteristics). Clearly, coverage rates are highest for the most basic labor market opportunities and become increasingly smaller if more desirable opportunities are considered (Figure 6.1). For example, as of 2011, the overall employment rate was 92.3 percent. However, individuals employed full time are only 66.5 percent of the labor force; those employed for a wage account for 75.8 percent (Figure 6.1, panel b). The general employment and full-time employment indicators improved between 2000 and 2011, whereas wage employment was roughly constant.

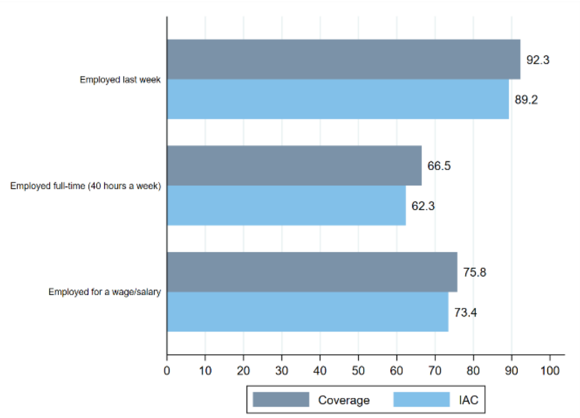
The IAC adjusts coverage by the inequality observed across groups defined by circumstances and characteristics. While it is obvious that the IAC rate is always lower than the coverage rate for any labor market opportunity considered, the gap is remarkably large in some cases, particularly for the opportunities that incorporate some degree of job quality. The difference between the IAC and coverage is relatively small, and, in two cases out of three, namely, employment and wage employment, it has declined over time (Figure 6.2).

Figure 6.1. Overall Coverage and Inequality-Adjusted Coverage of Labor Market Opportunities, 2000 and 2011

a. 2000



b. 2011

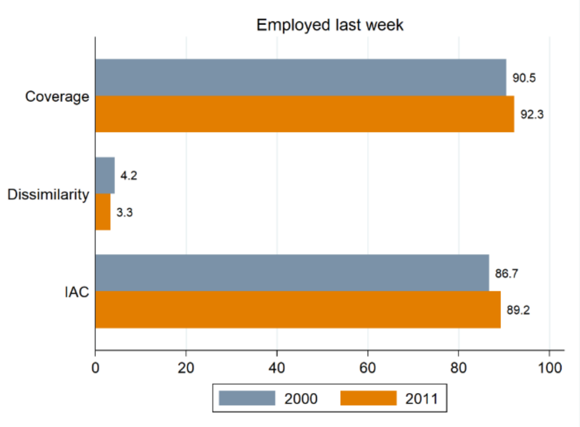


Source: Based on data of the Housing and Population Census, Statistics Mauritius.

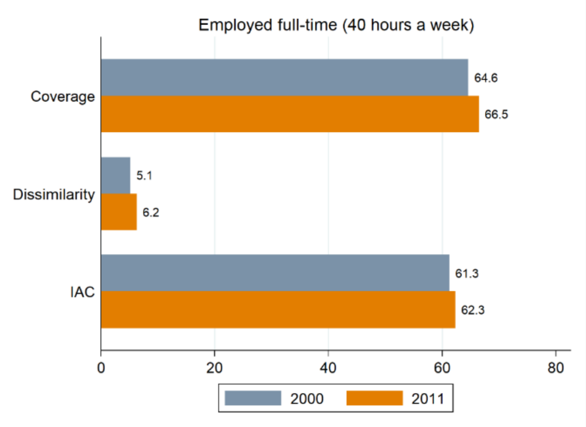
The dissimilarity index can be interpreted as the share of the total number of opportunities that needs to be reallocated among all groups with different circumstances and characteristics to ensure equality of opportunity, that is, to ensure an equal coverage rate for all groups. Figure 6.2 shows that the dissimilarity index is small for the most basic labor market indicators, thus demonstrating that the distribution of these opportunities is fairly equal across groups.

Figure 6.2. Overall Coverage, Dissimilarity Index, and Inequality-Adjusted Coverage, Labor Market Opportunities, 2000 and 2011

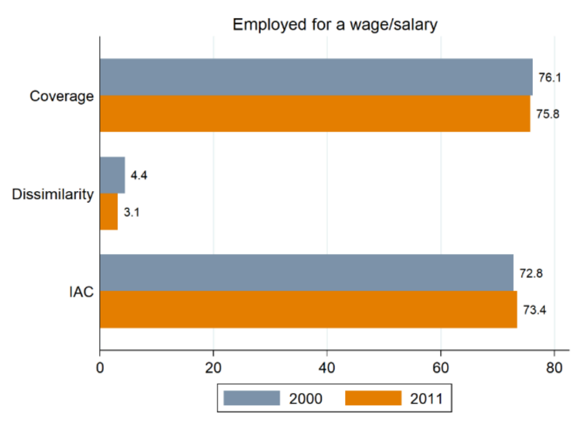
a. Employed the previous week



b. Employed full time



c. Employed for a wage or salary



Source: Based on data of the Housing and Population Census, Statistics Mauritius.

The next step is to understand how much of the inequality in access to labor market opportunities is attributable to circumstances and characteristics. Contributors to inequality of opportunity can be identified through a Shapley decomposition technique, whereby the total contribution is decomposed to isolate the share attributable to circumstances, which captures the part of inequality that is unfair, and the share attributable to education and age. This method allows the direct contribution of circumstances to be isolated to inequalities in the labor market, whereas it does not capture the role played by circumstances in labor market opportunities through their effect on human capital accumulation, that is, the indirect effect.

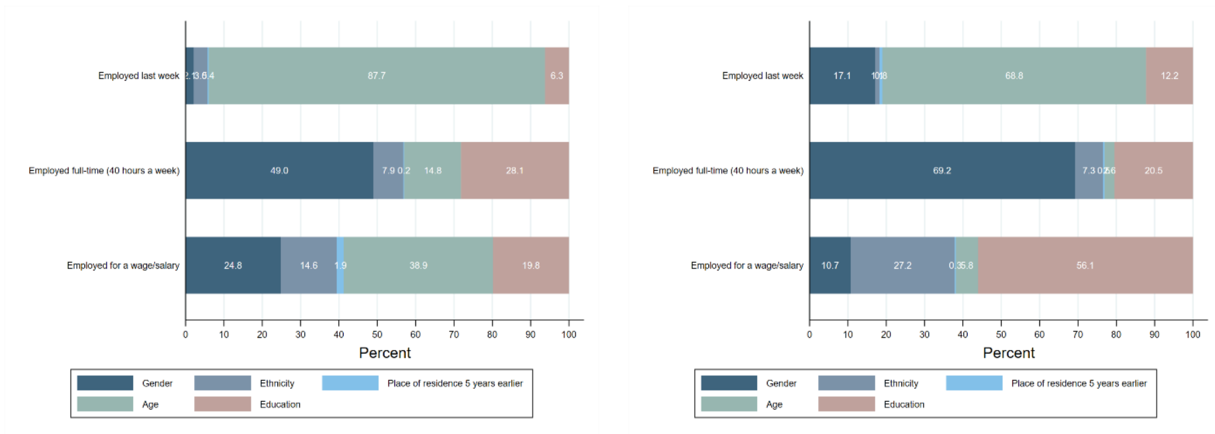
Figure 6.3 illustrates the results of the decomposition and shows that the contribution of circumstances ranged between 11 and 77 percent in 2011 depending on which labor market opportunity is taken into consideration. For example, the role of circumstances appears considerable in the case of full-time employment (76.9 percent) and wage employment (38.2 percent). Among the group of circumstances, gender plays a primary role in the case of full-time employment because many women workers combine part-time work with family and household care duties. Education is a key contributor to inequality in the case of wage employment because education is correlated with skills and employability, and it is therefore an important factor affecting access to good jobs. However, even for the best opportunities in the labor market, circumstances do play a major role.

The contribution of age to inequality of opportunity is extremely large in the case of the most comprehensive employment indicator. This is in line with the high unemployment rates observed among youth ages 16–24, which have been about three times as high as the overall unemployment rate over the course of the last decade and significantly higher compared with the unemployment rate among individuals ages 25–29.

A decade earlier, circumstances contributed to a larger extent to inequality of opportunities in the case of full-time and wage employment compared with other employment indicators. It also appears that the contribution of circumstances to inequality of opportunity rose among high-quality job opportunities, thus pointing to increasingly unequally distributed opportunities, net of age and education.

Figure 6.3. Contributors to Inequality: Circumstances and Characteristics, 2000 and 2011

a. 2000 **b. 2011**



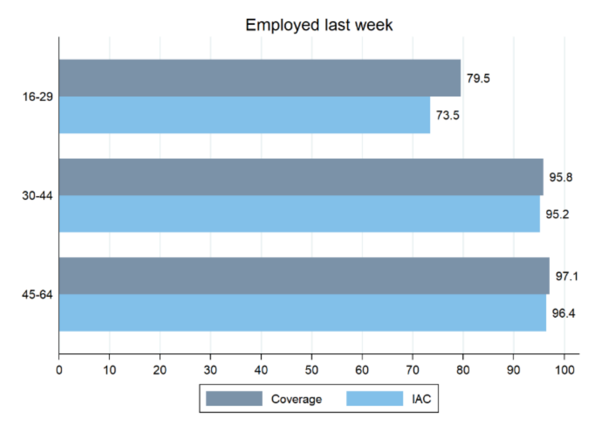
Source: Based on data of the Housing and Population Census, Statistics Mauritius.

Similar patterns are observed using recent CMPHS data (2012–15). This data source also allows the analysis of inequality of opportunities to be extended to one additional labor market outcome, that is, employment in a job that pays above the poverty line. The results, shown in Annex A, indicate that about 75 percent of the employed had jobs that paid above the poverty line in 2015, and this share had been roughly constant between 2012 and 2015. The dissimilarity index is estimated at 8.6 percent in 2015. Age and education capture over half the inequality observed in this employment indicator; gender alone contributes over a third (37 percent), while ethnicity explains less than 20 percent.

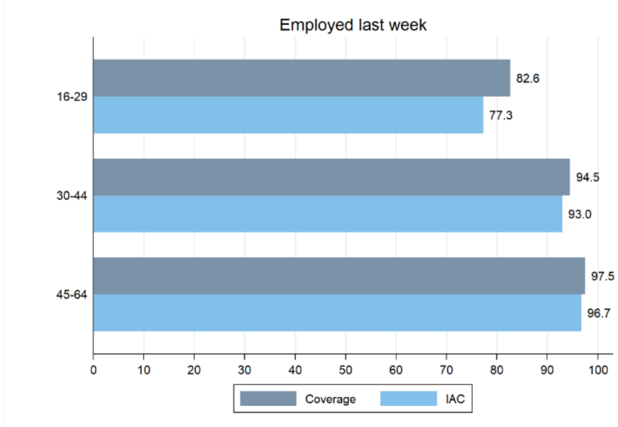
Given the relevance of age as a characteristic, the analysis of equality of opportunities can fruitfully be broken down by age-group. Figure 6.4 (left panels) illustrates that, in 2000, coverage rates were typically higher among middle- and old-age workers compared with youth along all dimensions. For example, the employment rate among youth ages 16–29 was 79.5 percent in 2000, which compares with 95.8 and 97.1 percent among individuals ages 30–44 and 45–64, respectively. Similar differences exist in terms of full-time and wage employment across individuals in different age-groups. In 2000, the youth coverage rate was at 8.4 percent, twice as high among individuals ages 30–44 (16.8 percent), and over three times as high among the oldest age-group (29.9 percent). By about 10 years later, labor market opportunities had improved, particularly among youth. By 2011, coverage had risen among youth in terms of employment, full-time employment, and wage employment.

Figure 6.4. Overall Coverage and Inequality-Adjusted Coverage of Labor Market Opportunities, by Age-Group, 2000 and 2011

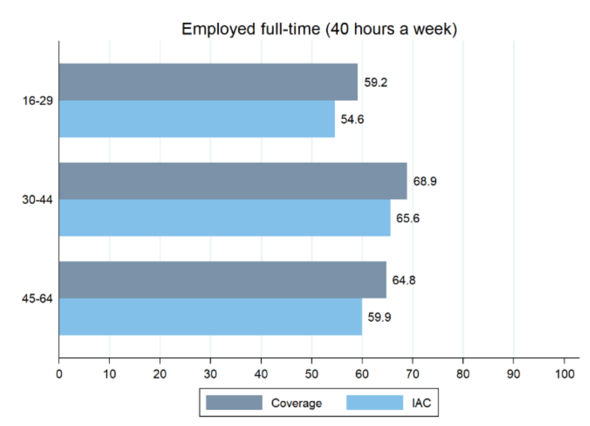
a. Employed the previous week, 2000



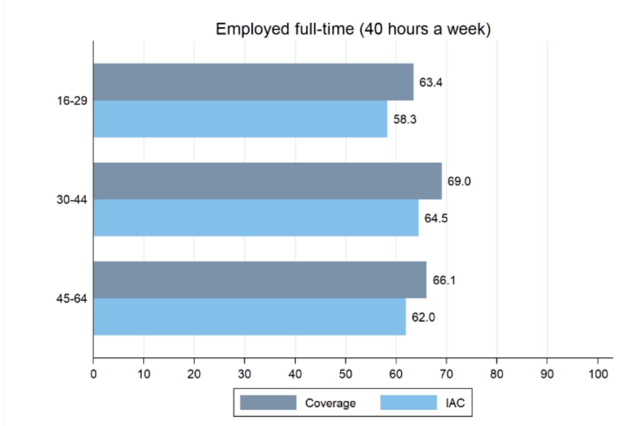
b. Employed the previous week, 2011



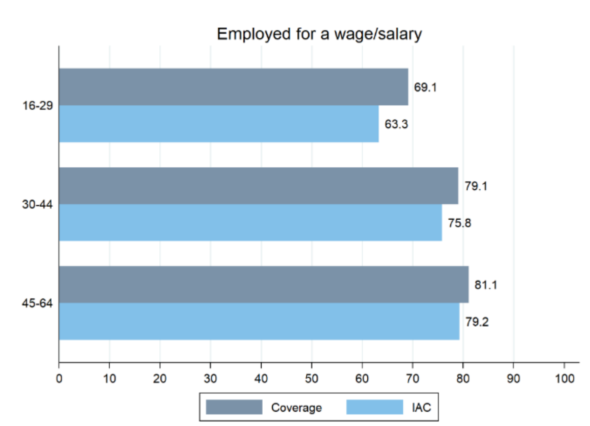
c. Employed full time, 2000



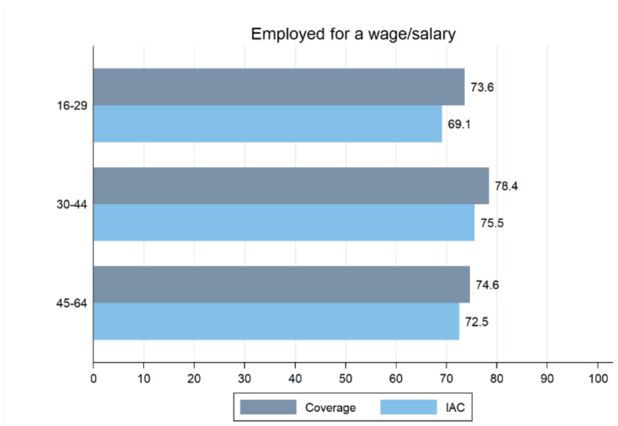
d. Employed full time, 2011



e. Employed for a wage or salary, 2000



f. Employed for a wage or salary, 2011



Source: Based on data of the Housing and Population Census, Statistics Mauritius.

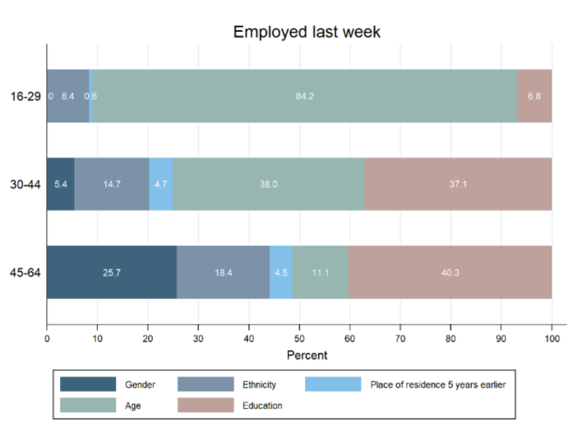
In parallel, the IAC increased among youth across all employment indicators, while, among the oldest age-group, it did so for employment and employment full time. As a result, inequality of opportunity declined considerably among the youngsters.

Despite these changes, the level of inequality of opportunity is still considerably higher among youth compared with other age-groups; middle- and old-age individuals still suffer greater inequality. The changes observed over the last decade have been particularly beneficial to the young generations because they brought about not only an expansion in coverage, but also a decline in inequality of opportunities. The opportunities have become more equally distributed across groups defined by circumstances and characteristics.

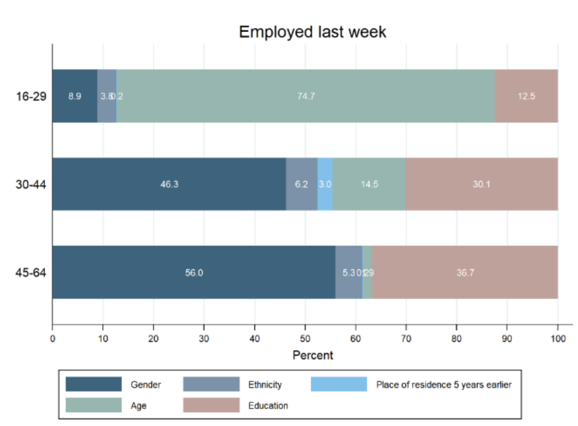
How do circumstances contribute to inequality of opportunity across age-groups? First, the role of circumstances, particularly gender, is considerable across all age-groups in the case of full-time employment, ranging between 45 percent and 72 percent by 2011. Gender also plays a major role in the basic labor market indicator—employment in the previous week—among individuals in the 30–44 and 45–64 age-groups. This reflects the gender gap observed in the labor market, particularly as women out of school enter the labor market and approach the age of marriage (Figure 6.5). Second, the role of circumstances declined over time for most labor market indicators among individuals in the 30–44 and 45–64 age-groups, and, by contrast, it increased among the youngsters, notably in full-time employment. Breaking down the analysis by age-groups does not wash out the role of age in explaining access to employment among individuals in the 16–29 age-group. Within this age–group, it is possible to identify a sort of threshold between the youngest, ages 16–24, and people ages 25–29; the first is strongly affected by high unemployment rates even compared with their counterparts who are closest in age.

Figure 6.5. Contributors to Inequality: Circumstances and Characteristics, by Age-Group, 2000 and 2011

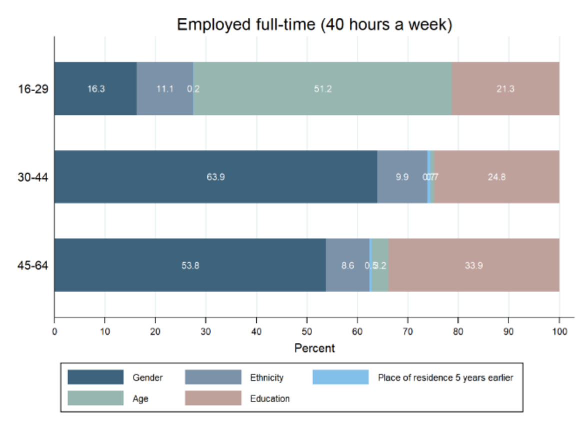
a. Employed the previous week, 2000



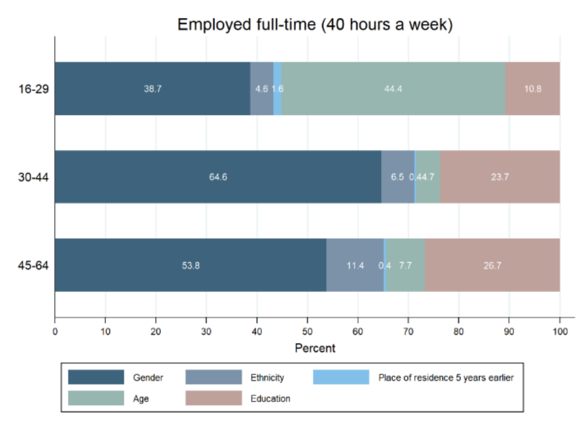
b. Employed the previous week, 2011



c. Employed full time, 2000

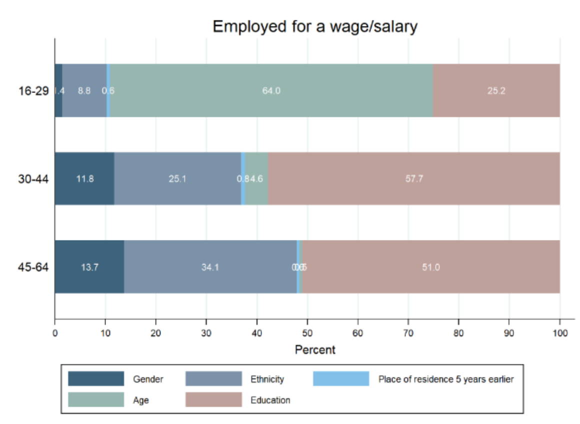


d. Employed full time, 2011



e. Employed for a wage/salary, 2000

f. Employed for a wage/salary, 2011



Source: Based on data of the Housing and Population Census, Statistics Mauritius.

Box II.1. Equality of Opportunity in the Labor Market: Controlling for Parental Background

The IAC rate and the dissimilarity index are a function of the set of circumstances available for the analysis (see Annex D). It is not possible to identify and observe in readily available microdata all relevant circumstances for a certain set of opportunities. For this reason, the estimated inequality of opportunities is typically considered to be a lower bound of the true inequality of opportunity that could be measured if all possible circumstances could be observed and included in the analysis. This is because a property of the index guarantees that adding additional circumstances can only increase the value of the dissimilarity index.

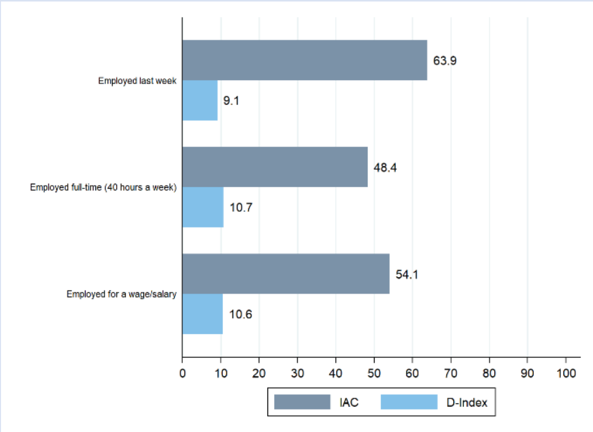
To provide some ballpark estimates of how inequality of opportunity would change and the extent to which the role of the circumstances included in the analysis would differ by adding important circumstances, such as the parental background of individuals, a sensitivity test is performed by restricting the sample of analysis to individuals in the 16–25 age-group who were still living with their parents at the time of the census. While this is clearly not a random sample of all individuals in the age-group, the purpose is to assess the extent to which adding a set of circumstances that are typically considered important in the analysis of equality of opportunity and yet missing in the main sample affect the main findings.

The additional set of circumstances is composed of the educational attainment of the mothers and fathers level as well as the father's occupational category.

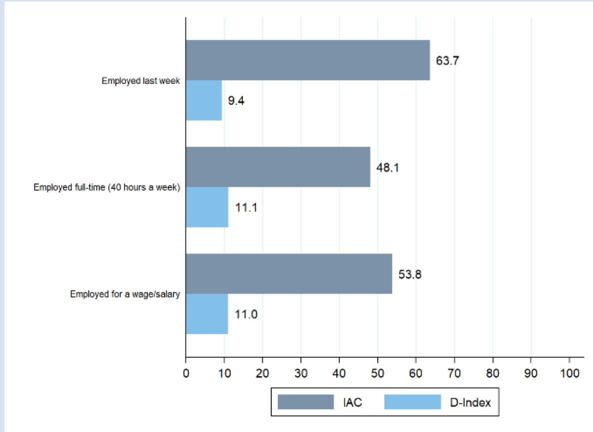
Figure BII. illustrates, for 2000 (panels a and b) and 2011 (panels c and d), the estimated IAC and the dissimilarity index with and without the additional circumstances. In both years, the value of the dissimilarity index does not change considerably. As expected, it increases, although modestly, if the set of circumstances is completed by information on parental background. For example, the value of the D-index calculated for wage employment in 2011 increases from 8.2 to 8.5, while that for full-time employment rises from 9.6 to 9.9.

Figure BII.2.1. Inequality-Adjusted Coverage of Labor Market Opportunities and the Dissimilarity Index, Coresident Children Ages 16–25, 2000 and 2011

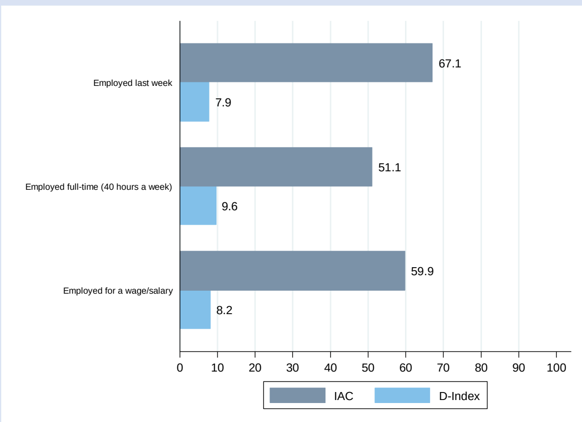
a. Basic set of circumstances, 2000



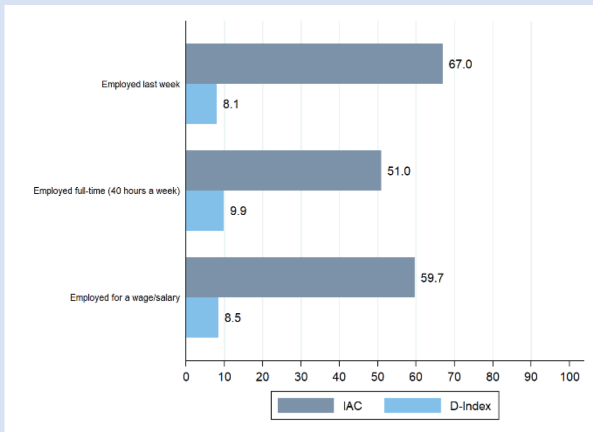
b. Full set of circumstances, 2000



c. Basic set of circumstances, 2011



d. Full set of circumstances, 2011



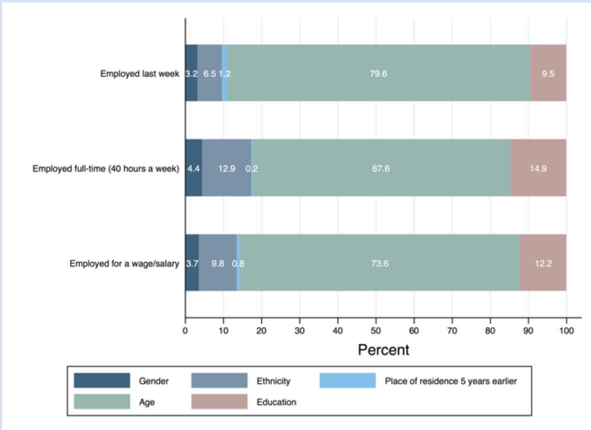
Source: Based on data of the Housing and Population Census, Statistics Mauritius.

Having ascertained that the level of inequality of opportunities is not considerably affected by the inclusion of additional circumstances for the three labor market indicators considered, one might usefully investigate what happens to the relative contribution of circumstances and characteristics in a decomposition exercise. Figure BII. illustrates the relative contribution of circumstances and characteristics in the case of a basic (left-hand side panels) and a full set of circumstances (right-hand side panels) in both 2000 and 2011. The contribution of the set of circumstances to inequality of opportunity increases with the number of circumstances included in the analysis. For example, in 2011, the total contribution of circumstances to inequality of opportunity in wage employment rises from 9 percent to 47 percent if parental background information is included. However, the variables the relative weights of which fade away the most are characteristics, particularly education. By contrast, the relative contribution of basic circumstances, including gender, ethnicity, and place of residence, remains largely unchanged.

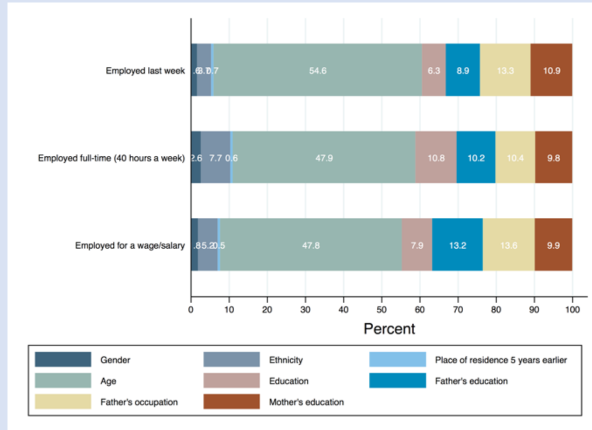
The test indicates that, controlling for additional, important circumstances, such as parental background, on a sample of individuals in the 16–25 age-group who are living with their parents does not significantly raise the level of inequality of opportunity measured through three of the five labor market indicators analyzed in this report. Moreover, while the overall relative contribution to inequality of circumstances increases if additional circumstances are included in the analysis, the contribution of basic circumstances does not change considerably. While this is by no means proof that findings based on the full sample of the working-age population would pass the test with the same degree of confidence, it is the best that can be done to validate the robustness of the equality of opportunity exercise in the case of the inclusion of parental background.

Figure BII.2.2. Contributors to Inequality: Basic and Full Set of Circumstances and Characteristics, Coresident Children Ages 16–25, 2000 and 2011

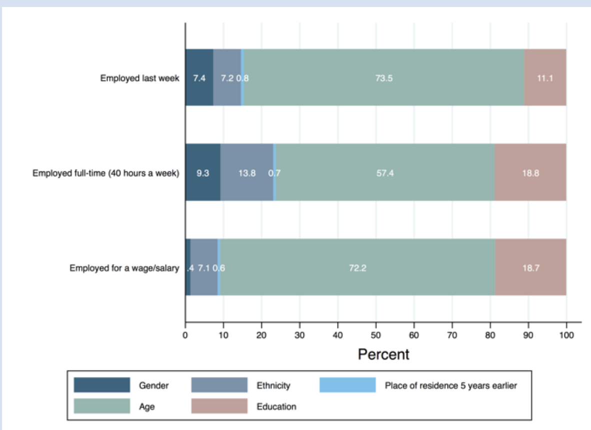
a. Basic set of circumstances, 2000



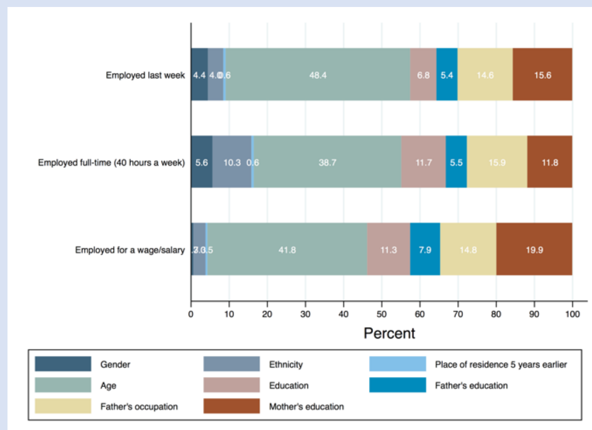
b. Full set of circumstances, 2000



c. Basic set of circumstances, 2011



d. Full set of circumstances, 2011



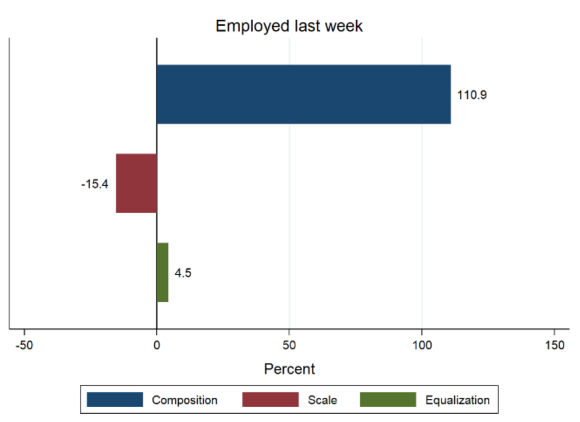
Source: Based on data of the Housing and Population Census, Statistics Mauritius.

The IAC rate is determined by group-specific coverage rates and their shares in the reference population. This means the overall indicator can change if one of the two or both components change. More precisely, any change in the index can be attributable to either changes in the distribution of circumstances—also known as the *composition effect*— or changes in some group-specific coverage rates—known as the *coverage effect*. The latter can be further decomposed into changes caused by changes in the inequality of opportunity (the *equalization effect*) and changes arising from average coverage rates (the *scale effect*). For example, if all group-specific coverage rates increased proportionally, the degree of equality of opportunity would remain unchanged, and the IAC rate would increase only because of the change in the average coverage rate, the scale effect. On the other hand, if coverage improved among the most vulnerable—defined as individuals with below-average coverage—and were compensated by a corresponding decline in coverage rates among the nonvulnerable groups, that is, those with above-average coverage, then overall coverage would stay the same, and the IAC rate would rise because of the reduction in the degree of inequality of opportunity, the equalization effect.

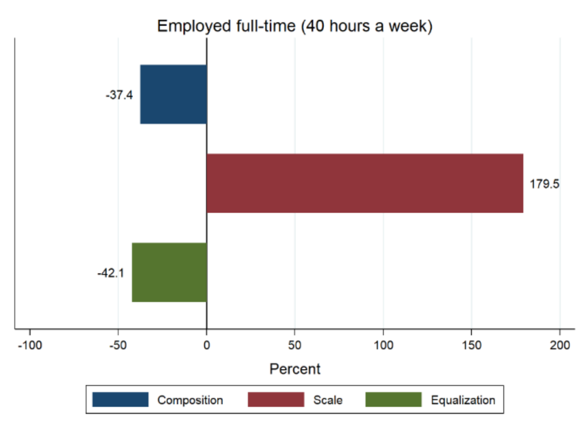
Figure 6.6 shows the results of the decomposition of the changes occurring between 2000 and 2011 in IAC rates for each of the labor market opportunities considered. The changes observed in labor market opportunities are largely ascribable to composition effects, with the exception of full-time employment. The composition effect indicates change in average circumstances (and characteristics), including ethnicity, gender, and place of residence (and age and education). The changes observed in circumstances are relatively minor. By contrast, larger changes occurred in terms of characteristics, and these reflect partly demographic changes and partly important investments in education. For example, the share of active individuals with incomplete primary education declined by almost 14 percentage points, and the share of those with postsecondary or higher education rose from 6 percent to 15 percent; the population has aged, and the share of individuals in the 45–64 age-group therefore increased from 23.8 percent to 34.8 percent, while the share of younger individuals, particularly those in the 16–29 age-group, declined.

Figure 6.6. Decomposition of Changes in the Inequality-Adjusted Coverage of Labor Market Opportunities, 2000 and 2011

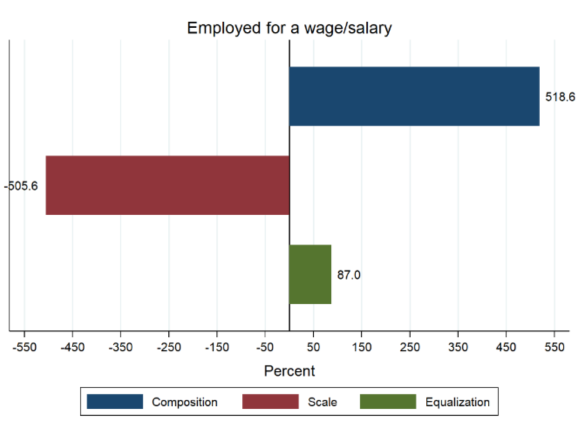
a. Employed the previous week



b. Employed full time



c. Employed for a wage or salary



Source: Based on data of the Housing and Population Census, Statistics Mauritius.

By contrast, the role of the equalization effect is relatively small and even negative in some cases. This effect captures improvements in the coverage of labor market opportunities among the most vulnerable groups. The scale effect, measuring increases in average coverage, is sizable and positive in the case of full-time employment. It is, however, negative in the case of wage employment because of a reduction in average coverage.

The equalization effect is clearly at the center of the analysis of equality of opportunities. A society that desires to level the playing field should focus on expanding opportunities, particularly among individuals belonging to vulnerable circumstance groups. The evidence indicates that, between 2000 and 2011, the equalization effect never had a primary role. The coverage effect is dominated by the scale effect, which means improved coverage rates arose mainly through greater coverage for the entire population and not primarily for the most vulnerable. Moreover, in the case of full-time employment, the equalization effect worked against an increase in inequality of opportunity.

Table 6.1. Most-Advantaged And Most-Disadvantaged Circumstances and Characteristics Groups, Workers Ages 16–64, by Labor Market Opportunity, 2000 and 2011

	Employed last week		*Employed full time*		*Employed for a wage or salary*	
	Most advantaged	*Most disadvantaged*	*Most advantaged*	*Most disadvantaged*	*Most advantaged*	*Most disadvantaged*
				2000		
Gender						
Female	24.0	37.1	0.2	93.5	70.8	5.2
Place of residence 5 years earlier						
Mauritius Island	99.6	98.6	99.4	98.6	100.0	94.9
Other islands	0.4	0.4	0.0	1.1	0.0	1.8
Abroad	0.0	1.1	0.6	0.4	0.0	3.3
Educational level						
No education, preprimary	1.6	2.5	0.0	18.1	1.0	3.8
Incomplete primary	41.6	31.8	11.8	20.1	21.3	36.2
Complete primary	5.2	11.0	8.8	1.1	1.8	12.1
Lower secondary	6.2	19.0	30.9	0.9	2.8	18.8
Incomplete upper secondary	12.7	19.5	33.1	1.4	3.2	19.2
Upper secondary, school certificate	11.8	8.7	15.1	3.8	7.2	6.9
Upper secondary, higher school certificate	10.6	6.0	0.4	32.2	28.5	1.6
Postsecondary/tertiary	10.4	1.4	0.0	22.4	34.3	1.4
Age-group						
16–29	1.6	99.3	0.6	54.1	6.2	80.5
30–44	1.8	0.7	38.1	31.1	32.5	18.3
45–64	96.6	0.0	61.3	14.8	61.3	1.3
				2011		
Gender						
Female	8.3	63.0	0.8	99.7	49.5	19.0
Place of residence 5 years earlier						
Mauritius Island	99.8	97.8	99.4	97.6	99.2	99.3
Other islands	0.2	0.9	0.0	0.9	0.8	0.0
Abroad	0.0	1.4	0.6	1.5	0.0	0.7
Educational level						
No education, preprimary	0.0	1.0	0.0	9.1	0.0	1.0
Incomplete primary	16.2	16.0	0.2	37.2	0.0	17.7
Complete primary	5.9	5.1	0.4	3.3	0.0	18.5
Lower secondary	5.3	26.9	0.0	11.3	0.0	24.2
Incomplete upper secondary	13.1	20.1	41.3	0.0	0.0	23.2
Upper secondary, school certificate	22.3	9.6	56.4	0.0	0.0	8.6
Upper secondary, higher school certificate	5.9	19.2	1.1	5.3	0.0	6.9
Postsecondary/tertiary	31.2	2.1	0.6	33.8	100.0	0.0
Age-group						
16–29	0.2	95.9	17.1	32.4	28.4	34.6
30–44	3.2	4.1	33.3	39.8	40.1	34.6
45–64	96.6	0.0	49.5	27.8	31.5	30.7

Source: Based on data of the Housing and Population Census, Statistics Mauritius.

To operationalize the levelling of the playing field for all individuals active in the labor market, it is important to trace the profile of the most- and least-disadvantaged groups in terms of access to certain labor market opportunities. The idea is to profile individuals who are, respectively, at the bottom and at the top of the probability distribution of opportunities in terms of circumstances and characteristics.

The exercise is carried out in three steps. First, individuals are ranked in ascending order according to their individual predicted probability of having access to a certain labor market opportunity. Second, the most-disadvantaged (least-disadvantaged) group is identified by grouping individuals from the bottom (top) of the distribution up (down) to the point where they represent 10 percent of the overall reference population. Third, the distribution of circumstances and characteristics is calculated for the most- and least-disadvantaged groups.

Table 6.1 shows the profiles of the two groups for each labor market opportunity and separately for the two census years. The profiles reveal that there are sizable differences between the most- and least-disadvantaged groups along a number of dimensions. For example, women appear disadvantaged compared with men in access to most labor market opportunity, but particularly to full-time employment, and no improvement has been recorded over the last decade. In terms of educational level, which is itself the by-product of the circumstances of individuals, some of the most well educated individuals fall in the most-disadvantaged group in access to employment and full-time employment. Youth are overrepresented among the most-disadvantaged groups in terms of access to employment, whereas no particular age-specific disadvantage is observed in terms of access to full-time and wage employment. This is in line with what is observed by the World Bank (2017a): highly educated youth are increasingly more likely to be unemployed because of an expanding educational mismatch, among several factors.

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Part III – Annexes

Annex A: Statistical Annex

Table A 1. Reason for not being available to work among inactive individuals aged 55-64, by gender, 2005-15: Q1-Q4

Reason for not being available to work	Female	Male	Total
Studying/training	0.2	5.1	0.7
Retired/too old to work	0.0	1.1	0.1
Permanent disability	3.8	65.8	10.2
Temporary illness/injury	4.5	20.8	6.2
Parents or spouse not agreeable	1.5	0.0	1.4
Household/family responsibilities	88.2	1.0	79.1
Not interested to work	1.0	0.0	0.9
New job or own business to start soon	0.1	0.8	0.2
Suitable jobs not available	0.2	0.0	0.2
Other	0.5	5.4	1.0
Total	100	100	100

Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Table A 2. Main source of income or support to meet daily needs among inactive individuals aged 55-64, by gender, 2005-15: Q1-Q4

Main income source	Female	Male	Total
Parents	2.6	14.1	3.8
Spouse/Partner	83.2	4.9	74.9
Children	5.2	3.1	5.0
Other relatives/nonrelatives	1.2	8.8	2.0
Maintenance alimony (ex-spouse)	0.3	0.0	0.2
Savings/property income	0.2	6.1	0.8
Government pension/assistance	6.5	56.9	11.8
Other pension/work compensation	0.9	3.7	1.2
Other	0.0	2.6	0.3
Total	100	100	100

Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Table A 3. Weak and Strong Unconditional Convergence estimates (at the mean), by initial characteristics, pooled 2005-15.

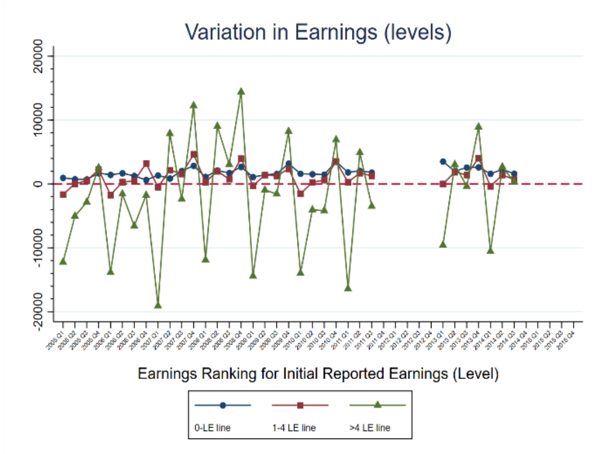
Initial characteristics	WUC (Reported)	WUC (Predicted)	WUC (Average)	SUC (Reported)	SUC (Predicted)	SUC (Average)
Male	−0.256***	−0.132***	−0.0819***	−0.292***	−0.157***	−0.129***
Female	−0.159***	−0.0931***	−0.0571***	−0.0953**	−0.0287	0.0254
30-34	−0.233***	−0.118***	−0.0844***	−0.252***	−0.0542	−0.0984
35-39	−0.238***	−0.147***	−0.0956***	−0.371***	−0.242***	−0.184**
40-44	−0.225***	−0.126***	−0.0924***	−0.255***	−0.167**	−0.127**
45-49	−0.176***	−0.0997***	−0.0535***	−0.275***	−0.152*	−0.103
50-54	−0.140***	−0.0519***	−0.0301*	−0.144***	−0.0563	−0.0192
Up to Complete Primary	−0.307***	−0.206***	−0.116***	−0.447***	−0.290***	−0.190***
Lower Secondary	−0.325***	−0.200***	−0.134***	−0.318***	−0.195***	−0.0891
Upper Secondary	−0.271***	−0.190***	−0.114***	−0.414***	−0.305***	−0.205***
Postsecondary/Tertiary	−0.156***	−0.0802***	−0.0359*	−0.279***	−0.191***	−0.125***
Married	−0.197***	−0.110***	−0.0674***	−0.256***	−0.136***	−0.0976***
Single	−0.241***	−0.118***	−0.0941***	−0.260***	−0.12	−0.143
Wage worker	−0.169***	−0.0883***	−0.0544***	−0.201***	−0.0928***	−0.0625**
Nonwage worker	−0.321***	−0.234***	−0.140***	−0.469***	−0.386***	−0.306***
Primary Sector	−0.336***	−0.244***	−0.142***	−0.514***	−0.268***	−0.229**
Manufacturing	−0.218***	−0.133***	−0.0740***	−0.394***	−0.332*	−0.216
Other Secondary Sectors	−0.332***	−0.175***	−0.0958***	−0.220***	−0.0736	0.0237
Trade	−0.222***	−0.0960***	−0.0474*	−0.261***	−0.0151	−0.0779
Transports	−0.305***	−0.186***	−0.101***	−0.286***	−0.234***	−0.127
Hotels and Restaurants	−0.229***	−0.136***	−0.0610*	−0.369***	−0.131*	−0.144
Other Services	−0.160***	−0.0979***	−0.0760***	−0.216***	−0.133***	−0.0958**

Public Sector	−0.234***	−0.141***	−0.0897***	−0.260***	−0.159***	−0.0963
Private Sector	−0.229***	−0.133***	−0.0837***	−0.275***	−0.153***	−0.116***
Legislators, Senior Officials, Managers	−0.227***	−0.161***	−0.0933**	−0.387***	−0.322***	−0.214***
Professionals	−0.160***	−0.117***	−0.0513*	−0.271***	−0.173**	−0.0835
Technicians	−0.192***	−0.0948***	−0.0664**	−0.317***	−0.175***	−0.151
Clerks	−0.260***	−0.164***	−0.0948**	−0.193**	−0.130*	0.0556
Service and sales workers	−0.221***	−0.124***	−0.0530**	−0.299***	−0.188***	−0.0554
Skilled agricultural	−0.393***	−0.300***	−0.163***	−0.358***	−0.263***	−0.0631
Craft workers	−0.371***	−0.243***	−0.135***	−0.519***	−0.320***	−0.302**
Machine operators	−0.273***	−0.166***	−0.0886***	−0.441***	−0.295***	−0.235***
Elementary occupations	−0.297***	−0.198***	−0.137***	−0.459***	−0.298***	−0.204**

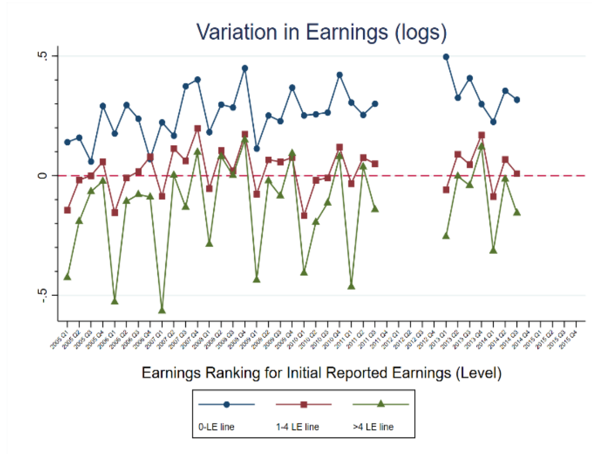
Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Figure A 1. Weak and Strong Unconditional Convergence Estimates Based on Reported Earnings, 2005–15

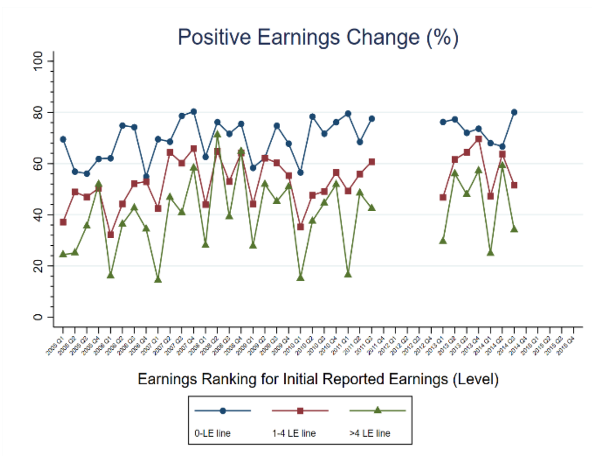
a. Earnings change (levels)



b. Earnings change (logs)



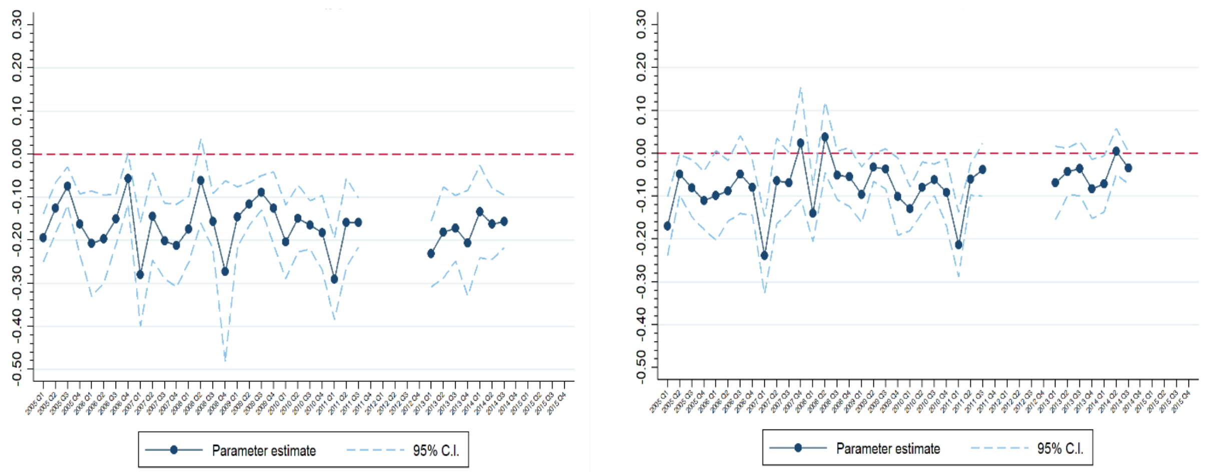
c. Share with positive earnings change



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

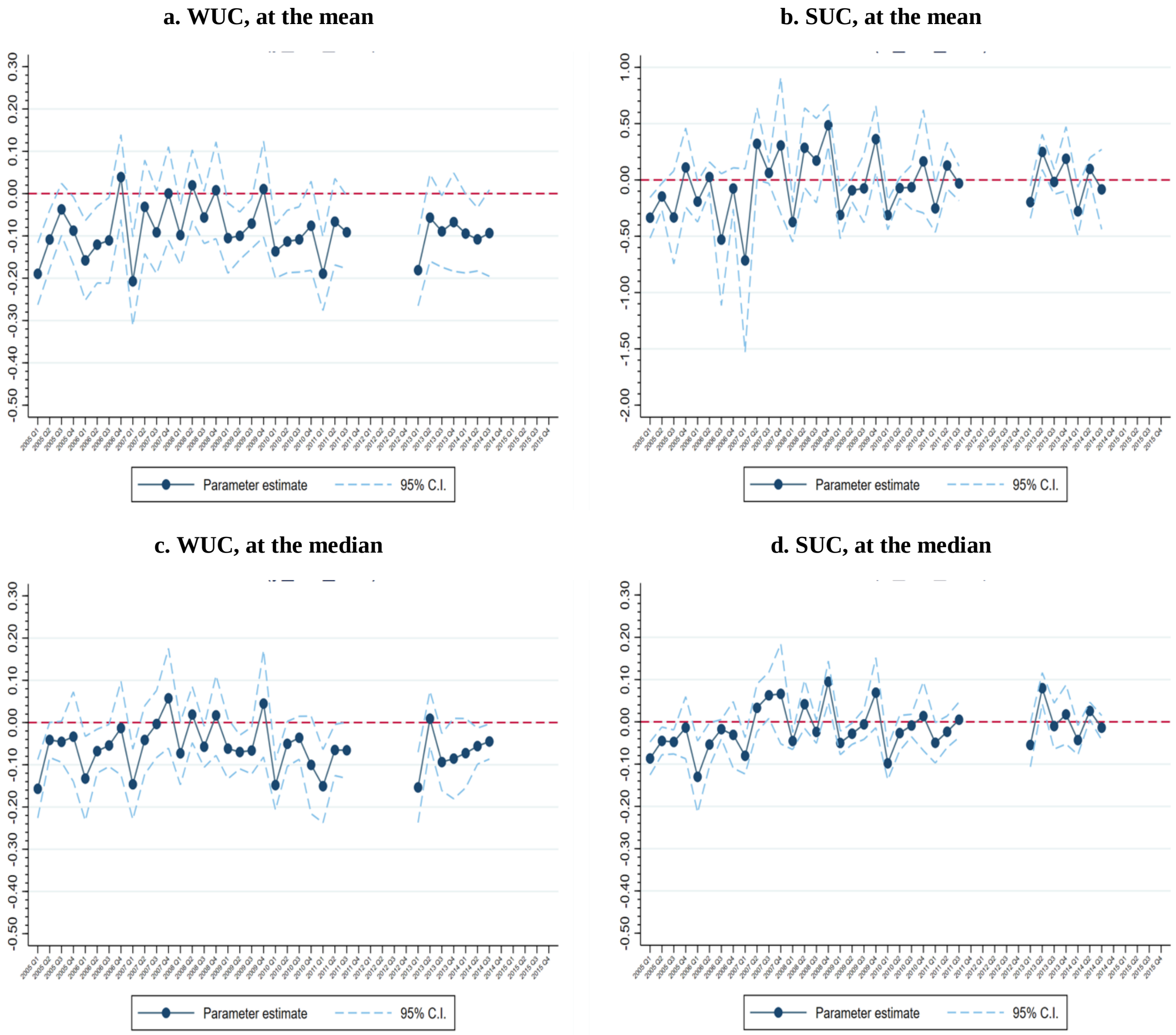
Figure A 2. Weak and Strong Unconditional Convergence estimates using reported earnings, pooled 2005–15

a. WUC, trimmed earnings change **b. SUC, trimmed earnings change**



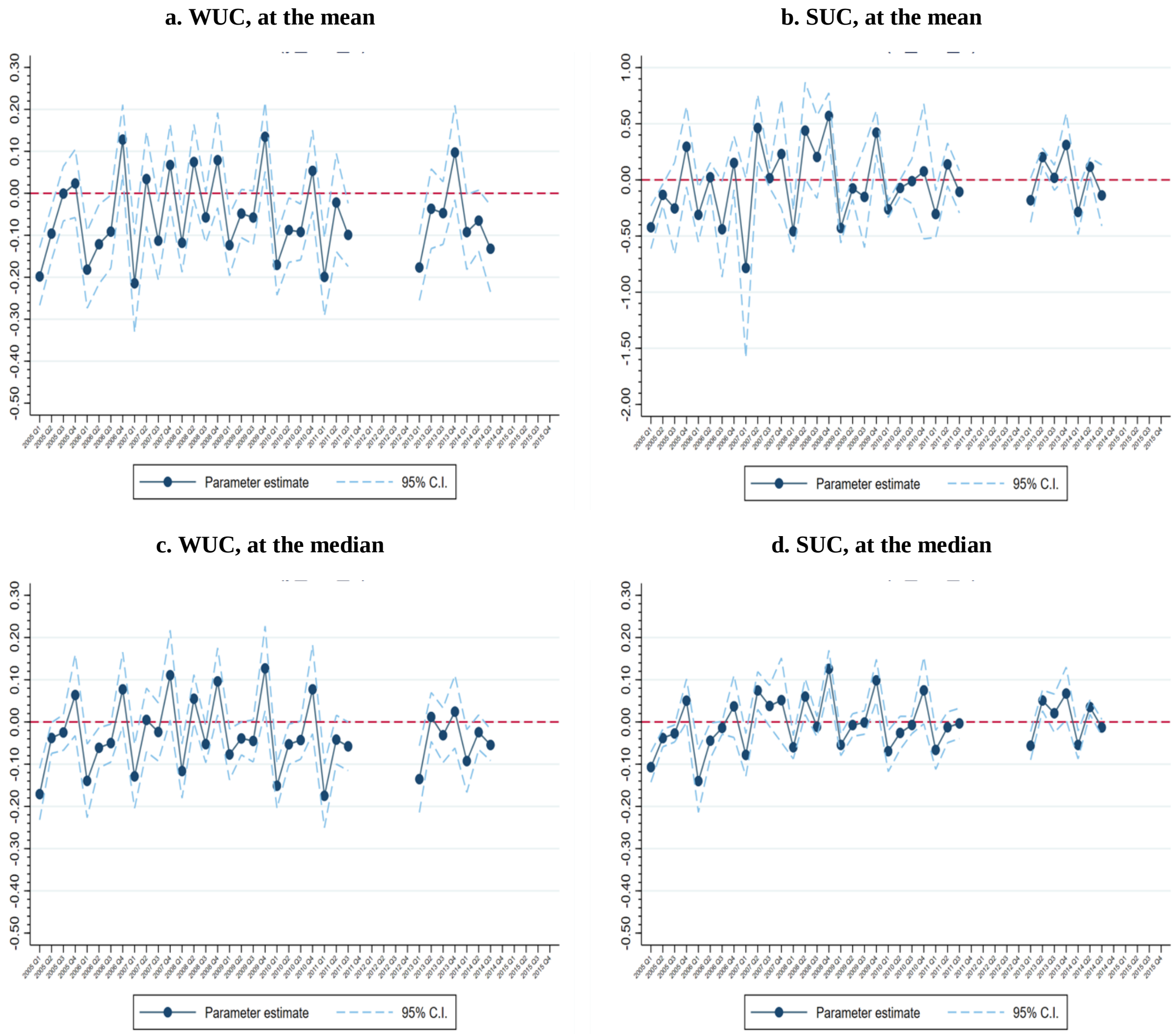
Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.
Note: Estimates are obtained using reported earnings as explanatory variable. Panels a and b show parameters from OLS regressions at the mean, after trimming earnings change smaller than the 5th and larger than the 95th percentile.

Figure A 3. Weak and Strong Unconditional Convergence estimates using predicted earnings, over time 2005–15



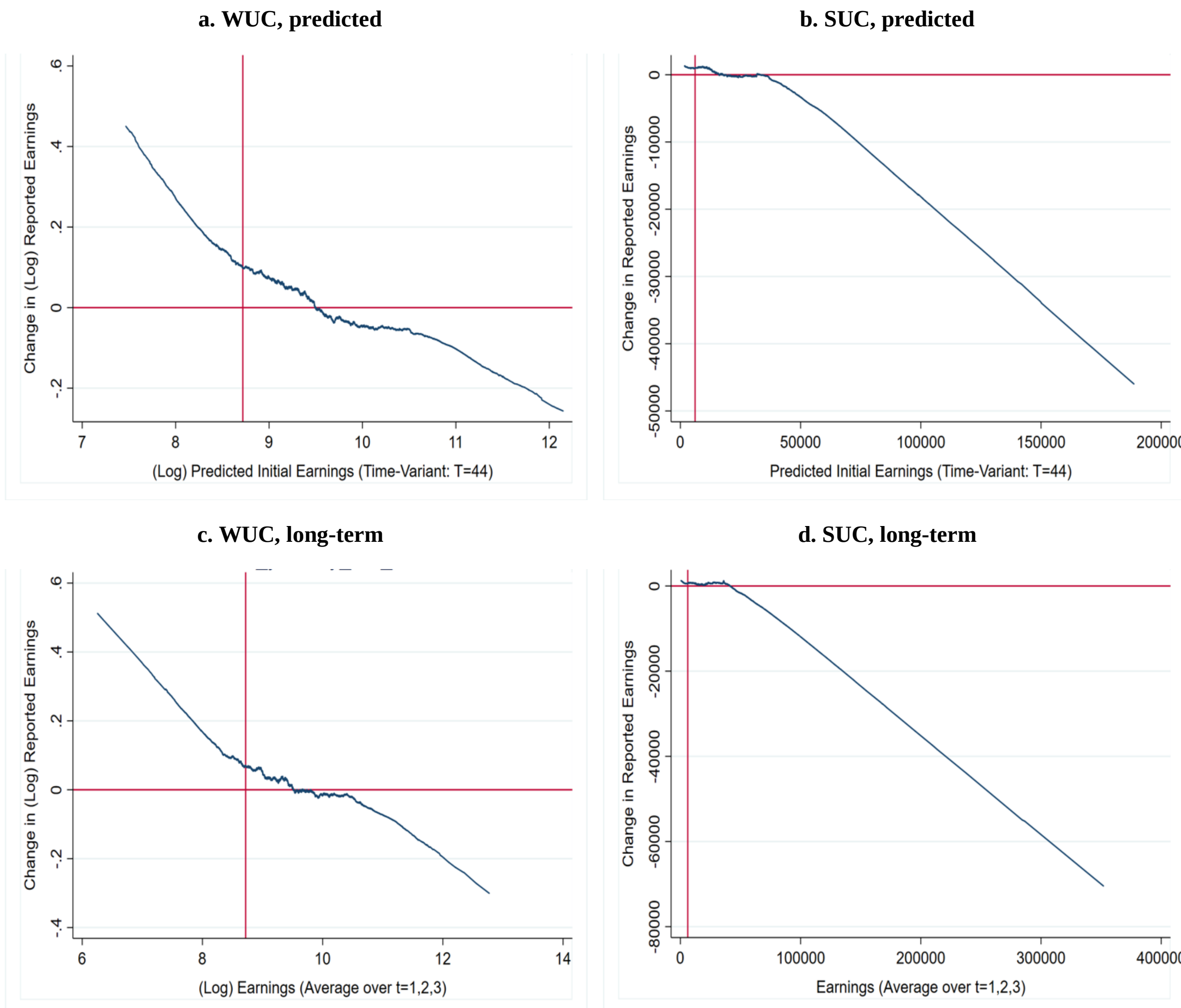
Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.
Note: Estimates are obtained using predicted earnings as explanatory variable. Panels a and b show parameters from OLS regressions at the mean, while panels c and d illustrate estimates from UQR regressions at the median.

Figure A 4. Weak and Strong Unconditional Convergence estimates using average earnings, 2005–15



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.
Note: Estimates are obtained using long-term earnings as explanatory variable. Panels a and b show parameters from OLS regressions at the mean, while panels c and d illustrate estimates from UQR regressions at the median.

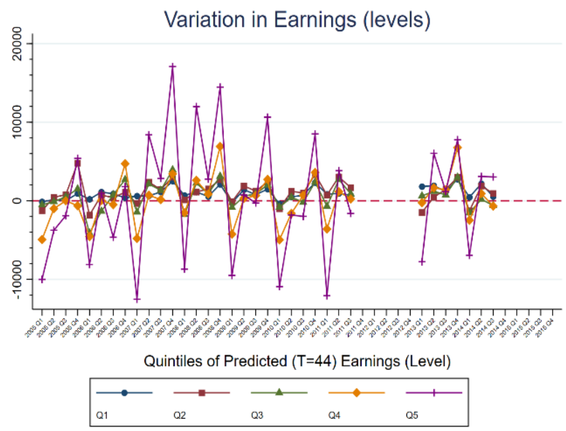
Figure A 5. Weak and Strong Unconditional Convergence nonparametric estimates using predicted and average earnings, pooled 2005–15



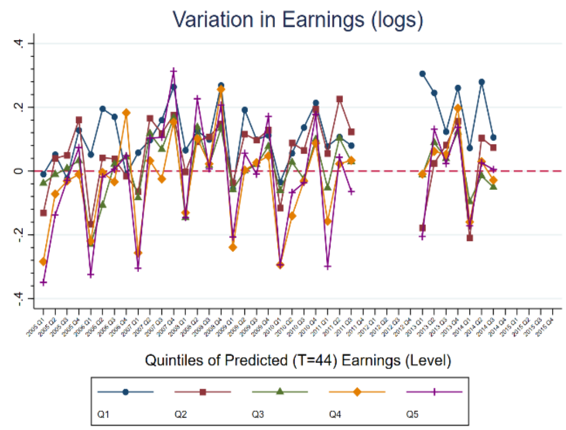
Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.
Note: Estimates are obtained using predicted (panels a and b) and long-term (panels c and d) earnings as explanatory variables. The red vertical line represents the poverty line.

Figure A 6. Weak and Strong Unconditional Convergence estimates using predicted earnings, 2005–15

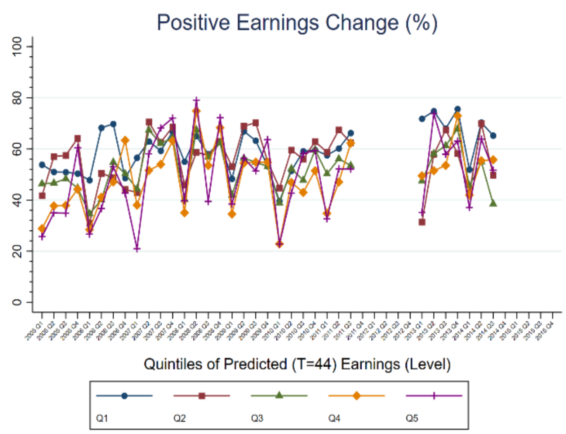
a. Earnings change (levels)



b. Earnings change (logs)



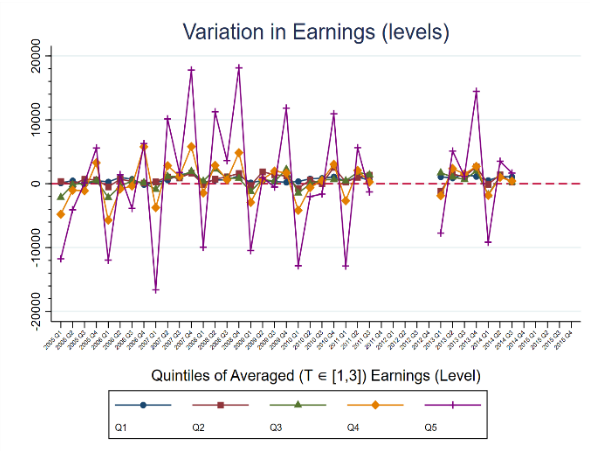
c. Share with positive earnings change



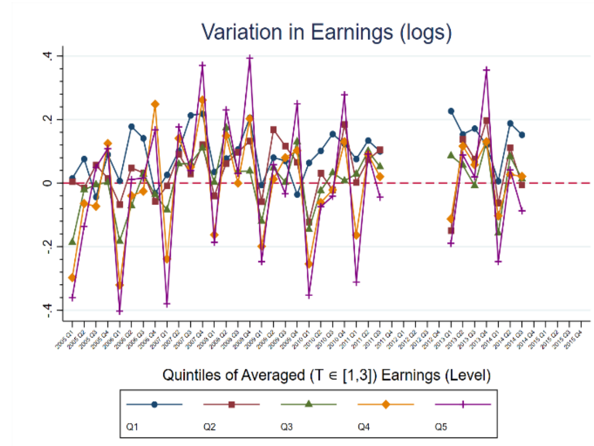
Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Figure A 7. Weak and Strong Unconditional Convergence estimates using average earnings, 2005–15

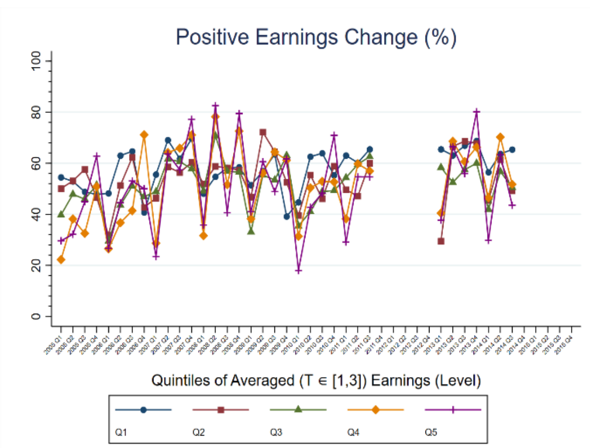
a. Earnings change (levels)



b. Earnings change (logs)



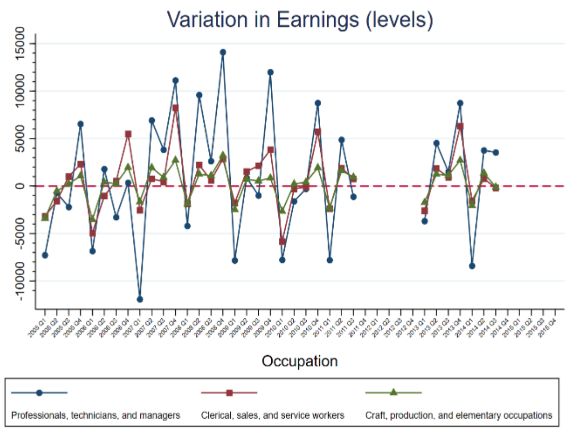
c. Share with positive earnings change



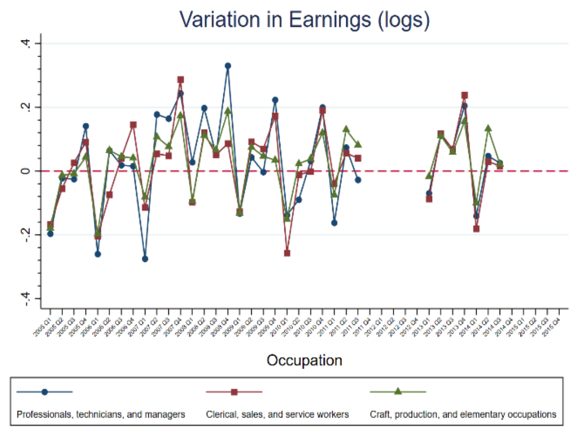
Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Figure A 8. Weak and Strong Unconditional Convergence estimates using reported earnings, 2005–15

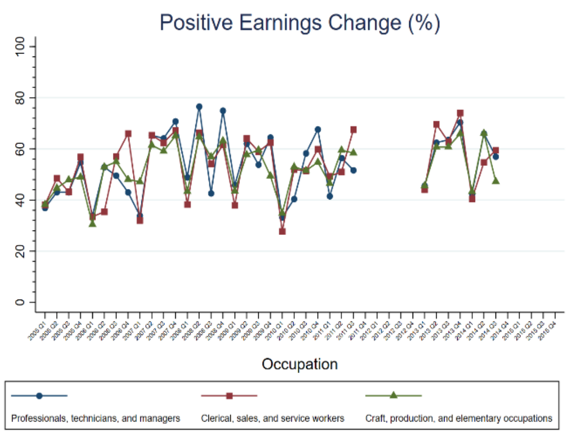
a. Earnings change (levels)



b. Earnings change (logs)



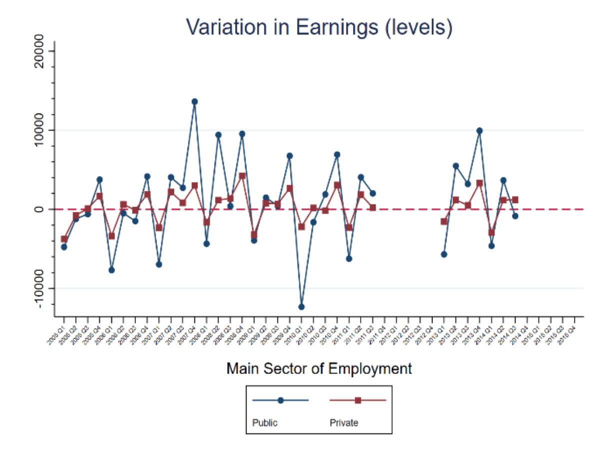
c. Share with positive earnings change



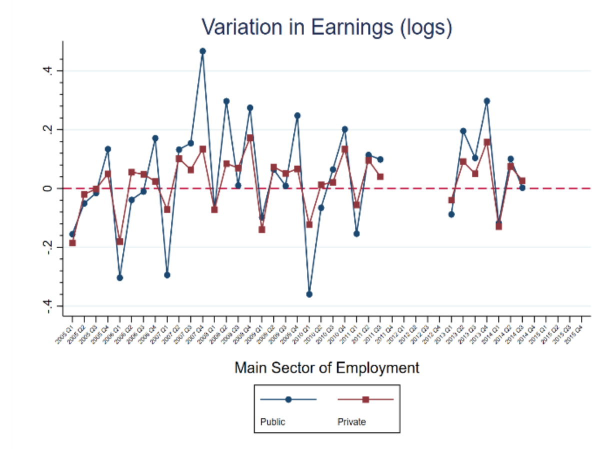
Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Figure A 9. Weak and Strong Unconditional Convergence estimates using reported earnings, 2005–15

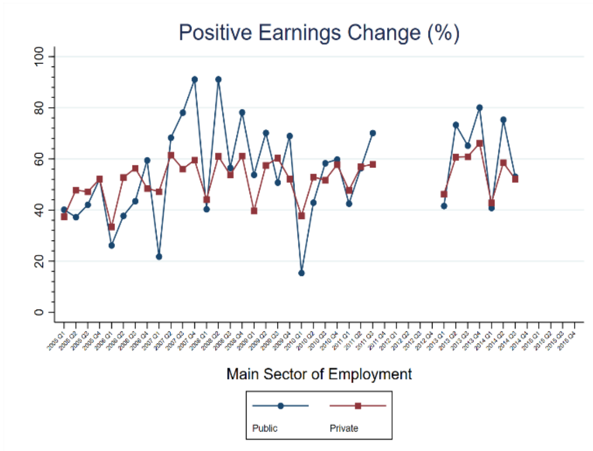
a. Earnings change (levels)



b. Earnings change (logs)



c. Share with positive earnings change



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Table A 4. Weak and Strong Unconditional Convergence estimates (at the median) by initial characteristics, pooled 2005–15

Initial characteristics	WUC (Reported)	WUC (Predicted)	WUC (Long-Term)	SUC (Reported)	SUC (Predicted)	SUC (Long-Term)	N
Male	−0.139***	−0.0763***	−0.0402***	−0.0466***	−0.0280***	−0.0153***	8,661
Female	−0.0803***	−0.0527***	−0.0305***	−0.0214***	−0.00932*	−0.000875	3,507
30–34	−0.135***	−0.0767***	−0.0508***	−0.0452***	−0.0169*	−0.00744	2,124
35–39	−0.140***	−0.0940***	−0.0653***	−0.0441***	−0.0331***	−0.0191***	2,462
40–44	−0.101***	−0.0584***	−0.0300***	−0.0384***	−0.0280***	−0.0128***	2,871
45–49	−0.0915***	−0.0503***	−0.0228**	−0.0353***	−0.0215***	−0.0104*	2,594
50–54	−0.0830***	−0.0379***	−0.0208*	−0.0294***	−0.0111	−0.00413	2,117
Up to Complete Primary	−0.174***	−0.122***	−0.0624***	−0.113***	−0.0945***	−0.0412***	4,784
Lower Secondary	−0.204***	−0.137***	−0.0906***	−0.119***	−0.0946***	−0.0419**	1,366
Upper Secondary	−0.137***	−0.104***	−0.0523***	−0.0642***	−0.0571***	−0.0225***	4,735
Postsecondary/Tertiary	−0.0770***	−0.0395***	−0.0196	−0.0392***	−0.0260***	−0.0140**	1,283
Married	−0.107***	−0.0645***	−0.0352***	−0.0360***	−0.0210***	−0.00997***	10,358
Single	−0.126***	−0.0645***	−0.0493***	−0.0430***	−0.0251***	−0.0150**	1,810
Port Louis	−0.129***	−0.0554***	−0.0463***	−0.0634***	−0.0193	−0.00811	1,136
Pamplemousses	−0.127***	−0.0621***	−0.0355**	−0.0712***	−0.0297***	−0.0176*	1,431
Riv. du Rempart	−0.120***	−0.0699***	−0.0371**	−0.0347***	−0.0102	0.00114	1,317
Flacq	−0.137***	−0.106***	−0.0634***	−0.0497***	−0.0410***	−0.0185**	1,501
Grand Port	−0.114***	−0.0596***	−0.0189	−0.0636***	−0.0387***	−0.0175*	1,363
Savanne	−0.120***	−0.0675***	−0.0439***	−0.0562***	−0.0231**	−0.0167	1,077
Plaine Wilhems	−0.0880***	−0.0539***	−0.0291***	−0.0293***	−0.0198***	−0.0101**	2,163
Moka	−0.0920***	−0.0394**	−0.0126	−0.0436***	−0.0242**	−0.00736	1,124
Black River	−0.121***	−0.0722***	−0.0553***	−0.0318***	−0.0175**	−0.0148**	1,056

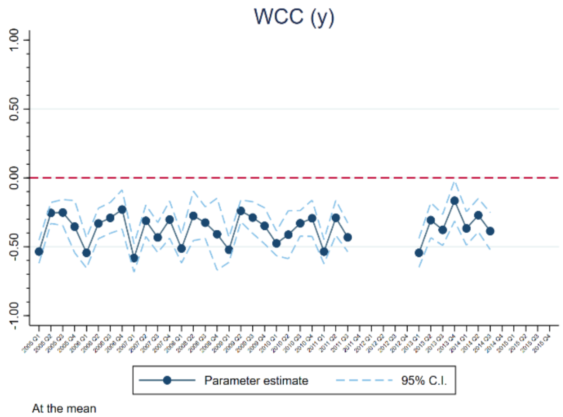
Full Time	−0.117***	−0.0556***	−0.0242***	−0.0347***	−0.0185***	−0.00771**	7,394
Part Time	−0.0996***	−0.0710***	−0.0478***	−0.0375***	−0.0217***	−0.0131***	4,774
Waged	−0.0915***	−0.0512***	−0.0301***	−0.0300***	−0.0157***	−0.00718***	9,908
Non Waged	−0.202***	−0.159***	−0.0779***	−0.0768***	−0.0666***	−0.0384***	2,260
Primary Sector	−0.189***	−0.149***	−0.0702***	−0.0996***	−0.0770***	−0.0426***	1,172
Manufacturing	−0.123***	−0.0717***	−0.0385***	−0.0332***	−0.0271***	−0.0118**	2,441
Other Secondary Sector	−0.201***	−0.117***	−0.0421*	−0.0813***	−0.0357**	−0.00749	1,576
Trade	−0.138***	−0.0859***	−0.0446***	−0.0560***	−0.0332***	−0.0228***	1,397
Transports	−0.197***	−0.129***	−0.0550**	−0.0938***	−0.0675***	−0.0376**	906
Hotels and Restaurants	−0.110***	−0.0489**	−0.0195	−0.0433***	−0.0192	−0.00519	827
Other Services	−0.0782***	−0.0518***	−0.0366***	−0.0259***	−0.0155***	−0.00715**	3,849
Public Sector	−0.151***	−0.0973***	−0.0630***	−0.0644***	−0.0423***	−0.0251***	2,562
Private Sector	−0.120***	−0.0740***	−0.0414***	−0.0340***	−0.0222***	−0.0101***	9,606
Legislators, Senior Officials, Managers	−0.102***	−0.0692**	−0.0363	−0.0608***	−0.0543**	−0.0320**	388
Professionals	−0.0748***	−0.0503***	−0.0318**	−0.0425***	−0.0223*	−0.0134	654
Technicians	−0.0957***	−0.0468**	−0.0186	−0.0628***	−0.0359***	−0.0148	1,075
Clerks	−0.139***	−0.0978***	−0.0444*	−0.0789***	−0.0631***	−0.0131	705
Service and sales workers	−0.123***	−0.0803***	−0.0323**	−0.0824***	−0.0562***	−0.0211**	2,242
Skilled agricultural	−0.293***	−0.248***	−0.134***	−0.194***	−0.190***	−0.0725***	476
Craft workers	−0.222***	−0.161***	−0.0785***	−0.122***	−0.121***	−0.0534***	2,301
Machine operators	−0.181***	−0.131***	−0.0655***	−0.0915***	−0.0923***	−0.0325***	1,731
Elementary occupations	−0.151***	−0.107***	−0.0629***	−0.0851***	−0.0718***	−0.0316***	2,596
Q1 (Reported)	−0.206***			−0.112***			2,580
Q2 (Reported)	−0.132*			−0.0415			2,507

Q3 (Reported)	−0.0807			−0.0781			2,427
Q4 (Reported)	−0.147**			−0.165***			2,382
Q5 (Reported)	−0.128***			−0.0838***			2,272
Q1 (Predicted)		−0.115***			−0.026		2,545
Q2 (Predicted)		−0.169**			−0.121		2,528
Q3 (Predicted)		−0.14			−0.131		2,473
Q4 (Predicted)		0.130*			0.0953		2,369
Q5 (Predicted)		−0.0507***			−0.0412***		2,253
Q1 (Long-Term)			−0.0796***			0.0196	2,559
Q2 (Long-Term)			0.0103			0.101	2,492
Q3 (Long-Term)			−0.0963			−0.0966	2,436
Q4 (Long-Term)			−0.0538			−0.0861	2,411
Q5 (Long-Term)			−0.0469**			−0.0395***	2,270
0-LE line (Reported)	−0.272***			−0.186***			1,712
1-4 LE line (Reported)	−0.116***			−0.0872***			8,349
>4 LE line (Reported)	−0.127***			−0.0860***			2,107
0-LE line (Predicted)		−0.175***			−0.0686		1,332
1-4 LE line (Predicted)		−0.0817***			−0.0519***		9,189
>4 LE line (Predicted)		−0.0620***			−0.0505***		1,647
0-LE line (Long-Term)			−0.0949***			−0.0269	1,611
1-4 LE line (Long-Term)			−0.0440***			−0.0205**	8,574
>4 LE line (Long-Term)			−0.0616***			−0.0436***	1,983

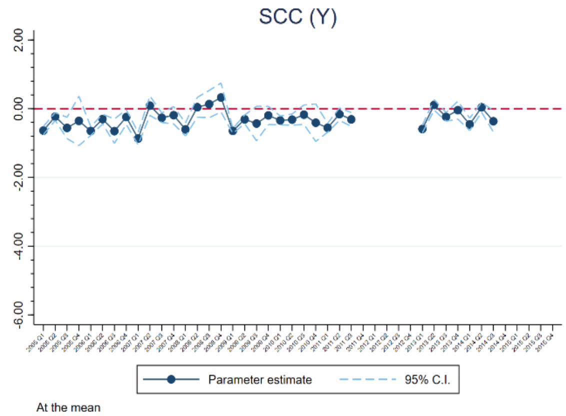
Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Figure A 10. Weak and Strong Conditional Convergence estimates using reported earnings, 2005–15

a. Earnings change (logs)



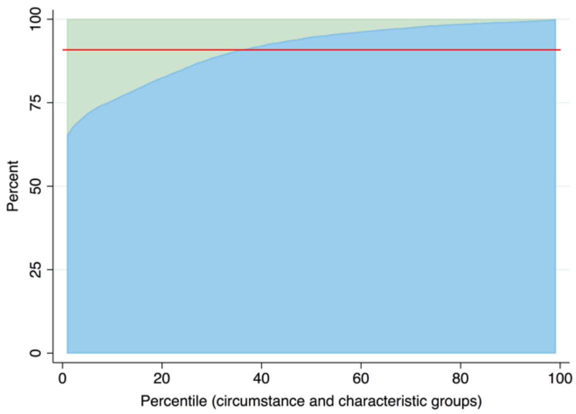
b. Earnings change (levels)



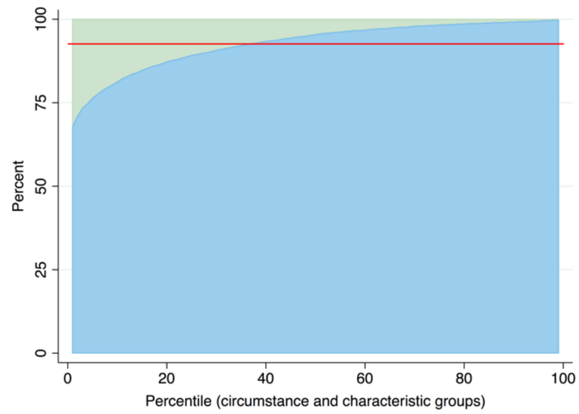
Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Figure A 11. Percentage of active individuals aged 16-64 with access to labor market opportunities, 2000 and 2011

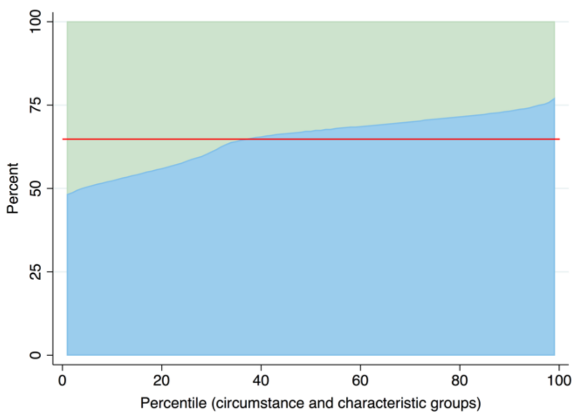
a. Employed last week, 2000



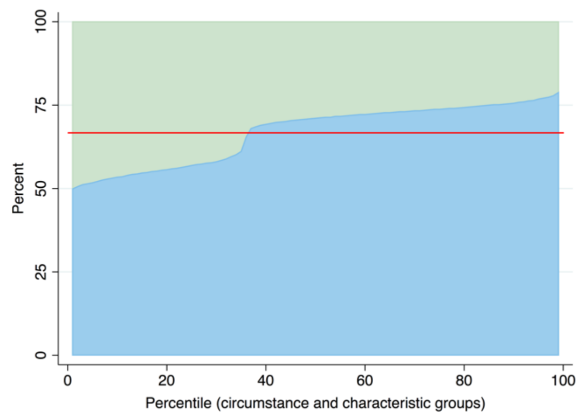
b. Employed last week, 2011



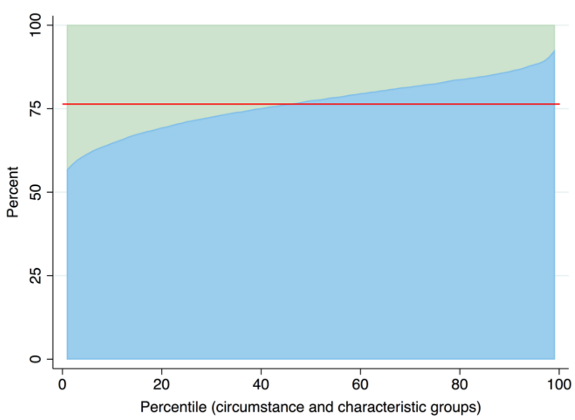
c. Employed full-time, 2000



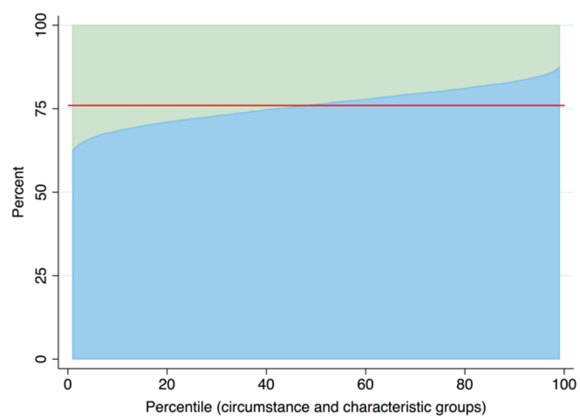
d. Employed full-time, 2011



e. Employed for a wage/salary, 2000



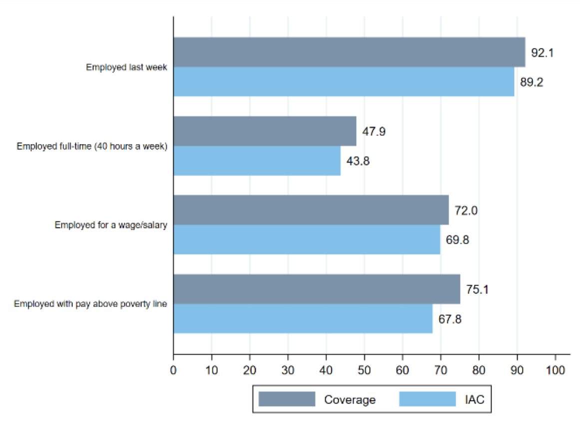
f. Employed for a wage/salary, 2011



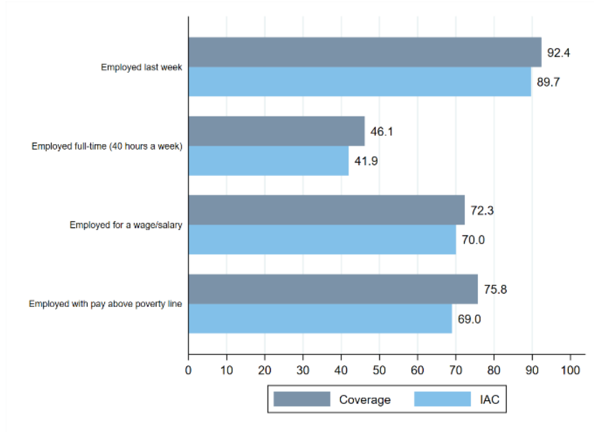
Source: Based on data of the Housing and Population Census, Statistics Mauritius.
Note: The horizontal red line indicates the average coverage rate. The light-blue area above the red line represents the proportion of unequally allocated opportunities; the light-blue area below the red line measures the IAC coverage rate.

Figure A 12. Overall Coverage and Inequality-Adjusted Coverage of Labor Market Opportunities, 2012–15

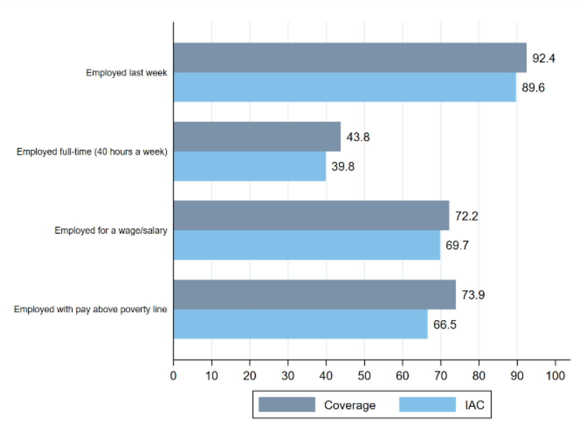
a. 2012



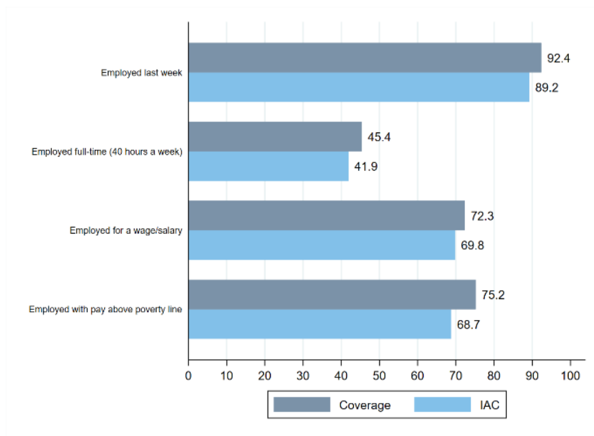
b. 2013



c. 2014



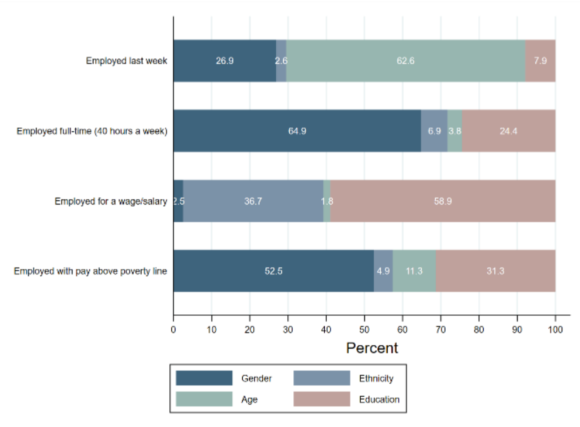
d. 2015



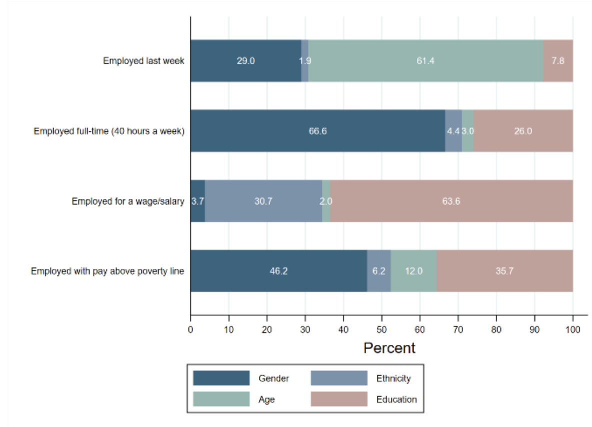
Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Figure A 13. Contributors to Inequality, Circumstances and Characteristics, 2012–15

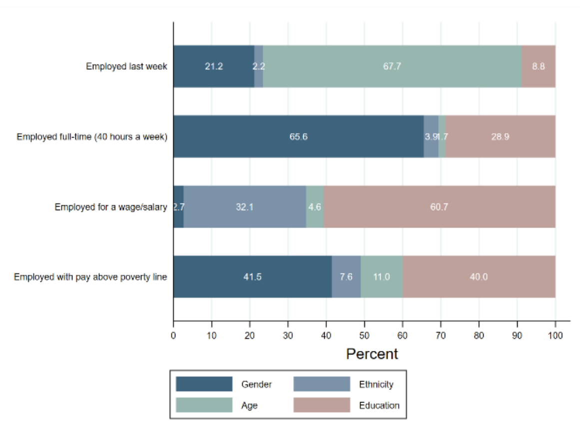
a. 2012



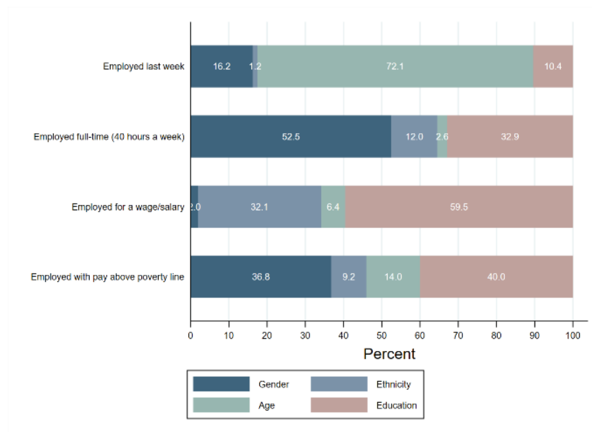
b. 2013



a. 2014



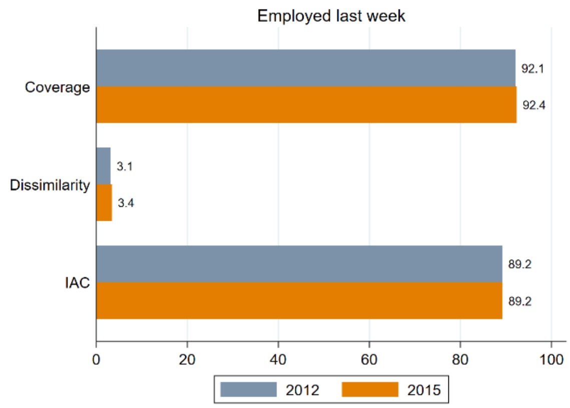
b. 2015



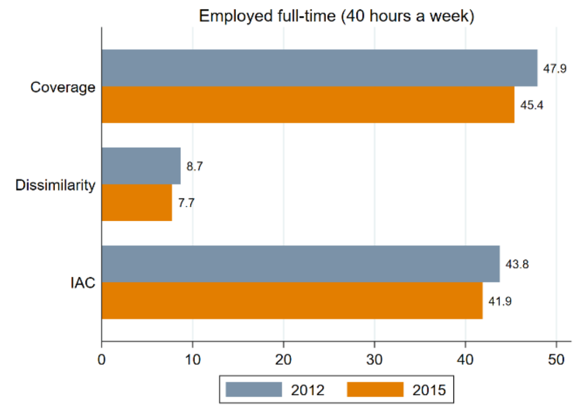
Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Figure A 14. Overall Coverage, Dissimilarity Index, and the Inequality-Adjusted Coverage of Labor Market Opportunities, 2012–15

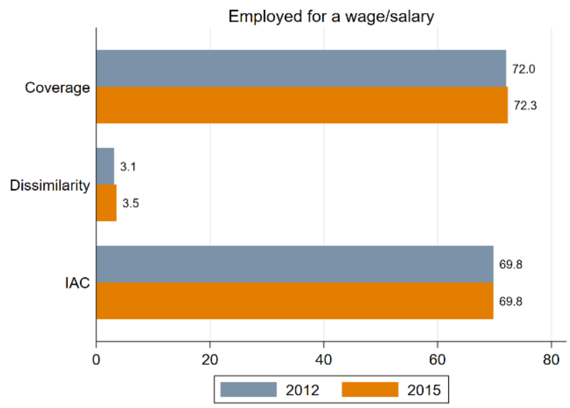
a. Employed the previous week



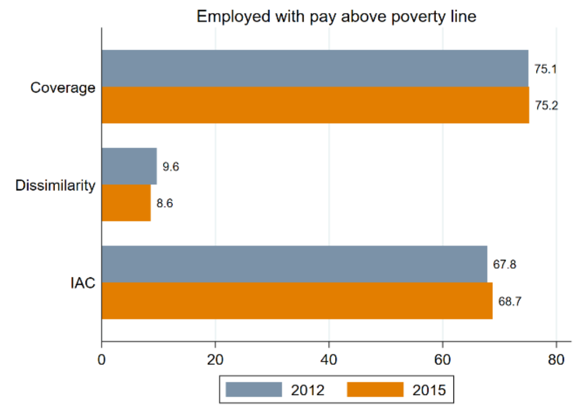
b. Employed full time



c. Employed for a wage or salary



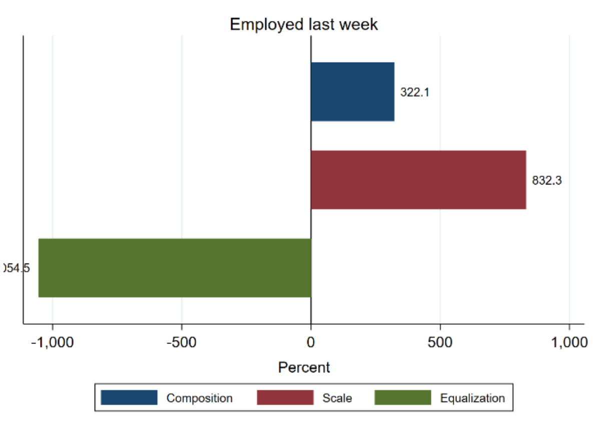
d. Employed, with pay above the poverty line



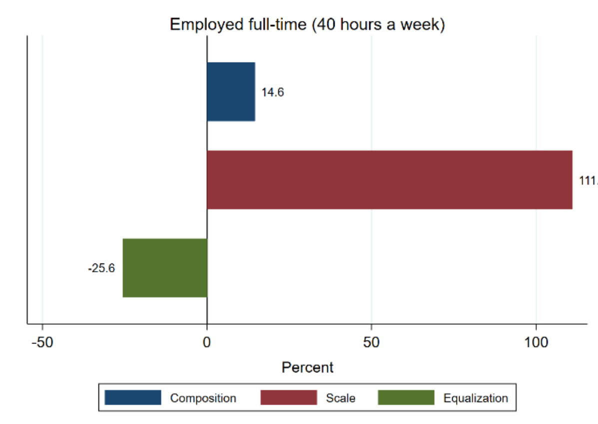
Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Figure A 15. Decomposition of Changes in the Inequality-Adjusted Coverage of Labor Market Opportunities, 2012–15

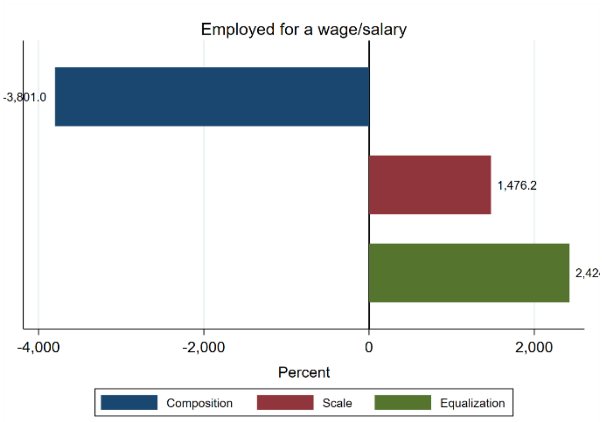
a. Employed the previous week



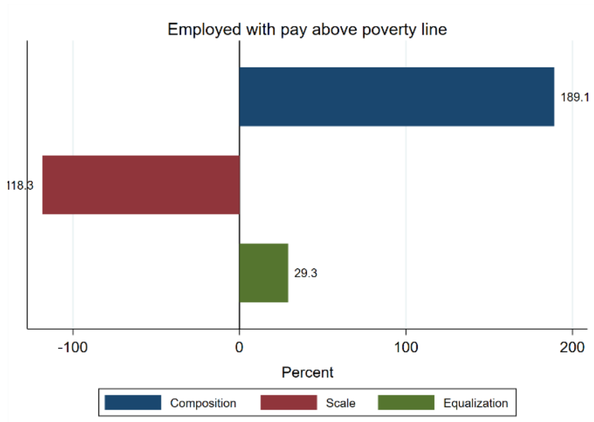
b. Employed full time



c. Employed for a wage or salary



d. Employed, with pay above the poverty line



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Annex B: Attrition

The annex is organized as follows: (1) a short introduction to the issue of attrition and why it might matter; (2) a brief explanation of the most common methods implemented in the literature to test whether attrition matters; (3) a description of the panel structure of the Continuous Multipurpose Household Survey (CMPHS); (4) an illustration of attrition rates at household and individual level (overall, by individual characteristics, and over time) to search for patterns in outcome and control variables of attriting individuals; (5) a discussion of results of attrition tests; and (6) a description of the implications of additional sample restrictions.

Why attrition matters? Is it all the same?

Longitudinal (or panel) data provide a unique opportunity to analyze welfare dynamics that is not possible with cross-sectional data. Yet, analysis based on panel data can be compromised by bias associated with sample attrition. The number of survey participants who do not respond in each round of data collection cumulates, and this reduces sample sizes over time and determines a reduction in the precision of estimates. What is damaging and often overlooked is nonrandom attrition: attrition that is selectively related to outcomes of interest. Nonrandom attrition can lead to an inference that is biased because it is based on selected nonattriting samples and to policy recommendations that are not applicable to a representative sample of the reference population.

Fitzgerald, Gottschalk, and Moffitt (1998) introduced a distinction between attrition on observables and unobservables. Both types of attrition do not necessarily lead to biased inferences, however in case they do, the first is certainly the type of attrition that can be more easily addressed via weighted least squares estimation. This consists of estimating the model of interest while using adjusted weights that equal survey weights multiplied by an adjustment factor given by the ratio between the probability of attriting conditional on observables and the probability of attriting conditional on initial year outcome and observables. Attrition on observables is observed if the probability of attriting conditional on observable characteristics and outcome of interest equals the probability of attriting conditional on the observable characteristics alone. Attrition based on unobservables manifest when the above mentioned condition does not hold: unobserved variables affect both the probability of attriting and the outcome variable of interest. In the case of attrition on unobservables, the existence of variables that affect attrition and do not affect the outcome variable is key. Information on interviewers and the interviewing process has been suggested and used to correct for this bias. However, such information is not captured in the CMPHS data and even if it were available, it would likely not be very useful as no permanent team of interviewers exist at Statistics Mauritius.

How to test whether attrition matters?

To understand to what extent attrition matters and might potentially bias the analysis, a simple test consists of comparing average (or median) first year values of outcome and control variables among attritors and nonattritors and checking there are no statistically significant differences. This test can provide some insights about how different eventual attritors and nonattritors are in terms of initial year characteristics.

A second step in the analysis of attrition is the estimation of an equation for the probability of attriting. Relative to the first approach, it allows to test whether the likelihood of attriting in the future is affected by the initial year value of the outcome of interest conditional on a number of observables. In case the outcomes of interest does not affect the probability of attiring conditional on observables, it can be argued that attrition is random conditionally on observables and does not introduce a bias in the analysis of that specific outcome.

An additional common test, known as BGLS test after the proposers (Becketti et al. 1988), consists in regressing the initial year value of the outcome variable on initial year characteristics comparing the full sample (attritors and nonattritors) with the sample of nonattritors. The idea is to determine whether estimates based on a sample of nonattritors are significantly different from those that would be estimated based on the full sample.

CMPHS panel structure

The CMPHS was launched by Statistics Mauritius in April 1999. Since then it has been conducted monthly with the exception of 2000 when the survey was suspended to avoid overlapping with the Housing and Population Census and in 2004 when it was carried out on a quarterly basis. To measure quarterly changes, starting with 2005 Statistics Mauritius has introduced a rotating panel for the island of Mauritius (excluding Rodrigues): 50 percent of the households sampled in a quarter are re-interviewed in the following quarter, rotated out of the sample for two quarters and then re-introduced for two additional quarters. For example, 50 percent of the households sampled in the first quarter of 2005 have been re-interviewed in the second quarter of 2005 and again in the first and second quarter of 2006. In other words, the rotating scheme allows to follows households and individuals therein over a maximum period of 16 months.

To maintain an updated list of residential households, a complete listing exercise has been performed in 2008, 2013, and 2016. While the 2008 new households list was used once the four panel interviews of each household were completed, the households that did not complete the four interviews by the end of 2012 were dropped out of the sample because the 2013 round of the CMPHS was based on a new list of Primary Sampling Units (PSUs) derived from the 2011 census. This means the panel rotation was interrupted in 2012 and started fresh in 2013.

Since 2005 sample size for each annual cross-section has been increased to 11,280 overall (10,560 for the island of Mauritius). In other words, each year 5,280 unique households are interviewed twice. A Stratified two-stage sampling design is used. At the first stage, PSUs are selected with probability proportional to size and at the second stage, a fixed number of households is selected from each selected PSU. A Relative Development Index (RDI) is used as spatial stratification factor. This index is based on 12 variables encompassing housing and living conditions, literacy and education, and employment derived from the 2000 Housing and Population Census to rank PSUs. The second stage stratification criteria are community, household size and average monthly expenditure of the household.

Each household that is not found is replaced with a different household from a list of replacement households. Replacement households do not become part of the panel rotation.

Definition of attrition

At the core of the analysis conducted in the report is short-term individual earnings mobility. Individuals between 16 (the minimum legal working age in Mauritius) and 64 years of age are retained in the sample. To exploit the longest panel time span, the reference horizon of the analysis is 16 months, which is the time that elapses between the first and the fourth interview. Moreover, only individuals who are found in all four interviews are retained in the final sample to exploit panel information fully and to implement correction methods that are aimed at avoiding confusion between transitory adjustments and a convergence process in earnings trajectories over a longer time period.

Attrition is attributable to the loss of single individuals within nonattriting households and/or of entire households that because of relocation cannot not be found and re-interviewed at follow-up. Within nonattriting households, individuals can attrite for a number of reasons including moving out of the original household as individuals get married and form their own family, migrating to other neighborhoods of the same city, to other areas, to other countries for studying and working reasons. These are common motivations behind the widely shared evidence of higher attrition rates among young, unmarried, from originally large households, and often times high educated individuals. The latter are the ones who are more likely to benefit from economic migration with high returns to share with household members left behind.

Technically, microdata can have lines corresponding to unique person identifiers that match the ones attached to original household members. Yet, once the matching process is refined by incorporating additional variables such as age and gender, it turns out that despite a perfect match of the personal identifier, the person interviewed at follow-up is not the same person interviewed at baseline.

Attrition in the CMPHS

Table B 1 illustrates attrition rates overall and broken down by individual characteristics for individuals aged between 16 and 64 at baseline. Column (1) shows attrition rates due to attriting households, in other words the attrition component attributable to the fact entire households are lost between one interview and the next, which is due to households relocating to a different dwelling. Overall, some 10 percent of households interviewed at round 1 are not found at one or more of the following three rounds. This translates into a loss of 9.7 percent of all the individuals who were interviewed at round 1. Household attrition is higher in the district of Port-Louis and Plaine Wilhems and among small-size households (with 1 or 2 members). A larger share of highly educated individuals is lost due to missing households compared with individuals with lower secondary and primary education. There are no sizable differences in attrition due to missing households by age, gender, and employment status.

Colum (2) shows total attrition rates that are obtained by adding up individuals lost due to missing households and individuals who attrited between interview 1 and 4 but their original household did not. Over a period of 16 months less than 22 percent of initially interviewed individuals aged 16-64 are lost to attrition, of which 13.4 percent to individual attrition, in other words due to household members leaving the original household. Total attrition rates are higher in the district of Port-Louis (27.8 percent), Plaine Wilhems (25 percent), and Black river (24.4 percent), among larger households (34.2 compared with 17 percent among households of at least 5 members and households with maximum 2 members), among unmarried individuals (27.1 versus 18.7 percent), among youth (23, 28, and 30 percent among 16-19, 20-24, and 25-29 years old) as opposed to middle- (21,3 percent among 35-39 years old) and old-age (17.3 and 19.5 percent among 55-59 and 60-64 years) individuals, among individuals with tertiary education (24.7 percent), and among unemployed (26 percent).

Table B 1. Household and individual attrition rates (16-64 years of age sample), average, 2005–15

Initial Year Characteristics	*Attrition rate due to attriting households (%)*	*Total attrition rate (%)*	*Share of attriting members belonging to nonattriting households*
Household Attrition Rate		10.3	
Individual Attrition Rate			
Total	9.7	21.8	13.4
District			
Port Louis	13.4	27.8	16.6
Pamplemousses	9.4	20.9	12.7
Riv. du Rempart	7.1	19.8	13.7
Flacq	7.0	20.0	14.0
Grand Port	7.6	18.6	11.9
Savanne	6.3	16.9	11.3
Plaine Wilhems	13.5	25.0	13.3
Moka	9.2	20.3	12.2
Black River	11.3	24.4	14.7
Gender			
Female	9.8	22.3	13.9
Male	9.7	21.3	12.9
Household size category			
1-2	11.4	17.0	6.4
3-4	9.1	21.1	13.2
5+	8.4	34.2	28.1
Marital status			
Single	9.5	27.1	19.5
Married	9.8	18.7	9.8
Age category			
16-19	9.2	23.1	15.3
20-24	8.5	28.0	21.3
25-29	10.3	29.9	21.9
30-34	10.9	25.2	16.1
35-39	10.4	21.3	12.1
40-44	9.0	17.4	9.2
45-49	9.6	17.2	8.4
50-54	9.2	17.0	8.6
55-59	9.7	17.3	8.4
60-64	10.6	19.5	10.0
Educational category			
No education/pre-primary	7.5	22.7	16.5

Incomplete Primary	8.0	20.3	13.4
Complete Primary	7.7	20.1	13.5
Lower Secondary	9.6	22.8	14.6
Upper Secondary	10.4	22.2	13.2
Postsecondary	12.8	22.4	11.0
Tertiary	14.3	24.7	12.1
Employment status			
Employed	9.8	21.7	13.2
Unemployed	9.0	26.1	18.8
Non-LF	9.7	21.2	12.8

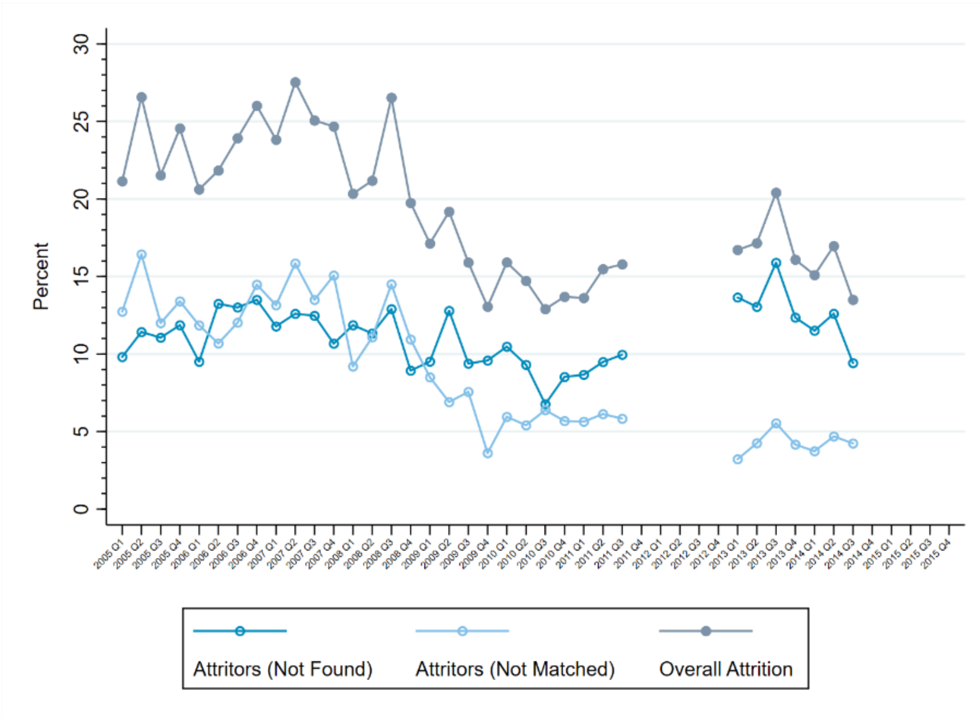
Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Column (3) provides the share of attritors who belong to nonattriting households. The largest differences are observed between individuals belonging to larger households that "produce" a larger percentage of attritors relative to small size households, between married and single individuals, between youngsters and middle/old-age individuals, between unemployed on the one hand and employed and inactive on the other hand.

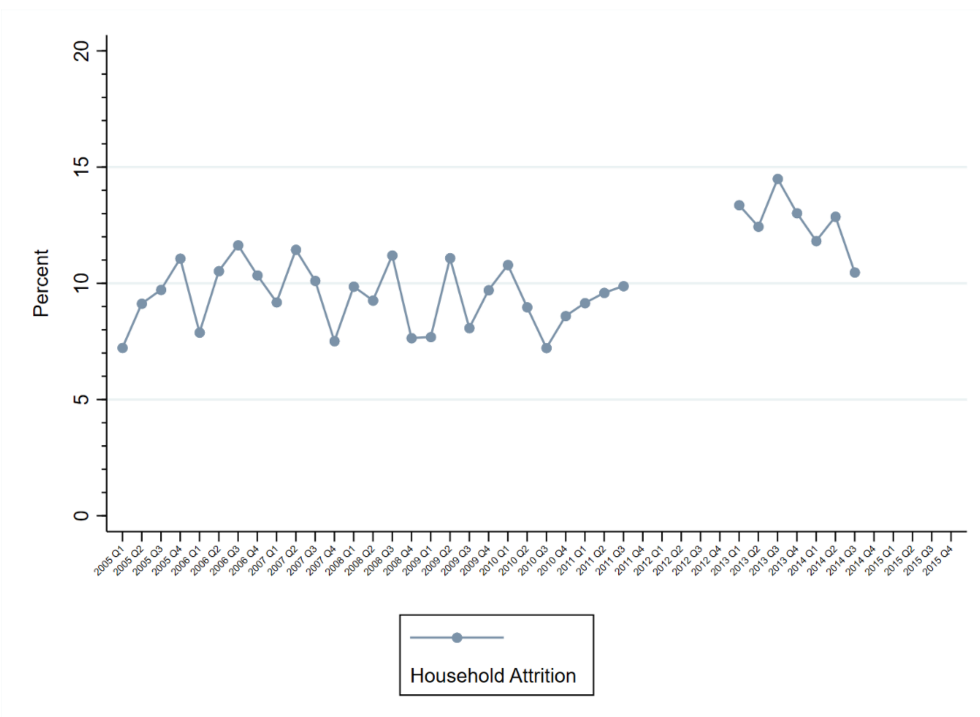
The average attrition rate calculated for the sample of individuals in working-age and measured over the 2005-15 period can be broken down by quarter. Figure B 1 shows that overall attrition has declined since the start of the panel in January 2005, particularly in 2010 and 2011. Total attrition ca be decomposed into a component due to individuals who attrited because they could not be found in the original dwelling and a component due to the fact that despite an individual with the same personal identifier of the original individual was found in the data, he/she was not a good match in terms of age and gender. The two components roughly overlap between 2005 and 2008; in 2009, attrition ascribable to bad matching started to decline, while attrition due to individuals not found in the original dwelling remains stable.

Figure B 1. Individual and household attrition rates (16-64 years of age sample) by reason for attrition and quarter, 2005–15

(a) Individual attrition



(b) Household attrition



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

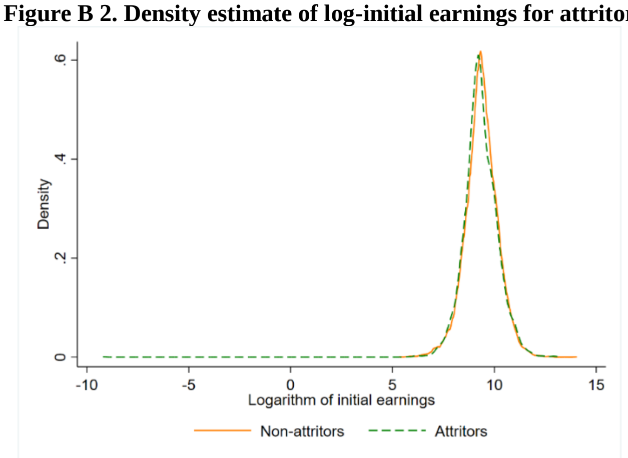
Attrition and earnings mobility in the CMPHS

A direct way of ascertaining whether attrition introduces a bias into the analysis of earnings mobility is to search for patterns in outcomes and observable characteristics of the attriting sample. Restricting the sample to individuals employed at baseline, Figure B 2 plots kernel densities for log-initial earnings of attritors and nonattritors who are employed at baseline. The two distributions are very close to one another, yet attritors seem to have a longer lower tail, in other words there are more attritors than nonattritors making low earnings at baseline.[15]

[15] This is corroborated by a Kolmogorov-Smirnov test of equality of the distributions: the test does not reject the hypothesis that the distribution of attritors has smaller values than that of nonattritors, yet the opposite hypothesis cannot be rejected.

Table **B 2** illustrates average values for a number of observable individual and household characteristics among attriting and nonattriting individuals together with differences between the two samples and tests for statically significant differences. Attritors are on average younger, not married, with higher educated, more likely to be employed in the private sector, particularly in the secondary sector and holding a low-end occupation, compared with nonattritors. For example, the share of individuals between 25 and 29 years of age is 18 percent among attritors and 11.2 percent among nonattritors; the share of individuals with tertiary education is 9.1 percent among attritors compared with 7.8 among nonattritors.

Figure B 2. Density estimate of log-initial earnings for attritors and nonattritors (16-64 years of age sample), 2005–15



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius

Table B 2. Average characteristics of attritors and nonattritors (16-64 years of age sample).

Initial Year Characteristics	Attritors	Nonattritors	Difference (A-NA)
		16-64	
Age category			
16-19	2.6	1.9	0.7***
20-24	10.9	7.6	*3.3****
25-29	18.0	11.2	6.8***
30-34	17.0	12.7	*4.2****
35-39	13.8	13.8	0.1
40-44	11.7	15.3	*−3.7****
45-49	10.2	14.5	−4.3***
50-54	8.4	12.0	*−3.6****
55-59	5.6	8.6	−3.0***
60-64	1.9	2.5	*−0.6****
Gender			
Male	64.2	67.8	*−3.5****
Educational category			
No education/pre-primary	1.8	2.0	−0.2
Incomplete Primary	4.9	5.4	*−0.5*
Complete Primary	26.5	29.3	−2.7***
Lower Secondary	11.9	11.1	*0.8**
Upper Secondary	40.4	39.2	1.3*
Postsecondary	5.4	5.2	*0.1*
Tertiary	9.1	7.8	1.3***
Marital status			
Married	60.6	72.7	*−12.1****
Household size category			
1-2	30.3	38.9	−8.6***
3-4	46.8	49.3	*−2.6****
5+	23.0	11.8	11.1***
District			
Port Louis	12.4	9.0	*3.5****
Pamplemousses	10.1	11.2	−1.1**
Riv. du Rempart	8.2	9.5	*−1.3****
Flacq	10.7	11.9	−1.2**
Grand Port	7.8	10.0	*−2.2****
Savanne	4.3	6.3	−2.0***
Plaine Wilhems	32.2	27.9	*4.3****
Moka	6.5	7.2	−0.7*
Black River	7.9	7.1	*0.8***

Labor market			
Wage worker	82.6	82.3	0.2
Public Sector	15.1	20.2	*−5.0****
Primary Sector	21.6	19.3	2.4***
Secondary Sector	29.5	26.8	*2.7****
Tertiary Sector	48.8	53.9	−5.1***
Professionals, technicians and managers	5.4	8.2	*−2.8****
Clerical, sales, and service workers	33.4	31.4	2.0***
Craft, production, and elementary occupations	61.2	60.4	*0.8*
Hours worked	40.1	39.2	0.9***

Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

The first multivariate analysis consists of estimating a regression for the probability of attrition on a set of observable characteristics at the time of the first interview including the value of initial earnings. A set of different specifications are presented ranging from a simple model that includes only initial earnings level or log to a specification that controls for a rich set of observable characteristics measured at the time of the first interview. Initial earnings levels enter each of the two specifications linearly, quadratically, and nonparametrically as a set of dummy variables for each quintile). The analysis shows evidence of statistically significant attrition effects for earnings both in the simple and in the full specification on a sample of individuals aged between 16 and 64 and employed at baseline. This is not unexpected as the evidence on attrition rates and characteristics of attritors has shown that attrition is largely due to individual attrition in nonmissing households and is a phenomenon that concerns largely youth and relatively more educated individuals.

To minimize the confounding effect of life cycle events on earnings changes such as youth transiting from partial to full participation in the labor market, older workers transiting from employment to inactivity, the sample is further restricted to individuals initially employed and between 30 and 54 years of age. Table B 4 shows results of the attrition regressions using the logarithm of initial earnings and estimated on the 30-54 years of age sample. The first three columns show some evidence of significant attrition effects for log-initial earnings. Attrition probabilities are nonlinear in earnings—lowest in the middle of the distribution and highest, though not significant, at high earnings levels. When additional controls are added, the initial earnings effects vanish (last three columns of Table B 4). Pseudo R-squareds from these regressions are extremely small ranging from 0.001 and 0.059. They explain very little of the variation observed in attrition and weights constructed based on these equations would likely have little effect on the estimates of earnings mobility equations. Based on the findings, the unconditional effect of initial earnings significantly covary with the probability of attriting. However, the effect disappears when the effect of earnings is conditioned on a set of covariates. The results provide support for some concern for attrition bias in unconditional distributions but not for conditional distribution of earnings.

The second test inverts the nature of the attrition regression test, that is the effect of initial outcome variables on future attrition. Separate initial earnings regressions are estimated for the sample of nonattritors and the total sample including attritors and nonattritors. The objective is to verify how different estimated coefficients would be from those in the total sample if only the nonattritors sample is used. Table B 5 illustrates for the sample of individuals employed at the time of the first interview and aged between 30 and 54 that most of the coefficients on the variables correlated with earnings do not differ between the two samples. Statistically significant differences appear for three out of eight dummy variables measuring educational attainments, namely complete primary, lower and upper secondary, for three out of nine dummy variables for districts, precisely Pamplemousses, Rivière du Rempart, and Black River, and one dummy variable for clerical, sales, and service workers. The education and occupation dummies are significant only at 5 percent. Living in the districts mentioned above as opposed to living in Port Louis is associated with higher monthly earnings. The differences indicate that such gaps in initial earnings are estimated to be larger in the full sample compared with the nonattriting sample by an amount ranging between MUR 500 and 980. To put things in perspective, the earnings differentials are not economically significant as they correspond to about of 3 and 6 percent of average initial earnings.

Tests for the joint significance of the differences in all the coefficients reject the hypothesis of equality between the two samples. A similar result is obtained when tests are conducted excluding the constant term. This evidence points to differences in the level of initial earnings conditional on other regressors; however, the differences are small and not economically significant.

Additional sample restrictions

There is a significant loss of sample size due to restrictions placed on the data to perform the analysis of earnings mobility. In addition to retaining nonattriting individuals aged 30-54 employed and not attending school at baseline, the final sample restricts the pool of individuals to workers with nonmissing relevant labor market variables (namely earnings, working hours, employment type, occupation, and sector) at baseline and in each of the three following interview rounds. The adjusted percentage of data loss combining loss to attrition and sample selection rate increases from 19.6 to 53.4 percent (Table B 6). This restriction is aimed at preventing large changes in earnings due to individuals entering and exiting employment from exerting undue influence on earnings data and on the analysis. Movements in and out of employment are investigated in a separate section.

Table B 3. Average characteristics of attritors and nonattritors, 30–54 age-group sample

Initial Year Characteristics	Attritors	Nonattritors	Difference (A-NA)
		30-54	
Age category			
16-19			
20-24			
25-29			
30-34	27.8	18.6	9.2***
35-39	22.7	20.2	*2.5****
40-44	19.1	22.4	−3.3***
45-49	16.7	21.2	*−4.5****
50-54	13.7	17.5	−3.8***
55-59			
60-64			
Gender			
Male	65.8	67.9	−2.0**
Educational category			
No education/pre-primary	1.8	1.7	*0.1*
Incomplete Primary	5.2	5.4	−0.2
Complete Primary	27.3	31.3	*−4.0****
Lower Secondary	10.6	11.0	−0.4
Upper Secondary	40.3	38.8	*1.4*
Postsecondary	5.7	4.9	0.7*
Tertiary	9.2	6.8	*2.4****
Marital status			
Married	72.5	83.8	−11.3***
Household size category			
1-2	37.5	44.9	*−7.4****
3-4	44.3	46.1	−1.8*
5+	18.2	9.0	*9.2****
District			
Port Louis	11.6	8.6	3.0***
Pamplemousses	9.7	11.4	*−1.7****
Riv. du Rempart	8.4	9.5	−1.0*
Flacq	10.6	12.1	*−1.5***
Grand Port	7.5	10.0	−2.6***
Savanne	3.7	6.2	*−2.4****
Plaine Wilhems	35.0	28.1	6.9***
Moka	6.0	7.2	*−1.2***
Black River	7.4	6.9	0.6

Labor market			
Wage worker	79.4	80.4	*−1.0*
Public Sector	16.3	20.5	−4.2***
Primary Sector	23.8	18.8	*5.1****
Secondary Sector	25.0	24.4	0.6
Tertiary Sector	51.1	56.9	*−5.7****
Professionals, technicians and managers	5.9	8.7	−2.8***
Clerical, sales, and service workers	34.8	32.8	*2.0***
Craft, production, and elementary occupations	59.3	58.5	0.8
Hours worked	40.0	39.4	*0.6***

Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Table B 4. Attrition probit regressions – Focus on initial earnings, 30–54 age-group sample

	(1)	(2)	(5)	(6)	(7)	(10)
		Basic Model			Full Model	
VARIABLES	Linear	Quadratic	Quintile	Linear	Quadratic	Quintile
Log Earnings	0.00350	−0.40029**		−0.00429	−0.28499	
	(0.01458)	(0.18437)		(0.02428)	(0.22451)	
(Log Earnings)^2		0.02168**			0.01556	
		(0.00982)			(0.01200)	
Log Earnings Q2			0.04989			0.01467
			(0.03677)			(0.04130)
Log Earnings Q3			−0.06709*			−0.04217
			(0.03731)			(0.04574)
Log Earnings Q4			−0.07635**			−0.02847
			(0.03646)			(0.04902)
Log Earnings Q5			0.01822			0.02391
			(0.03592)			(0.05739)
Age				−0.05103**	−0.05052**	−0.05108**
				(0.02318)	(0.02318)	(0.02320)
Age^2/100				0.03687	0.03597	0.03671
				(0.02798)	(0.02799)	(0.02800)
Female				0.02337	0.02539	0.02077
				(0.03220)	(0.03241)	(0.03272)
Incomplete Primary				−0.12321	−0.12275	−0.11966
				(0.09709)	(0.09712)	(0.09713)
Complete Primary				−0.18765**	−0.18751**	−0.18401**
				(0.08696)	(0.08700)	(0.08701)
Lower Secondary				−0.16479*	−0.16423*	−0.16033*
				(0.09267)	(0.09274)	(0.09279)
Upper Secondary				−0.14369	−0.14506	−0.13926

	(0.08935)	(0.08943)	(0.08950)
Postsecondary	−0.13480	−0.13936	−0.13485
	(0.10656)	(0.10667)	(0.10669)
Tertiary	−0.11745	−0.13479	−0.12738
	(0.10838)	(0.10886)	(0.10814)
Married	−0.22067***	−0.22059***	−0.21894***
	(0.03244)	(0.03245)	(0.03247)
Household Size	0.11762***	0.11773***	0.11710***
	(0.01050)	(0.01050)	(0.01051)
Presence of children aged 0-5	−0.06560**	−0.06690**	−0.06519**
	(0.03295)	(0.03298)	(0.03297)
Presence of children aged 6-15	−0.19226***	−0.19449***	−0.19298***
	(0.02800)	(0.02803)	(0.02803)
Pamplemousses	−0.24285***	−0.24252***	−0.24222***
	(0.04806)	(0.04808)	(0.04806)
Riv. du Rempart	−0.21422***	−0.21315***	−0.21467***
	(0.04952)	(0.04954)	(0.04954)
Flacq	−0.21067***	−0.20994***	−0.21018***
	(0.04805)	(0.04808)	(0.04809)
Grand Port	−0.30504***	−0.30420***	−0.30506***
	(0.05051)	(0.05054)	(0.05052)
Savanne	−0.42630***	−0.42577***	−0.42541***
	(0.05544)	(0.05545)	(0.05544)
Plaine Wilhems	−0.04689	−0.04707	−0.04651
	(0.04245)	(0.04249)	(0.04245)
Moka	−0.24793***	−0.24663***	−0.24728***
	(0.05162)	(0.05164)	(0.05164)
Black River	−0.09245*	−0.09255*	−0.09193*
	(0.05208)	(0.05210)	(0.05210)
Mining and quarrying	0.19309	0.19481	0.18972
	(0.29573)	(0.29587)	(0.29435)

Manufacturing	0.07643	0.07792	0.07474
	(0.06015)	(0.06019)	(0.06020)
Electricity, gas, steam and air conditioning supply	0.39831**	0.39532**	0.38789**
	(0.16291)	(0.16318)	(0.16295)
Water supply; sewerage, waste management and remediation activities	0.08586	0.08967	0.08949
	(0.13273)	(0.13278)	(0.13299)
Construction	0.05223	0.05512	0.05284
	(0.06698)	(0.06711)	(0.06702)
Trade and repair	0.10047	0.10376	0.10203
	(0.06398)	(0.06404)	(0.06401)
Transportation and storage	0.05327	0.05301	0.05359
	(0.07221)	(0.07226)	(0.07223)
Accommodation and food	0.08353	0.08676	0.08604
	(0.06921)	(0.06925)	(0.06928)
Information and communication	−0.00998	−0.00783	−0.01179
	(0.11670)	(0.11658)	(0.11672)
Finance and insurance	0.20882**	0.19880**	0.20262**
	(0.09790)	(0.09806)	(0.09777)
Real estate	−0.31715	−0.31795	−0.31509
	(0.25745)	(0.25721)	(0.25826)
Professional, scientific, and technical activities	0.14629	0.13877	0.14274
	(0.11276)	(0.11301)	(0.11263)
Administration, support, and service activities	−0.03269	−0.02969	−0.03213
	(0.08114)	(0.08115)	(0.08111)
Public administration, defense, and social security	0.00785	0.00891	0.00594
	(0.08412)	(0.08414)	(0.08412)
Education	−0.10690	−0.09705	−0.10014
	(0.08751)	(0.08768)	(0.08770)
Health and social work	−0.02895	−0.02760	−0.02310
	(0.09274)	(0.09281)	(0.09284)

Art, entertainment, and recreational activities	0.12553	0.13077	0.12999
	(0.11911)	(0.11916)	(0.11921)
Other service activities	−0.08874	−0.08628	−0.08394
	(0.11955)	(0.11973)	(0.11958)
Household activities	−0.05615	−0.06504	−0.05811
	(0.07824)	(0.07877)	(0.07847)
Activities of extra-territorial organizations and bodies	−0.00701	−0.02494	−0.00574
	(0.47528)	(0.47233)	(0.47122)
Waged employee	−0.04644	−0.04364	−0.04572
	(0.03481)	(0.03488)	(0.03489)
Public Sector	−0.09423*	−0.09679*	−0.09449*
	(0.05080)	(0.05082)	(0.05108)
Professionals	−0.10438	−0.08819	−0.09800
	(0.08103)	(0.08166)	(0.08079)
Technicians	−0.17316**	−0.15077**	−0.16332**
	(0.07340)	(0.07488)	(0.07310)
Clerks	−0.23979***	−0.21291**	−0.21922***
	(0.08098)	(0.08296)	(0.08118)
Service and sales workers	−0.30513***	−0.28033***	−0.29103***
	(0.07285)	(0.07456)	(0.07243)
Skilled agricultural workers	−0.44235***	−0.41375***	−0.42811***
	(0.10284)	(0.10432)	(0.10257)
Craft workers	−0.31534***	−0.29013***	−0.29734***
	(0.07651)	(0.07829)	(0.07620)
Machine operators	−0.33923***	−0.31333***	−0.32278***
	(0.07752)	(0.07931)	(0.07719)
Elementary occupations	−0.34831***	−0.32293***	−0.33301***
	(0.07814)	(0.07974)	(0.07762)
Hours worked	−0.00075	−0.00036	−0.00071
	(0.00248)	(0.00251)	(0.00246)
(Hours worked)^2/100	0.00240	0.00196	0.00236

				(0.00301)	(0.00304)	(0.00300)
Tenure				0.00019	0.00019	0.00021
				(0.00040)	(0.00041)	(0.00041)
Tenure^2/100				−0.00012	−0.00012	−0.00012
				(0.00011)	(0.00012)	(0.00012)
Log Consumption Q2				−0.07831**	−0.07623**	−0.07245**
				(0.03620)	(0.03624)	(0.03631)
Log Consumption Q3				−0.04274	−0.04066	−0.03594
				(0.03670)	(0.03674)	(0.03696)
Log Consumption Q4				−0.21261***	−0.21230***	−0.20920***
				(0.03936)	(0.03939)	(0.03963)
Log Consumption Q5				−0.09556**	−0.10499**	−0.10257**
				(0.04378)	(0.04418)	(0.04390)
Constant	−0.86918***	0.99602	−0.82098***	1.24069**	2.45754**	1.19060**
	(0.13759)	(0.86389)	(0.02617)	(0.52746)	(1.13757)	(0.48594)
Observations	17,430	17,430	17,430	17,430	17,430	17,430
Pseudo R2	4.02e-06	0.000	0.001	0.0585	0.059	0.059
Test: Earnings' variables=0		5.015	18.137		1.710	3.892
Prob > F		0.081	0.001		0.425	0.421

Robust standard errors in parentheses

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

Table B 5. Initial earnings regression: full and nonattritors sample, 30–54 age-group sample

	All sample	Nonattritors sample	Difference (All Nonattritors)	T-test	P-value
Hours worked	130.1***	131.7***	−1.60	0.01	0.934
(Hours worked)^2/100	13.74	0.108	13.63	0.16	0.688
Female	−6754.5***	−6993.5***	239.05	2.67	0.102
35-39	1362.1***	1479.1***	−116.99	0.39	0.531
40-44	2528.1***	2412.4***	115.69	0.28	0.597
45-49	2926.0***	2736.0***	190.04	0.55	0.458
50-54	4416.2***	3974.7***	441.43	1.27	0.259
Incomplete Primary	223.6	−50.20	273.80	2.17	0.140
Complete Primary	886.5	549.0	337.48	3.89	0.049
Lower Secondary	2307.2**	1931.3	375.91	3.69	0.055
Upper Secondary	4992.0***	4579.4***	412.67	4.21	0.040
Postsecondary	11968.8***	11715.0***	253.83	0.22	0.638
Tertiary	27715.4***	27474.5***	240.88	0.08	0.779
Pamplemousses	593.1	77.58	515.47	6.00	0.014
Riv. du Rempart	−130.7	−691.0	560.24	6.74	0.009
Flacq	627.1	642.6	−15.53	0.00	0.955
Grand Port	186.2	85.16	101.04	0.30	0.585
Savanne	−678.1	−963.3	285.26	2.50	0.114
Plaine Wilhems	1813.6***	1800.6***	12.97	0.00	0.956
Moka	−359.7	−386.1	26.38	0.02	0.891
Black River	1892.9***	910.3	982.54	6.90	0.009
Waged employee	−1855.3***	−1604.4***	−250.86	1.37	0.242
Public Sector	2164.9***	2259.6***	−94.71	0.11	0.745
Secondary Sector	520.8	672.3	−151.52	1.10	0.295
Tertiary Sector	1379.0**	1136.5*	242.54	2.04	0.153
Clerical, sales, and service workers	−10218.0***	−9628.4***	−589.59	3.77	0.052
Craft, production, and elementary occupations	−11074.7***	−10681.4***	−393.30	1.85	0.173

Tenure	24.24***	26.24***	−2.00	0.88	0.348
(Tenure)^2/100	−2.615***	−2.913***	0.30	0.48	0.490
Constant	12424.1***	12693.6***			
N	17430	14008			
Test all variables no constant				58.25	0.001
Test all variables with constant				53.71	0.003

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

Table B 6. Attrition rates by source of attrition and base year characteristics, 30–54 age-group sample

	Attrition				Attrition + Sample Selection	
Initial Year Characteristics	*Total attrition rate*	*Attrition rate due to attriting household*	*Attrition rate due to individual not found within nonattriting household*	*Attrition rate due to individual found but not matched within nonattriting household*	*Attritors OR Not Employed OR In Education OR with Missing Labor Market Variables at t=1*	*Attritors OR Not Employed OR In Education OR with Missing Labor Market Variables at t=1&2&3&4*
Total	19.6	9.8	11.1	9.2	46.3	53.4
District						
Port Louis	25.4	13.4	14.5	12.3	52.0	58.3
Pamplemousses	17.9	9.1	10.4	8.1	45.4	53.2
Riv. du Rempart	17.6	7.3	8.9	9.4	45.7	52.0
Flacq	18.3	7.4	8.7	10.5	46.9	53.9
Grand Port	16.5	7.5	8.9	8.1	46.4	53.0
Savanne	14.1	6.1	7.3	7.0	44.1	51.6
Plaine Wilhems	23.8	14.0	15.3	9.2	47.7	55.0
Moka	17.8	9.2	10.4	8.1	44.0	51.8
Black River	21.8	11.6	12.7	9.9	41.3	48.4
Gender						
Female	19.1	9.7	10.8	9.1	65.5	73.2
Male	20.1	10.0	11.5	9.4	27.0	33.4
Household size category						
1-2	16.2	11.0	11.4	5.1	41.0	48.3
3-4	19.3	9.0	10.5	9.6	47.7	54.7
5+	33.1	8.9	12.7	22.8	59.4	65.6
Marital status						
Single	30.5	10.8	14.7	17.7	53.0	61.7
Married	17.2	9.6	10.3	7.4	44.8	51.5
Age category						
30-34	25.2	10.9	13.8	12.5	51.5	59.3
35-39	21.3	10.4	11.7	10.2	45.5	52.6

40-44	17.4	9.0	10.1	8.1	42.6	49.3
45-49	17.2	9.6	10.3	7.6	44.8	51.5
50-54	17.0	9.2	9.7	7.7	47.5	54.6
Educational category						
No education/pre-primary	21.4	7.7	8.8	14.0	61.7	69.1
Incomplete Primary	19.5	7.6	9.0	11.8	49.3	57.7
Complete Primary	17.9	7.4	8.7	9.9	48.8	56.0
Lower Secondary	18.7	9.7	11.0	8.6	47.1	53.3
Upper Secondary	20.3	11.0	12.3	8.6	43.9	50.2
Postsecondary	21.1	14.5	15.9	5.7	37.8	46.4
Tertiary	25.4	16.5	18.0	8.0	40.3	50.0
Employment status						
Employed	19.7	10.2	11.4	9.0	23.7	33.7
Unemployed	21.8	9.7	11.8	10.9	100.0	100.0
Non-LF	19.1	8.9	10.2	9.8	100.0	100.0

Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Annex C: Transitions across Labor Market Statuses

At the center of the earnings mobility analysis is a group of individuals ages 30–54 who are in employment and not attending school at the time of all four interviews. As explained in detail in annex B, the age selection is dictated by selective attrition that is significantly correlated with earnings for young- and old-age individuals. However, before delving into the analysis of mobility and despite the presence of nonrandom selection because of attrition, it is interesting to looks at transitions across labor market statuses, namely, employment, unemployment, and inactivity, for the whole panel of nonattritors of working age (16–64). The objective is to describe potentially numerically large movements across labor market statuses that are not the focus of the earnings mobility analysis. The first part investigates labor market transitions among individuals belonging to two age-groups: individuals ages 30–54 who are also at the core of the earnings mobility analysis and individuals ages 55–64 who are excluded because of selective attrition. The second part turns the spotlight on youth ages 16–24 and 25–29.

Adults

Overall, individuals between 30 and 54 years of age exhibit persistence in employment; 93.7 percent of the initially employed are found in employment after 16 months (Table C 1). However, while still considerably high, the share of women employed in both periods is almost 10 percentage points lower than the share of men (87.8 percent vs 96.7 percent), presumably because of life-cycle events, such as maternity or lower labor market attachment. Similarly, the share of individuals employed in the first quarter who are out of the labor market in the fourth quarter, that is, inactive (on average 4.3 percent), is substantially higher among women (9.5 percent) than men (1.7 percent).

On average, 4 initially unemployed individuals out of 10 are found to be employed in the fourth quarter, while about 2 in 10 remain unemployed and 3 in 10 leave the labor market. Gender differences are even wider in this context: 71.8 percent of men eventually transition to employment as opposed to a meager 28.3 percent of women; 14 percent of men are unemployed as opposed to twice as large a share among women; and 14.1 percent exit the labor market in stark contrast with a striking 42.4 percent among women.

For both men and women, the rate of persistence in inactivity is considerable, at 82.9 percent, which is indicative of a potential systematic detachment from the labor market. Nonetheless, the extent of persistence in inactivity is lower among men than women (74.3 percent vs 83.6 percent). This is accompanied by a higher share of initially inactive men who manage to find a job in the fourth quarter relative to women (22.4 percent vs 11.7 percent) and by similar transition rates to unemployment (3.4 percent and 4.7 percent among men and women, respectively).

In both quarters, the share of inactive men is low (only 4.0 percent and 4.8 percent, respectively), while the portion of women out of the labor market in the same period is about 10-fold higher (48.1 percent and 47.0 percent). These figures highlight how the burden of factors likely related to the management of household tasks and responsibilities, such as eldercare and childcare, may constitute a significant obstacle preventing women from reentering or remaining in the labor force or from joining it in the first place.

In fact, 88.2 percent of inactive women report that they are not available to work because of their need to take on household and family responsibilities as opposed to 1 percent of inactive men, whose most cited reason for not being available is permanent disability (65.8 percent) and temporary injury or illness (20.8 percent).[16] Accordingly, a similar share of inactive women (83.2 percent) report spouse or partner income as their main income source as opposed to inactive men who report government pensions or assistance (56.9 percent).

Table C 1. Labor Market Status, Transition of Individuals Ages 30–54, Overall and by Gender, Q1–Q4, 2005–15

		All		
		Labor status (t=4)		
Labor status (t=1)	*Employed*	*Unemployed*	*Non-labor force*	*Total*
Employed	93.7	2.0	4.3	100
Unemployed	39.4	25.4	35.2	100
Non-labor force	12.5	4.6	82.9	100
Total	70.5	3.5	26.0	100
		Women		
		Labor status (t=4)		
Labor Status (t=1)	*Employed*	*Unemployed*	*Non-labor force*	*Total*
Employed	87.8	2.7	9.5	100
Unemployed	28.3	29.3	42.4	100
Non-labor force	11.7	4.7	83.6	100
Total	47.8	5.2	47.0	100
		Men		
		Labor status (t=4)		
Labor status (t=1)	*Employed*	*Unemployed*	*Non-labor force*	*Total*
Employed	96.7	1.6	1.7	100
Unemployed	71.8	14.0	14.1	100
Non-labor force	22.4	3.4	74.3	100
Total	93.3	1.9	4.8	100

Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Higher educational levels are associated with higher persistence in employment and lower persistence in inactivity (Table C 2). The former increases from 91.5 percent among individuals with up to complete primary education to 97.3 percent among those with a postsecondary or tertiary education, while the latter decreases from 83.2 percent to 80.9 percent among individuals in the same two educational groups. This

[16] Statistics refer to Q1 2013–Q3 2014. See Annex A, Table A 1–A 2.

seems to suggest that higher educational levels help secure and maintain a job or that individuals with higher education show a higher labor market attachment.

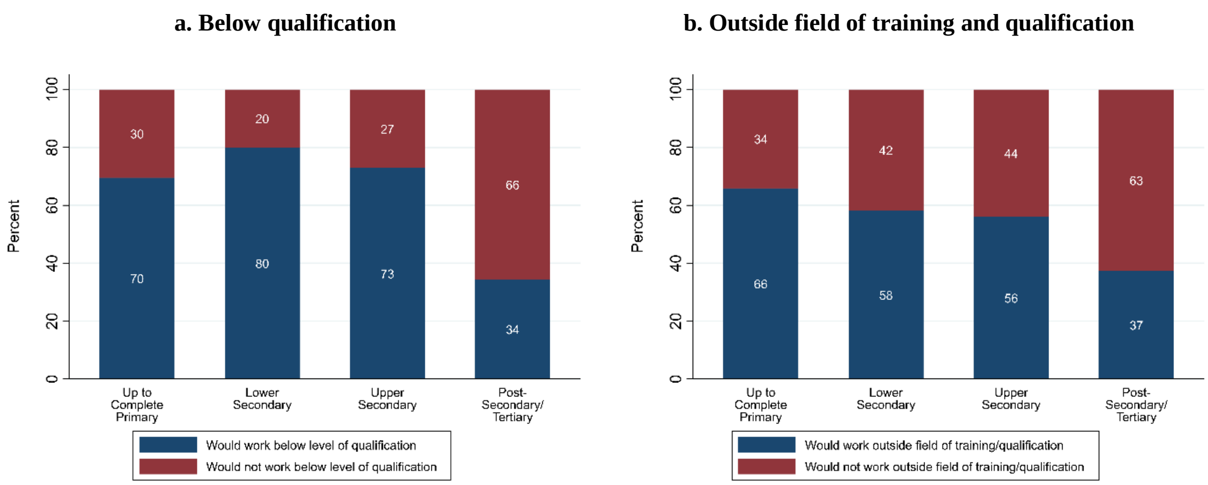
Table C 2. Labor Market Status, Transition of Individuals Ages 30–54, by Educational Level, Pooled, Q1–Q4, 2005–15

		Up to complete primary		
		Labor status (t=4)		
Labor status (t=1)	*Employed*	*Unemployed*	*Non-labor force*	*Total*
Employed	91.5	2.4	6.1	100
Unemployed	45.5	20.1	34.4	100
Non-labor force	13.0	3.8	83.2	100
Total	64.3	3.5	32.2	100
		Lower secondary		
		Labor status (t=4)		
Labor status (t=1)	*Employed*	*Unemployed*	*Non-labor force*	*Total*
Employed	92.7	2.4	4.9	100
Unemployed	36.3	29.7	34.0	100
Non-labor force	12.2	5.1	82.7	100
Total	67.5	4.1	28.4	100
		Upper secondary		
		Labor status (t=4)		
Labor Status (t=1)	*Employed*	*Unemployed*	*Non-labor force*	*Total*
Employed	95.2	1.7	3.1	100
Unemployed	33.5	30.6	35.9	100
Non-LF	11.6	5.8	82.6	100
Total	73.6	3.8	22.7	100
		Postsecondary, tertiary		
		Labor status (t=4)		
Labor status (t=1)	*Employed*	*Unemployed*	*Non-labor force*	*Total*
Employed	97.3	1.0	1.7	100
Unemployed	35.6	25.2	39.1	100
Non-labor force	14.2	4.9	80.9	100
Total	91.8	1.8	6.4	100

Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Lower persistence in unemployment is not linearly related to higher educational outcomes. In fact, the probability of being unemployed at the time of both the first and the fourth interviews rises steadily up to upper-secondary education (from 20.1 percent to 30.6 percent) and slightly declines among individuals holding postsecondary or tertiary education (25.2 percent). Accordingly, a parallel and inverse pattern can be observed in the transition rates out of unemployment into employment. This, in turn, could signal that individuals with higher educational attainment may experience difficulties in finding jobs matching their skills or be reluctant to accept jobs for which they are overqualified, thus leading them to experience prolonged periods of unemployment. The latter hypothesis appears to be corroborated by the negative relationship emerging between educational attainment and the willingness of individuals to accept jobs below their level of qualification or outside their fields of training and qualification (Figure C 1).[17] The share of individuals reporting they are willing to accept job offers below their level of qualification ranges from 70 percent among those with up to completed primary education to 34 percent among individuals with postsecondary or tertiary education. A similar pattern is observed among individuals willing to take up jobs outside their fields of training, which declines from 66 percent among those with up to completed primary education to 37 percent among the more well educated.

Figure C 1. Willingness to Accept Jobs among the Unemployed, Ages 30–54, by Educational Level



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.
Note: Statistics refer to Q1 2013–Q3 2014.

Table C 3 displays transition matrices for individuals ages 55–64. As expected, rates of employment persistence are much lower (79.6 percent), and flows out of the labor force become considerably more sizable as a greater number of individuals initially employed retire (19.4 percent). Similar to the 30–54 age-group, significant gaps are observed between men and women in the rates of both employment persistence (81.6 percent vs 74.8 percent) and the transition out of employment into inactivity (17.2 percent vs 24.8 percent).

Compared with the 30–54 age-group, the share of initially unemployed men who transition to employment is conspicuously lower (35.8 percent as opposed to 71.8 percent among the 30–54 age-group). Similarly,

[17] Statistics refer to Q1 2013–Q3 2014.

the share persisting in unemployment is also smaller (9.6 percent) and that transitioning out of the labor force, as a result, larger (54.7 percent), indicating a marked detachment from the labor force at ages around retirement.

Among women, a slightly higher share of the initially unemployed hold a job in the fourth quarter compared with the 30–54 sample (32.6 percent vs 28.3 percent). None of the women ages 55–64 initially unemployed keep seeking a job and transit instead to inactivity (67.5 percent; the share is about 30 percent in the 30–54 age-group).

Table C 3. Labor Market Status, Transitions of Individuals, Aged 55–64, Overall and by Gender, Pooled, Q1–Q4, 2005–15

		All		
		Labor status (t=4)		
Labor status (t=1)	*Employed*	*Unemployed*	*Non-labor force*	*Total*
Employed	79.6	1.0	19.4	100
Unemployed	34.3	5.1	60.6	100
Non-labor force	8.0	0.6	91.4	100
Total	39.9	0.8	59.3	100
		Women		
		Labor status (t=4)		
Labor status (t=1)	*Employed*	*Unemployed*	*Non-labor force*	*Total*
Employed	74.8	0.4	24.8	100
Unemployed	32.6	0.0	67.5	100
Non-labor force	5.9	0.4	93.8	100
Total	23.6	0.4	76.1	100
		Men		
		Labor status (t=4)		
Labor status (t=1)	*Employed*	*Unemployed*	*Non-labor force*	*Total*
Employed	81.6	1.2	17.2	100
Unemployed	35.8	9.6	54.7	100
Non-labor force	12.7	1.2	86.1	100
Total	57.2	1.3	41.5	100

Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

By and large, the same relationship holds between educational levels and persistence rates in employment and inactivity as in the 30–54 sample (Table C 4).

Table C 4. Labor Market Status Transitions of individuals aged 55-64 by educational level, 2005-15: Q1-Q4

		Up to Complete Primary		
		Labor Status (t=4)		
Labor Status (t=1)	Employed	Unemployed	Non-LF	Total
Employed	76.8	0.9	22.3	100
Unemployed	45.2	0.0	54.8	100
Non-LF	7.9	0.5	91.6	100
Total	33.4	0.7	66.0	100
		Lower Secondary		
		Labor Status (t=4)		
Labor Status (t=1)	Employed	Unemployed	Non-LF	Total
Employed	81.3	1.3	17.4	100
Unemployed	28.6	7.7	63.8	100
Non-LF	6.3	0.0	93.7	100
Total	42.4	0.8	56.7	100
		Upper Secondary		
		Labor Status (t=4)		
Labor Status (t=1)	Employed	Unemployed	Non-LF	Total
Employed	81.0	1.2	17.8	100
Unemployed	11.9	17.0	71.2	100
Non-LF	8.7	1.6	89.7	100
Total	50.3	1.6	48.2	100
		Postsecondary/Tertiary		
		Labor Status (t=4)		
Labor Status (t=1)	Employed	Unemployed	Non-LF	Total
Employed	87.9	0.5	11.6	100
Unemployed	0.0	0.0	100.0	100
Non-LF	10.9	0.0	89.1	100
Total	68.3	0.4	31.3	100

Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

As to the transitions out of unemployment into employment, an even stronger negative association can be observed between education levels and transition rates: 45.2 percent of initially unemployed individuals ages 55–64 with up to complete primary education hold a job at the fourth interview as opposed to 11.9 percent of those with upper-secondary education, and none of those with higher education, although this is mostly because of a different distribution of educational attainment, that is, older cohorts are less likely than their younger counterparts to have high educational levels.

Youth

This section focuses on two subsamples of youth, the 16–24 age-group and the 25–29 age-group. Because a large share of these individuals are undergoing a transition between formal education and the labor market, the matrices shown in **Error! Reference source not found.** comprise a larger number of possible statuses. Accordingly, youth can be classified as in employment only, in education only, both in employment and education, in unemployment, or not in the labor force or education (NLFE). Adding up the latter two statuses provides the number of youth not in employment, education, or training.

By comparing the top two matrices in Table C 5, a few intuitive facts emerge. The rate of persistence in the employment only category is slightly lower among individuals ages 16–24 (82 percent) with respect to those ages 25–29 (89.8 percent), while the converse is true for the rates of persistence in the education only category (70.8 percent vs 58.1 percent), and the employment and education category (41.3 percent vs 36.6 percent). This is because the two groups are observed in two distinct phases of their school-to-work transitions. The youngest are more frequently engaged (entirely or partially) in formal education and less in employment compared with the older group, which is in the last stages of the schooling cycle (tertiary education). As a result, the transition rates to employment only from education only and employment and education are lower among the 16–24 sample, 11.1 percent versus 29.1 percent and 46.2 percent versus 54.9 percent, respectively. For the same reason, more generally, flows out of part- or full-time employment toward part- or full-time education are more common within the 16–24 group.

Exploring the gender dimension of school-to-work transitions allows one to uncover two main facts. First, the rate of persistence in the employment only category is larger among men than women in both age-groups. This gap is about 10.5 percentage points in the 16–24 group and falls to about 6.5 percentage points within the 25–29 group. It appears to be larger among the younger cohorts because of the relatively larger shares of women still engaged in the school-to-work transition at young ages; 9.3 percent of women as opposed to 5.0 percent of men ages 16–24 go from employment only to either the education only category or the employment and education category. While, among the 16–24 group, persistence rates in the education only group are similar between genders (at around 70 percent), in the 25–29 group, the gender gap in persistence in education only is a staggering 21.3 percentage points. This is because both transition rates to employment only and to unemployment–NLFE statuses are larger among women than men, by 6.8 percentage points and 14.5 percentage points, respectively.

Table C 5. Labor Market Status Transitions of Individuals Ages 16–30, by Educational Level, Pooled Q1–Q4, 2005–15

All 16–24

Labor status (t=1)	*Labor status (t=4)* *Employment only*	*Education only*	*Employment and education*	*NLFE*	*Unemployment*	*Total*
Employment only	82.0	3.5	3.0	4.6	7.0	100
Education only	11.1	70.8	2.9	6.8	8.4	100
Employment and education	46.2	7.7	41.3	1.3	3.6	100
NLFE	20.9	12.7	1.8	51.0	13.6	100
Unemployment	51.9	9.1	3.5	10.1	25.5	100
Total	38.02	35.79	4.08	11.96	10.15	100

All 25–29

Labor status (t=1)	*Labor status (t=4)* *Employment only*	*Education only*	*Employment and education*	*NLFE*	*Unemployment*	*Total*
Employment only	89.8	0.9	2.1	3.4	3.8	100
Education only	29.1	58.1	0.0	3.3	9.5	100
Employment and education	54.9	4.8	36.6	0.5	3.1	100
NLFE	13.8	0.6	0.3	75.6	9.7	100
Unemployment	43.5	0.2	1.1	25.9	29.3	100
Total	66.27	2.41	3.08	20.94	7.29	100

Women 16–24

Labor status (t=1)	*Labor status (t=4)* *Employment only*	*Education only*	*Employment and education*	*NLFE*	*Unemployment*	*Total*
Employment only	75.2	4.0	5.3	8.6	6.9	100
Education only	8.5	71.5	2.6	8.0	9.4	100
Employment and education	45.7	9.6	41.9	0.0	2.8	100
NLFE	16.7	7.8	1.1	61.8	12.6	100
Unemployment	41.5	9.7	3.4	15.2	30.3	100
Total	28.46	37.06	4.24	18.96	11.28	100

Women 25–29

Labor status (t=1)	*Labor status (t=4)* *Employment only*	*Education only*	*Employment and education*	*NLFE*	*Unemployment*	*Total*
Employment only	85.6	0.7	2.0	7.4	4.3	100
Education only	33.5	44.2	0.0	9.5	12.8	100
Employment and education	55.0	3.3	35.6	1.2	4.9	100
NLFE	12.6	0.3	0.3	76.9	9.9	100
Unemployment	31.6	0.0	1.1	36.4	30.9	100
Total	48.61	1.33	2.49	38.11	9.47	100

Men 16–24

Labor Status (t=1)	*Labor status (t=4)* *Employment only*	*Education only*	*Employment and education*	*NLFE*	*Unemployment*	*Total*
Employment only	85.6	3.2	1.8	2.4	7.1	100
Education only	13.7	70.1	3.1	5.7	7.4	100
Employment and education	46.5	6.0	40.7	2.4	4.4	100
NLFE	32.2	26.1	3.6	21.8	16.2	100
Unemployment	61.3	8.5	3.5	5.5	21.2	100
Total	46.89	34.62	3.93	5.46	9.1	100

Men 25–29

Labor status (t=1)	*Labor status (t=4)* *Employment only*	*Education only*	*Employment and education*	*NLFE*	*Unemployment*	*Total*
Employment only	92.2	1.0	2.1	1.2	3.6	100
Education only	26.7	65.5	0.0	0.0	7.8	100
Employment and education	54.8	6.1	37.4	0.0	1.8	100
NLFE	30.6	5.1	0.0	57.7	6.6	100
Unemployment	65.7	0.7	1.0	6.2	26.5	100
Total	84.66	3.54	3.7	3.07	5.03	100

Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

By looking at the two rightmost columns in the bottom four matrices, one is immediately struck by the fact that the shares of young women initially engaged in either education only or employment only who are NLFE in the fourth quarter are larger than the corresponding shares of men counterparts (8.0–8.6 percent vs 2.4–5.7 percent in the 16–24 group), and the gender gap grows in the second age-group (9.5–7.4 percent vs 0-1.2 percent in the 25–29 group), which once again points to a transition of women toward household duties as they become adults. On the other hand, the gender divide is less clear if one looks at the transition from education or employment toward unemployment, but appears more pronounced in the 25–29 group.

Persistence rates in NLFE are sizable and increase with age among both genders. They are particularly high among women (61.8 percent in the 16–24 group and 76.9 percent in the 25–29 group). For men, the rate of persistence in NLFE is 21.8 percent in the 16–24 group and more than doubles to 57.7 percent among individuals ages 25–29. Table C 6 and Table C 7 illustrate further characteristics on these individuals that help outline their profiles. Among women ages 16–29 persisting in NLFE status, the great majority (76.4 percent) reported they were not available to work because of household or family responsibilities, while smaller shares based their unavailability to work on permanent disability (8.4 percent) or no interest in work (6.5 percent). Some 71.2 percent listed their spouse or partner as their main source of income, while a smaller portion stated they relied on their parents as their main economic support (23.2 percent). A rather different profile can be sketched for men, who listed permanent disabilities as their main reason for not being available to work (58.9 percent), followed by not being interested in work (12 percent) and temporary illness or injury (10.9 percent); they report parents and government pensions or assistance as the major source of income (77.5 percent and 22.5 percent, respectively).

Lastly, persistence in unemployment is more modest among both genders, but slightly higher among women than men: 30.3 percent and 30.9 percent for women in the age-groups 16–24 and 25–29, respectively, but 21.2 percent and 26.5 percent for men in the same age-groups. For many young women, unemployment seems to be a precursor of inactivity: only 3 in 10 (4 in 10 among the youngest) are found in employment after 16 months as opposed to twice as many young men.

Among the initially unemployed, it emerges that those who eventually find employment are generally more inclined to accept any type of employment (Table C 8). The only exceptions can be found in the public sector and in temporary employment for men. Among the latter, the greatest differences in terms of willingness to accept jobs between individuals who find a job and those who remain unemployed pertain to working below one's level of qualification and outside one's field of training or qualification. Among women, the greatest difference can be found in both temporary and permanent employment.

Almost all men who persist in unemployment (97.7 percent) report their parents as their main income source, while their women counterparts rely, respectively, on parents (66.5 percent), spouses or partners (22.9 percent), and other relatives (10.6 percent) for their financial support (Table C 9).

On the transitions from NLFE status to employment, two main facts emerge. First, the transition rates are considerably higher among men. Second, for men, such transitions increase or remain relatively stable across age-groups (32.2 percent versus 30.6 percent for the NLFE–employment only category transition between age-groups 16–24 and 25–29). Among women, NLFE–employment only transition rates decrease from 16.7 percent to 12.6 percent among the age-groups 16–24 and 25–29, indicating the likely presence of increasing barriers to entry to the labor market as women enter adulthood.

Table C 6. Reason for not being available to work among individuals aged 16-29, persisting outside of the labor force or education (NLFE), by gender, 2005-15: Q1-Q4

Reason for not being available to work	Female	Male	Total
Will resume studies soon	2.5	4.0	2.8
Permanent disability	8.4	58.9	18.1
Temporary illness/injury	0.8	10.9	2.7
Too young to work	1.0	6.6	2.1
Parents or spouse not agreeable	4.4	0.0	3.6
Household/family responsibilities	76.4	0.0	61.7
Not interested to work	6.5	12.0	7.6
New job or own business to start soon	0.0	4.7	0.9
Other	0.0	2.8	0.5
Total	100	100	100

Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Table C 7. Main source of income or support to meet daily needs among individuals aged 16-29, persisting outside of the labor force or education (NLFE), by gender, 2005-15: Q1-Q4

Main income source	Female	Male	Total
Parents	23.2	77.5	33.4
Spouse/Partner	71.2	0.0	57.9
Other relatives/nonrelatives	0.7	0.0	0.6
Maintenance alimony (ex-spouse)	0.9	0.0	0.7
Government pension/assistance	4.0	22.5	7.5
Total	100	100	100

Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Table C 8. Propensity to accept certain kinds of job among initially unemployed individuals aged 16-29, by employment status at t=4 and gender, 2005-15: Q1-Q4

		Initially Unemployed		
Willing to accept		Unemployed at t=4 (%)	Employed at t=4 (%)	Difference (pct points)
Full-time employment	M	92.2	98.3	−6.2
	F	*91.0*	*93.6*	*−2.5*
Part-time employment	M	48.8	60.5	−11.7
	F	*49.6*	*63.5*	*−13.9*
Permanent employment	M	74.7	80.0	−5.3
	F	*67.0*	*83.6*	*−16.6*
Temporary employment	M	53.1	49.7	3.4
	F	*35.2*	*60.4*	*−25.2*
Employment in the Public Sector	M	92.2	88.0	4.2
	F	*94.1*	*85.9*	*8.2*
Employment in the Private Sector	M	88.2	98.9	−10.7
	F	*88.3*	*93.1*	*−4.8*
Work below level of qualification	M	48.2	71.0	−22.8
	F	*54.5*	*59.6*	*−5.1*
Work outside field of training/qualification	M	48.3	66.7	−18.3
	F	*53.7*	*59.8*	*−6.1*

Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Table C 9. Main source of income or support to meet daily needs among individuals aged 16-29, persisting in unemployment, by gender, 2005-15: Q1-Q4

Main income source	Female	Male	Total
Parents	66.5	97.7	79.8
Spouse/Partner	22.9	0.0	13.1
Other relatives/nonrelatives	10.7	0.0	6.1
Savings/property income	0.0	2.3	1.0
Total	100	100	100

Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

The transition matrices indicate high persistence in unemployment and in NLFE status, particularly among women ages 25–29, and low rates of transition toward employment. Who are the youth who are able to escape the trap of not being in employment, education, or training? What characteristics do they have? What pathway do they take?

Sequence analysis allows one to identify different pathways youth can take to transition from status *x* at time *1* to status *y* 16 months later. This technique compares sequences of statuses and identifies similar transition paths, leading to the identification of typical pathways.[18]

Starting with initially unemployed youth, sequence and cluster analysis supports the existence of two types of pathways (Figure C 2). The first cluster consists of youth who are initially unemployed and are able to transit quite rapidly to employment only (Figure C 2, panel a). Over 70 percent of youth in this cluster experience two episodes, that is, unemployment and employment only. They are predominantly men in the 16–24 age-group, with upper-secondary (43.6 percent) or higher education (21.0 percent). The second cluster, illustrated in Figure C 2, panel b, features a slow transition out of unemployment and largely to NLFE. As opposed to the first group, this cluster is largely composed of women with upper-secondary education (58 percent) and less likely to have postsecondary or tertiary education (13.7 percent).

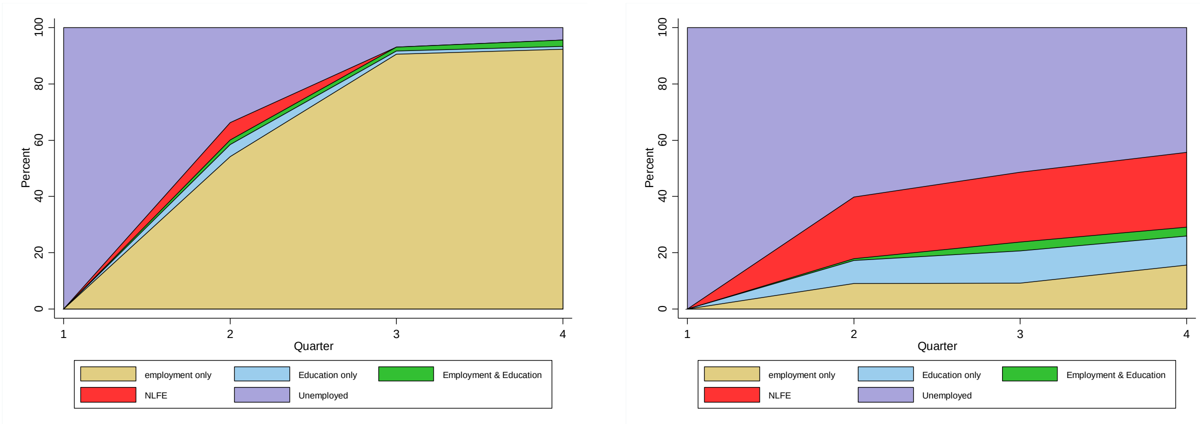
The identification of the two clusters and the characteristics of youth falling in each of them is to some extent corroborated by the findings of survival analysis performed on a sample of initially unemployed youth. In addition to identify, being female is the variable most significantly and negatively correlated with the probability of exiting unemployment status.

Youth initially in NLFE can be grouped into two typical clusters. The first cluster, which is not illustrated in Figure C 3, features a permanent NLFE status for all the 16 months of observation. Over 9 in 10 youth in this cluster are women, and 6 in 10 are in the 25–29 age-group. Over 1 in 3 has completed primary education or less; 22 percent have secondary education; and less than 40 percent have upper-secondary education. **Error! Reference source not found.** shows the share of youth belonging to the second cluster by activity status and quarter. This pathway leads most of the youth initially in NLFE status to employment only; some to unemployment; and a small share to education only by the end of the 16th month of observation. Youth in this cluster are ages 16–24 (65 percent), women (70 percent), and considerably more likely to have upper-secondary education (54 percent).

[18] The analysis requires individual sequences, known as trajectories, experienced over a period of time, four quarters in the case at hand, a measure of the distance between individual trajectories, and a rule to identify similar trajectories. The first step consists in identifying similar trajectories by assessing the degree of similarity among individual trajectories. Optimal matching, an explorative method of sequence analysis, is used. The procedure consists in computing the distance between each pairwise combination of sequences. The distance between two sequences is the number of steps one must take to make both sequences identical. The process is called alignment, and there are three possible operations: an item of a sequence can be substituted by another item; an item can be inserted into a sequence; or an item can be deleted from a sequence. The latter two operations are known as indel operations, that is, insert and delete. Following Brzinsky-Fay (2007), indel costs are set equal to one, and substitution costs equal to two. Because there is more than one possible alignment of two random sequences, the optimal matching algorithm chooses the alignment with the minimum distance between the two sequences that is found via the Needleman-Wunsch algorithm. On the basis of the distances calculated by optimal matching, similar sequences need to be grouped together. To do so, the pairwise distances are used to construct a distance matrix on which cluster analysis is performed. Ward's (1963) hierarchical agglomerative algorithm is used to group individual trajectories into clusters. The algorithm chooses the groupings that minimize the increase in the within-cluster error-sum-of-squares. Two stopping rules, which are conventional in cluster analysis, are implemented to determine the appropriate number of clusters.

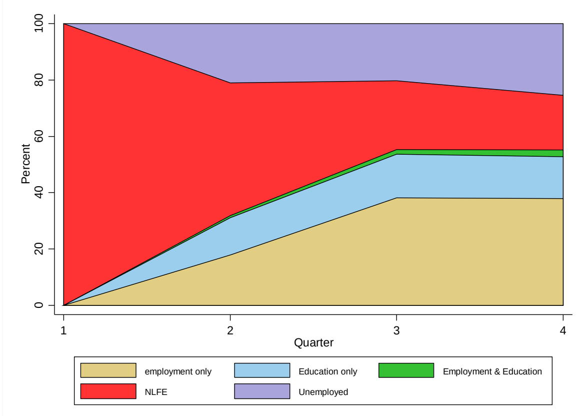
Figure C 2. Share of Youth Ages 16–29, Initially Unemployed, in Each Activity Status, by Cluster and Quarter, 2005–15

a. Fast pathway **b. Slow pathway**



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Figure C 3. Share of Youth Ages 16–29, Initially in NLFE, in Each Activity Status, by Quarter, 2005–15



Source: Based on data of the Continuous Multipurpose Household Survey, Statistics Mauritius.

Annex D: Earnings Correction for Transitory Shocks

The model introduced Table O 1 is very simple and for this reason it is very intuitive and appealing. However, the interpretation of estimation coefficients should be very careful, particularly because it could be possible to observe negative coefficients if for example workers are subject to transitory earnings shocks over time. In the short run, one could observe that earnings are convergent simply because workers who start with a positive earnings shock are then adjusting back to their lower permanent level of earnings, even if long term earnings do not converge.

To investigate whether convergence in earnings is occurring in a more permanent sense, this study adopts two approaches to derive a more permanent measure of initial earnings. First, an average of individual's earnings using the last three interviews of earnings information available is used instead of earnings from the first interview only (this is what it is referred to as longer-term average earnings throughout the study). Average earnings over repeated periods of time average out the ups and downs in earnings and are therefore expected to be less affected by transitory shocks. Second, the study follows the approach by Fields et al. (2015) to eliminate the impact of earnings reverting to the conditional mean. First of all, a definition of transitory earnings is necessary. Fields et al. (2015) propose the following model of earnings determination that can be estimated with short-term panel data. The authors decompose earnings at time t into a component related to characteristics permanently attached to the worker and another component that is considered transitory earnings as follows:

$$y_t = z\gamma_t + \delta\tau_t + \varepsilon_t \qquad (1)$$

Where z is a vector of observable characteristics permanently attached to an individual such as age, gender, educational level, etc., δ is a scalar capturing unobserved characteristics permanently attached to an individual, γ_t and τ_t are time-varying coefficient measuring the effect of these characteristics on earnings, and ε_t is the transitory shock component. Therefore, the component of earnings associated with permanent characterstics of the worker is given by:

$$y_t^p = z\gamma_t + \delta\tau_t \qquad (2)$$

Fields et al. (2015) assume that the three components are uncorrelated in the population, in other words the covariance between permanent observable characteristics and unobserved characteristics as well as between permanent observable characteristics and the transitory shock component, and between unobserved characteristics and the transitory shock component is zero. The latter is assumed to follow an AR(1) process.

It is then possible to first estimate equation (1) at the start of the period to get the component of initial earnings associated with permanent characteristics of the worker. Predictors of the permanent advantage of an individual include human capital variables like age, education, gender, and household consumption as a proxy for welfare. In a second stage, predicted values from the first regression are used to estimate the main relationship between change in earnings and initial permanent earnings (this is what is referred to as longer-term predicted earnings through the study). The estimated coefficient in this second stage regression captures how earnings changes are related to the component of initial earnings associated with permeant characteristics of the worker and it is a better measure of how earnings changes are related to a more permanent measure of initial advantage.