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Explaining Changes in Sri Lanka's Wage Distribution, 1992-2014: A Quantile Regression Analysis

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Abstract

This paper investigates the evolution of Sri Lanka's wage distribution during 1992-2014, a period of robust economic growth following the adoption of liberal economic policies. Using unconditional quantile regression, the analysis reveals wages grew across the distribution and more strongly at lower quantiles, causing inequality to fall. The decline in inequality came almost entirely from changes to wage returns consistent with rising relative demand for less- skilled labor. However, changes in workforce composition widened income gaps, most notably through educational and occupational upgrading. The study further demonstrates selection bias overestimates average incomes and underestimates inequality in a given year, while also mis-measuring changes in those variables over time. The study discusses the negative implications of persistent inequities along education, occupation and gender divisions, and recommends policies to address them.

Keywords: income inequality, developing countries, decomposition methods, labor market

*The empirical analysis in this paper was conducted with household survey data collected by the Department of Census and Statistics, Government of Sri Lanka. All errors are my own.

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1 Introduction

A large body of literature examines trends in national income and inequality after countries implement market-based reforms. This literature is motivated by the adoption of liberal economic policies in numerous developing countries in the 1980s and 1990s. The reforms transformed inward-oriented, centrally-planned economies into open markets with a greater role for the private sector, foreign investment, and trade. Robust economic growth ensued (Dollar and Kraay, 2004). A key question for researchers and policymakers is whether the benefits of growth have been broadly shared. Specifically, how has growth affected the distribution of income?

Early empirical research pointed to rising inequality in newly liberalized economies, which ran counter to neo-classical theory. The Heckscher-Ohlin model predicts a narrowing income distribution when labor-abundant/capital-scarce countries become more open. Puzzled, researchers offered alternative explanations for the rise in inequality, such as skill-biased tech- nical change (Berman and Machin, 2000; Pavcnik, 2003; Conte and Vivarelli, 2011), offshore outsourcing (Feenstra and Hanson, 1996), firm heterogeneity (Melitz, 2003; Verhoogen, 2008; Helpman and Itskhoki, 2015), and the rise of China (Wood, 1997). That developing countries face an inherent tradeoff between growth and equity became a widely held view (Ravallion et al., 1999).

Then, starting in the mid 1990s, the upward trends in inequality started to reverse in Latin America, even as income and employment continued to rise. The decline began a few years after the adoption of pro-market policies and has continued steadily ever since (Robertson, 2015). Although the region's celebrated income transfer programs are hailed for reducing in- come gaps, studies reveal narrowing dispersion of labor earnings played an even larger role (Esquivel et al., 2010; Barros et al., 2010; Gasparini and Lustig, 2011; Ferreira et al., 2014), leading to an emerging consensus that the labor market is the mainspring of falling inequality in Latin America (Robertson, 2015). Studies from other parts of the developing world, how- ever, are scarce. The bulk of evidence comes from cross-country regressions of aggregate data, which show weak correlations between growth and inequality (Ravallion, 1995, 1999; Dollar and Kraay, 2002). This approach has been criticised for masking the diverse experiences of countries, prompting calls for 'deeper micro empirical work' on distributional change (Ravallion, 2001).

In response, a growing body of country-specific analyses has emerged. Most examine clas- sic inequality measures such as the Gini coefficient, Thiel index, variance, and income shares (Wagle, 2007; Cruces and Gasparini, 2008; Gunatilaka and Chotikapanich, 2009; Bergh and Nilsson, 2010; Mah, 2013; Ferreira et al., 2014). However, collapsing the entire income distri- bution into a single statistic conceals important information. Recent work from developed and developing countries reveals substantial variation along the entire income distribution, not only in how incomes evolve, but also with regard to the factors driving those changes (Bourguignon et al., 2005; Machado and Mata, 2005; Firpo et al., 2011; Azam, 2012). In addition, income data themselves reflect individuals' non-random choices. For instance, individuals select into employment based on gender, education, household structure, and other observed and unob- served characteristics. Failure to account for non-random selection can seriously bias estimates of income distribution (Juhn, 2003; Blau and Kahn, 2006). The extent of this problem when measuring income dispersion in China is demonstrated by Chen and Fu (2015). Yet, studies on income distribution in developing countries largely ignore selection issues.

The goal of this paper is to address these shortcomings in the literature by conducting a micro-empirical analysis of changes at different points of the wage distribution among Sri Lankan workers, while accounting for selection into employment. The period of analysis is 1992-2014, a time of robust economic growth in Sri Lanka following the adoption of liberal economic policies in the late 1980s/early 1990s. Changes in the wage distribution are decom- posed using the method of unconditional quantile regressions proposed in Firpo et al. (2009) and Firpo et al. (2011). This method allows wage changes at each quantile of the distribution to be decomposed into the 'coefficient' and 'endowment' effects of every covariate, thus improv- ing upon previous decomposition methods found in the literature. Such estimates are revealing for policymakers because they not only highlight those factors contributing to labor income growth, but also identify how varying segments of the income ladder were impacted.

To address selection bias, wages are imputed for non-participants by matching their characteristics to those of workers. This is a method used extensively in the literature (Johnson et al., 2000; Juhn, 2003; Neal, 2004; Blau and Kahn, 2007). Wage imputation requires neither precise estimates of missing wages nor the estimation of 'structural' selection models (Heck- man, 1979) for which suitable instruments are difficult to find. Rather, each non-participant is assigned a wage conditional on characteristics that identify his/her likely location in the wage distribution. To overcome uncertainty in the imputation process, multiple imputation rounds are conducted Rubin (1978, 1987). Comparing results with and without imputation reveals the extent of selection bias and its impact on distributional statistics. Because selection effects likely differ by gender, the analysis is conducted separately for men and women.

In sum, the paper's aim is to address a number of limitations of previous research on in- equality in developing countries. First, it looks beyond aggregate statistics by examining the full income distribution and its microeconomic determinants. Second, it evaluates mismeasure- ment stemming from selection effects. Third, it expands the current research base of country- specific analysis regarding market-driven growth and inequality. To the best of the author's knowledge, this is the first study of inequality in Sri Lanka to examine changes across the labor earnings distribution, and is one of just two studies to address selection bias in the Sri Lankan context.[1] The rest of the paper is organized as follows. Section 2 discusses Sri Lanka's experience with policy reform, growth, and inequality. Section 3 presents the empirical frame- work. Section 4 describes trends in wages and labor market characteristics. Section 5 discusses the results of the quantile wage regressions, decomposition analysis, and selection correction exercise. Section 6 concludes.

2 Background

Sri Lanka provides a useful case study on the implications of pro-market policies on growth, inequality, and social welfare. In line with most developing countries at the time, Sri Lanka subscribed to import-substitution industrialization (ISI) soon after gaining independence from British rule in 1948. By the mid 1970s, it had one of the most inward-oriented and regulated economies outside the Soviet states (Athukorala and Jayasuriya, 2000). Spending on broad welfare programs significantly improved education and health outcomes, but import restrictions and the inefficiencies of ISI led to a stagnant economy with high unemployment, further straining the welfare system (Abeyratne, 2004). Income per-capita, having exceeded those of South Korea and Thailand in the 1950s, had fallen well behind by the 1970s. From the ensuing social discontent emerged two militant social movements led by youth from lower socio-economic classes. Following this came a landslide victory for the opposition right-wing United National Party (UNP) in the 1977 parliamentary elections. Having campaigned on a platform of liberalization and privatization, the UNP began dismantling the decades-long ISI regime. After political turmoil halted the reforms, a more aggressive wave of liberalization came in the late 1980s and early 1990s. Consequently, Sri Lanka was among the most open economies of the developing world by the start of the new millennium, with broad support for market-oriented policies across the political spectrum (Athukorala and Rajapatirana, 2000).

This dramatic policy shift led to a rapid turnaround in the economy. Fueled by private consumption and investment, growth in per-capita income surged after 1990 and the service sector expanded (Newhouse et al., 2016; Central Bank, 2016). Despite losing its ISI protections, manufacturing has held steady at 28% of gross domestic product (GDP) since 1977 (Central Bank, 2016), buoyed by productivity and export growth (Athukorala and Rajapatirana, 2000). Notably, the economy's sectoral composition transformed to reflect the pattern of comparative advantage, with labor-intensive sectors increasing their shares of output and exports (Athukorala and Rajapatirana, 2000). The corresponding increase in labor demand brought down unemployment from 14.8% in 1978 to 4.4% in 2014 (Central Bank, 2016).

Yet, far from being appeased, the social tensions borne out of the ISI era intensified, escalating into two armed insurrections, one of which lasted until 2009. Some argue market-driven growth failed to address economic disparities, and possibly even exacerbated them (Lakshman, 1997; Dunham and Jayasuriya, 2000). Indeed, some studies find household consumption spending became more dispersed along educational and geographic lines (Kumara and Gunewardena, 2009; Gunatilaka and Chotikapanich, 2009; De Silva, 2016). Large and costly welfare programs, often a means of achieving political patronage rather than helping the poor, were ineffective at redistribution (Dunham and Kelegama, 1997). Recent evidence, however, points to downward trends in inequality. Per-capita household consumption has risen fastest for poorer households (Newhouse et al., 2016) and its inequities along geographic lines has also declined (Kumara, 2015b). Yet, the political landscape remains volatile to this day. Within this context, the debate on inequality in Sri Lanka remains unresolved despite its enormous economic, political, and social ramifications.

Clarifying the debate on income distribution, as this study aims to do, can assist in as- suaging seemingly intractable socio-economic problems and contribute to policymaking. Prior studies on the subject focus exclusively on household consumption, which, although a critical measure of welfare, limits our understanding of distributional change. Consumption expendi- ture comprises numerous market and non-market components, including wages and salaries, asset returns, pensions, government transfers, subsidies, and borrowing. Failure to separate these components can lead to potentially erroneous conclusions about the forces driving distri- butional change. As it did in Latin America, liberalization in Sri Lanka coincided with broad changes to welfare programs (Glewwe, 1986; Dunham and Kelegama, 1997), meaning multi- ple sources operating in different directions could have influenced the income distribution. For example, the UNP government was less directly concerned with redistribution than its socialist predecessors, believing growth alone could achieve this goal (Gunatilaka and Chotikapanich, 2009). One of its policies was to replace food rations with fixed-income food stamps whose real value eroded with inflation, effectively reducing poor households' absolute and relative consumption (Glewwe, 1988).

This paper's focus on wage income helps avoid some of these confounding effects. More- over, wage income, as the largest component (one-third) of total household spending (HIES, 2012), is the primary driver of consumption changes (Newhouse et al., 2016) and is arguably more directly linked to liberalization and growth than any other income source of most Sri Lankan households. That labor earnings are chiefly responsible for Latin America's recent distributional shifts further justifies this focus. The study thus brings a new dimension to the debate on inequality in Sri Lanka, and aims to shed light on critical unanswered questions about distributional change and its underlying sources.

3 Empirical Framework

3.1 Decomposing Changes in the Mean

The log hourly wage w_{it} of individual i in survey year t is assumed to take the following functional form:

$$w_{it} = X_{it}\beta_t + \epsilon_{it} \tag{1}$$

The vector X_{it} is a set of endowments or characteristics that determine individual i's wages. The error term ϵ_{it} captures unobserved determinants of wages and is assumed to have a stan- dard normal distribution with mean zero. The returns to endowments are given by the vector β_t and are allowed to differ from year to year. The difference in the mean wage between years A and B can be expressed as follows:

$$\begin{aligned}\overline{w}_B - \overline{w}_A &= \overline{X}_B \beta_B - \overline{X}_A \beta_A \\ &= \left(\overline{X}_B - \overline{X}_A\right) \beta_A + \overline{X}_B \left(\beta_B - \beta_A\right)\end{aligned} \tag{2}$$

The decomposition is achieved by adding and subtracting on the right side $\overline{X}_B \beta_A$. This is the counterfactual mean wage if workers in year A had the endowments of workers observed in year B. The first term on the right side is the 'endowment effect', the portion of the change in the mean wage attributable to changes in average endowments, holding wage returns constant at their year A values. The second term, the 'structure effect', is due to changes in returns and unobservables, holding endowments fixed at their year B averages. This is the standard Blinder-Oaxaca decomposition of differences in means (Blinder, 1973; Oaxaca, 1973). Equa- tion 2 can be further broken down into the endowment and structure effects of each individual covariate k:

$$\overline{w}_B - \overline{w}_A = \sum_{k=1}^{K} \left(\overline{X}_B^k - \overline{X}_A^k\right) \beta_A^k + \sum_{k=1}^{K} \overline{X}_B^k \left(\beta_B^k - \beta_A^k\right) \tag{3}$$

3.2 Decomposing Changes in Quantiles

Researchers have developed a number of methods to extend the Blinder-Oaxaca framework to other distributional statistics. Popular techniques include residual imputation based on para- metric regressions (Juhn et al., 1993), nonparametric reweighting procedures (DiNardo et al., 1996), semi-parametric hazard models (Paarsch et al., 2000), and conditional quantile regres- sions (Machado and Mata, 2005). However, these methods cannot be straightforwardly applied to detailed decompositions such as Equation 3 (Fortin et al., 2011).

The technique employed here not only allows for detailed decompositions, but does so for distributional statistics other than the mean. Proposed by Firpo et al. (2009, 2011), the method estimates the effect of the explanatory variables on the unconditional quantiles of the outcome variable. To do so, the outcome variable is transformed into the recentered influence function (RIF) of the distributional statistic of interest. In the case of quantiles, the RIF regression for quantile τ of the wage distribution is:

$$RIF(w_{it}, q_\tau) = X_{it}\beta_{\tau t} + \varepsilon_{i\tau t} \tag{4}$$

where the left-hand term is:

$$RIF\,(w_{it}, q_\tau) = q_\tau + \frac{\tau - \mathbf{I}[w_{it} \leq q_\tau]}{f_w(q_\tau)}$$

The term $f_w(q_\tau)$ is the density of log hourly wages at quantile τ. The indicator variable $\mathbf{I}[w_{it} \leq q_\tau]$ takes the value 1 if individual i's wage outcome is less than q_τ and 0 otherwise. The estimator of q_τ is the sample quantile, while $f_w(\cdot)$ is estimated with Kernel density methods. The RIF captures the influence of a small change in the distribution of the outcome variable on the chosen distributional statistic — in this case, quantile τ. Firpo et al. (2009) show the average derivative from RIF regression corresponds to the marginal effect of X on quantile q_τ of the outcome variable's unconditional distribution. Thus, Equation 4 can be estimated via OLS and the Blinder-Oaxaca decomposition applied directly.[2]

Changes in the unconditional quantile τ between years A and B can be decomposed as:

$$
\begin{aligned}
W_{\tau B} - W_{\tau A} &= \overline{X}_B \beta_{\tau B} - \overline{X}_A \beta_{\tau A} \\
&= \left(\overline{X_C} - \overline{X}_A\right) \beta_A + \overline{X_B} \left(\beta_{\tau B} - \beta_C\right) + E_1 + E_2
\end{aligned} \tag{5}
$$

As in Equation 2, the first and second terms on the right measure the 'endowment' and 'structure' effects. But there is a key difference in the form of $\overline{X}_C$. This is a counterfactual distribution of covariates obtained by re-weighting the distribution of Xs in year A to look similar to that of year B (see Appendix A for description). Regressing the RIF-adjusted wages from year A on this re-weighted sample yields the counterfactual coefficients, $\beta_{\tau C}$. The re-weighting ensures the estimated structure effect reflects its 'true' value, thereby avoiding bias by a potentially non-linear relationship between the dependent variable and one or more covariates (Firpo et al., 2007). The errors generated from the re-weighting procedure are the terms E_1 and E_2, and they should be small if the linear regression model is well-specified. In practice, the error terms are computed as $E_1 = \left(\overline{X}_C \beta_{\tau C} - \overline{X}_A \beta_{\tau A}\right) - \left(\overline{X_C} - \overline{X}_A\right) \beta_A$ and $E_2 = \left(X_B \overline{\beta_{\tau B}} - X_C \overline{\beta_{\tau C}}\right) - X_B \left(\overline{\beta_{\tau B}} - \beta_C\right)$.

3.3 Selection into Wage Employment

The OLS and quantile regression coefficients may be biased if selection into employment is non-random. Wage earners may differ from non-participants and the self-employed in observ- able and unobservable characteristics. If so, calculated wages will capture these selection ef- fects and lead to incorrect conclusions about the wage distribution. The literature has two well-known popular methods to address selection bias. One models the participation decision directly, constructs a selection-correction term, and uses this as an explanatory variable in the wage regression (Heckman, 1979). However, most researchers avoid this strategy due to diffi- culties in finding suitable instruments for the participation equation that can be excluded from the wage equation. The application to quantile regressions is even more challenging.

The second strategy, which is used in this study, directly imputes wages for non-participants from the wages of observationally similar participants (Rubin, 1986; Juhn, 2003; Neal, 2004).

Wage imputation uses all available information about participants and non-participants without having to determine the reason for (non-)participation. For quantile regressions, the actual value of the imputed wage does not matter as long as we have an idea of its location along the wage distribution. Some studies assume non-participants' potential wages lie below the median, which may be justified when the vast majority of non-participants have few labor market endowments (such as education) (Johnson et al., 2000). But this is a flawed assumption for women, many of whom opt out of the workforce despite having characteristics associated with high wages.

The imputation strategy used in this study starts with defining an indicator variable, I_{it}, which takes on the values 1, 2, 3 or 4 if worker i in year t is within quartile 1, 2, 3 or 4 of the wage distribution. An ordered logit model is used to estimate the relationship between I_{it} and the following explanatory variables: age group, highest completed education level, ethno- religious group, marital status, household status (household head, spouse, adult child, parents of head, other), number of children age 0-14, number of adults in the household, number of wage earning adults in the household, and district controls. The estimates yield the predicted probability, $\hat{P}_{itq}$, of having a latent wage within quartile q, conditional on characteristics.

The next step is to construct the selection-corrected wage distribution. Using the estimated model, each non-participant i at time t is assigned a wage in quartile q with probability $\hat{P}_{itq}$, based on his/her characteristics. Each worker retains his/her reported wage. To overcome uncertainty in the imputation process, multiple imputed samples are constructed (Rubin, 1986, 1987) and the decomposition applied to each. The reported statistics come from averaging across the imputed samples.

Without knowing how people make employment decisions, it is difficult to predict ex- ante how correcting for selection will affect the results. In developed countries, male non- participants tend to be low potential earners, which means failing to correct for selection in- flates lower-tail wages and underestimates inequality (Johnson et al., 2000; Juhn, 2003). This could certainly be the case for Sri Lanka, although the absence of social safety nets such as unemployment insurance may compel a higher proportion of low-skill men to accept work. For women, participation depends on both market and non-market factors, the latter including children, marriage, and husband's income (Blau and Kahn, 2007). In developing countries like Sri Lanka, non-market influences are particularly potent due to entrenched social norms restricting women's employment options (Contreras and Plaza, 2010; Chamlou et al., 2011; Gunatilaka, 2013; Klasen and Pieters, 2015). Female non-participants could conceivably be among both low and high potential earners, thereby having an ambiguous impact on inequality statistics.

4 Data

The analysis uses data from the Sri Lanka Labour Force Survey (LFS), a cross-sectional, nationally representative survey of households conducted each quarter by the Sri Lankan government's Department of Census and Statistics (DCS). Available data cover the period 1992-2014. The LFS is the source of official labor force statistics released by the Sri Lankan government and by international institutions such as the World Bank and International Labour Organiza- tion.

Previous studies examining inequality in Sri Lanka focus on household consumption and use data from the Household Income and Expenditure Survey (HIES). The focus on labor earn- ings in this paper makes the LFS preferable to the HIES. The former is much larger in scope, covering 25,000 households compared to 2,500 in the HIES. Further, the LFS records more details about employment and earnings, while retaining the same information on individual and household characteristics found in the HIES.

The sample is restricted to individuals age 15-65. Although 55 is the official retirement age in Sri Lanka, its enforcement is largely limited to the public sector outside of which people continue working well into their 60s (Vodopivec and Arunatilake, 2011). Excluded from the sample are students, military personnel, and those who reported illness or disability prevented them from working. Also excluded are the self-employed, unpaid workers, and part-time work- ers (less than 35 hours per week).[3] The sample thus consists of two types of individuals: 1) wage/salaried employees who reported working at least 35 hours during the week preceding the survey, and 2) those who did not work at all (non-participants). The non-participant group includes those who did not work but stated they were available for employment.

4.1 Descriptive Statistics

Descriptive statistics for the data sample are summarized in Tables A1 (men) and A2 (women) in Appendix A. In all years, men comprise the majority of workers, with less than one-quarter of women choosing wage employment. This gender disparity likely stems from the presence of traditional gender norms designating women as secondary earners in the household. Social stigmas may also hinder women's economic activity, particularly when their education levels are low and only low-wage manual jobs are available to them (Boserup, 1970; Goldin, 1995; Gunatilaka, 2013; Mammen and Paxson, 2000; Klasen and Pieters, 2015). For both men and women, the share of wage employment has increased since the early 1990s, corresponding with the economy's shift from agriculture to manufacturing and services. In line with this trend, the share of 'white-collar' occupations — professional, managerial, service and sales — has also increased.

Compared to non-participants, wage workers are younger and more likely to be university graduates. Male workers have a higher rate of marriage and more children than male non-participants, while the reverse it true for women. The differences between workers and non-participants are also much greater among women, implying self-selection plays a larger role in female employment outcomes. Correcting for selection bias should, therefore, have a larger effect on the results for women.

4.2 Wage Trends

The primary measure of labor earnings is real hourly wages, calculated by dividing monthly wages by total hours worked. Monthly wages are self reported for the month preceding the survey interview. Because the LFS records hours worked per week but not weeks worked per month, total hours are computed as weekly hours times the average number of weeks in a month (52/12). Nominal hourly wages are converted into real values.[4] The log real hourly wage is the dependent variable in the wage regressions.

[Figure 1 near here]

Figure 1 shows the change in log hourly wage between 1992 and 2014 at different quantiles of the wage distribution. Wage growth among male workers was fastest at the lower quantiles and slowest at the upper quantiles, leading to falling inequality over time. For women, wage growth was weakest around the median, meaning inequality fell between low and middle earn- ing women, and widened between middle and high earning women. Figure 2 plots the kernel density of male and female log hourly wages for selected years. It shows the entire wage dis- tribution shifted rightwards during 1992-2003 and more so during 2003-2014. The shift was larger for women, particularly in the 2000s. Such a result is consistent with the expansion of labor-intensive sectors following the implementation of liberal economic reforms (Athukorala and Rajapatirana, 2000).

[Figure 2 near here]

5 Results

5.1 OLS and Unconditional Quantile Regressions

The regressions are run separately by gender. The independent variables are as follows: age and age-squared, seven education dummies ranging from pre-primary to university graduate[5], the number of pre-school and school-age children residing in the household, and indicators for ethno-religious group, marital status, occupation, public sector employment, and district of residence. Full results for survey years 1992, 2003 and 2014 are given in Tables A3 through A5 in Appendix A. The following discussion focuses on keyvariables.

Residual Wages

The regression constant represents the log wages of the reference demographic group. These workers have not completed primary schooling, do not belong to either Muslim or Tamil mi- nority ethnic groups, are employed in elementary occupations, are unmarried, and reside in the Colombo district (the country's largest metropolis). The constant term can be thought of as the unexplained or 'residual' wage that cannot be accounted for by observed worker characteris- tics. For both sexes and all years, residuals wages increase steeply with quantile. In 1992, for example, the residual wage for male workers at the 10^{th} quantile was rupees 4.50 per hour, but jumped to rupees 17.80 and 62.60 at the 50^{th} and 90^{th} quantiles, respectively. The wage labor market thus has a substantial level of inequality that cannot be explained by observed worker characteristics, with top incomes particularly large relative to the rest.

The average residual wage grew roughly 30% between 1992-2003 and 39% between 2003-2014. Growth occurred faster at lower quantiles, reducing the gap between the 90^{th} and 10^{th} quantiles by one-half for men and three-quarters for women. These changes coincided with annual GDP growth rates of 4.5% and 6.3% in the 1990s and 2000s, respectively (World Bank, 2017), suggesting economic growth prompted rising labor demand, particularly among low- wage workers.

Education and Employment

As expected, the returns to education are positive and this pattern holds across the distribution in all survey years. Returns vary by quantile, most notably for the university premium. Relative to those with incomplete primary schooling, male university graduates earned premia of 39% at the 10^{th} quantile, 48% at the median, and 157% at the 90^{th} quantile in 1992. By contrast, the returns to secondary education either remains flat or declines at higher quantiles. That wage dispersion is greater among the educated implies educational upgrading by the workforce may not only increase average wages, but also widen wage dispersion. These effects could be reinforced with the growing share of higher-paying white-collar jobs as they are mostly limited to highly educated workers.

Government jobs also pay large premia (over private sector jobs). As public salaries are set by government-appointed commissions based on service grade and seniority, large premia indicate the state's willingness to inflate remuneration above private sector levels. This may reflect the state's desire to recruit and retain good workers in otherwise unattractive jobs, but also conforms with the government's long history of using state employment to garner broad political support (Dunham and Kelegama, 1997). As the push for privatization shrank the public sector, its wage structure also evolved. In the 1990s, low earners enjoyed the largest public sector premia, while this switched to high earners by 2014. Both the decline in government jobs and its changing pay structure would have contributed to greater inequality.

5.2 Decomposition

Worker Sample (Not Corrected for Selection Bias)

Tables 1 and 2 below present decomposition results for the change in log hourly wages of male and female full-time employees. The classic Blinder-Oaxaca decomposition for the mean is shown in the first column, followed by the RIF regression results for quantiles 10, 25, 50, 75 and 90. The model appears to work well as the re-weighting errors are small in both absolute and relative terms.

The results show mean hourly wages for men and women grew 61 and 66 log points (83% and 94%), respectively, between 1992 and 2014. Of this, the endowment effect contributed 25 log points (29%) for women, compared to just 10 log points (11%) for men. The endowment effect was strongest among high wage earners, as educational and occupational upgrading to- gether increased wages by 44 log points (56%) for women at the 90th quantile. That education enhances inequality is consistent with the Latin American experience and is attributed to edu- cational returns being convex (Bourguignon et al., 2005). In Sri Lanka, too, educational returns rise faster with higher attainment (Tables A3-A5). This effect is reinforced by the positive as- sociation between higher education and white-collar employment, while the shrinking of the public sector, which had an equalizing wage structure in 1992, widened inequality further. On net, the changing composition of Sri Lanka's workforce has increased income inequality.

[Table 1 near here]

[Table 2 near here]

By contrast, shifts in labor market returns were equalizing. Signaling rising relative de- mand for low-skill workers, residual wage growth was strongest in the lower tail and (relative) returns to primary and secondary schooling increased. The expansion of labor-intensive sectors coupled with labor productivity improvements from technological change are the most likely explanations (Newhouse et al., 2016). These results are in line, once again, with Latin America where rising relative returns to low-skill labor has helped bring down income inequality in Argentina (Cruces and Gasparini, 2008), Brazil (Ferreira et al., 2014) and Mexico (Esquivel et al., 2010).

Bucking this equalizing trend is the changing wage structure in public sector jobs in favor of high earners. Why has the state altered its compensation in this manner? One possibility is the need for qualified public servants (e.g. clerks, statisticians, teachers) as an expanding economy demands improved government services. Political pressure may have also compelled the state to favor educated workers as the burgeoning private sector absorbs less-skilled labor. Double-digit unemployment persists among educated youth, despite aggregate unemployment falling to less than 3% since economic reforms were implemented. In response, successive governments have hired educated workers to contain protest and social unrest, often creating jobs specially for them (Little and Hettige, 2013). The share of Advanced Level and university graduates in the state sector rose from 20% to 51% between 1992 and 2014, compared to an increase from 7% to 17% in the private sector. This helps explain persistent political resistance against further privatization in Sri Lanka (Little and Hettige, 2013).

Selection-Corrected Sample

Decomposition results for the selection-corrected sample are reported in Tables 3 and 4 for men and women. Occupation and public sector controls are omitted because they do not exist for non-participants. Therefore, results for the worker sample are also reported as they are now slightly different. Both tables show wage imputation brings down the average wage, the decline stronger at lower quantiles. This says non-participants in the lower tail command the lowest wages in the labor market, possibly explaining their decision not to work. By contrast, at the 90th quantile, non-participants have greater earnings potential than their employed counterparts. As expected, selection effects are stronger for women. Imputation reduces female wages by 29% at the 10th quantile (compared to 12% for men) and increases them by 8% at the 90th quantile (compared to 0.6% for men). Selection bias thus compresses the wage distribution at both ends, underestimating the level of inequality. This mis-measurement is more severe for women.

[Table 3 near here]

[Table 4 near here]

That women show large selection effects reflects the complex set of factors governing their labor supply decisions. Women with high earning potential may opt out of the workforce because they receive income support from spouses or must care for children. Studies also point to the presence of social stigmas discouraging (married) women from 'unsuitable' jobs like factory work (Klasen and Pieters, 2015). These stigmas are more prevalent in developing economies where socially acceptable white-collar jobs are restricted to a small, educated elite (Boserup, 1970; Goldin, 1995; Mammen and Paxson, 2000). Consequently, female workforce participation in these countries is low except among university graduates, a pattern that also plays out in Sri Lanka. Figure A1 in the Appendix shows women with secondary schooling, while having the paper qualifications associated with high earnings, nevertheless have the low- est participation rates.[6] Male participation rates, by contrast, are much higher and do not vary nearly as much with education level.

With regard to changes over time, wage imputation reduces growth in female wages, most notably in the upper quartile. The decomposition reveals this is due to widening skill gaps between female workers and non-participants. Because highly educated women have the highest work propensity, rising tertiary education becomes concentrated among workers rather than non-participants. This is confirmed in the descriptive statistics, which show rapid growth in tertiary education among female workers but not among non-participants (Table A2). Conse- quently, selection bias overestimates the extent to which female wages grew due to educational attainment, as some of this growth came purely from selection effects. As a result, selection bias also overestimates the rise in upper-tail inequality among women.

Among men, the least educated became more likely to join the workforce over time (Figure **??**), which suppressed wage growth in the lower tail. Failing to correct for this selection effect both underestimates male wage growth and the extent to which inequality declined.

Several robustness checks were conducted. They include: 1) using monthly instead of hourly wages, 2) omitting observations with top coded earnings and hours worked, 3) changing the criteria for full-time work to 30+ and 40+ hours, 4) switching the reference years in the decomposition analysis, 5) splitting the decomposition into sub-periods 1992-2003 and 2003-2014, 6) using industry controls instead of occupation controls, 7) including part-time workers in the sample, and 8) changing the reference categories of dummy variables. While quantitative results, such as regression coefficients, change in several cases, the qualitative outcomes are unaffected. Selected results are reported in Appendix C.

6 Conclusions

This paper investigated the evolution of Sri Lanka's wage distribution during 1992-2014, a period immediately following the adoption of liberal economic policies. The study was motivated by the yet unresolved debate about the distributional impacts of market-driven growth in developing countries, as well as recent evidence of declining levels of labor income inequality in Latin America following similar economic reforms. Using unconditional quantile regressions, changes in wages over time were decomposed across the full unconditional wage distribution. The study also accounted for selection into employment.

The analysis revealed wage growth was strongest at lower quantiles of the distribution. The decline in inequality came almost entirely from coefficient effects signaling rising relative demand for less-skilled labor. This coincided with expansion of labor-intensive sectors (manufacturing, trade, transport, construction) following economic liberalization, in line with comparative advantage. But changes in workforce composition served to widen income gaps. Educational and occupational upgrading increased upper-tail wages, a consequence of the positive association between tertiary education and white-collar employment, both of which earn large wage premia. That changes in the pay structure reduced inequality while compositional shifts served to widen it is broadly consistent with evidence from Latin America's post-reform growth experience.

The study also revealed failure to correct for selection into wage employment overestimates average income and underestimates the level of inequality in a given year. This is because the average non-participant has lower potential earnings than the average worker. However, women with high wage potential also opt out of the workforce in large numbers, reflecting the complex set of non-market factors influencing female labor supply. Thus, selection bias clearly leads to large mis-measurement of female wages at both the upper and lower tails of the distribution.

Selection effects also bias measurements of changes in inequality over time. Failure to correct for selection overestimates wage growth for high-earning women, thereby exaggerating the rise in upper-tail inequality. For men, selection bias suppresses wage growth among low earners, thus underestimating the decline in inequality in male wages.

The evidence presented here has important policy implications. That market-driven growth coincided with falling wage inequality suggests a growth-equity tradeoff is not necessarily inherent to developing countries. Wage increases in the lower tail of the distribution also brought about large reductions in poverty and an improvement in living standards for poor households, implying growth has been 'pro-poor' in Sri Lanka (Newhouse et al., 2016). However, stark inequities along education, occupation, and gender groupings prevail, and in some cases worsened, confirming previous findings from studies of household consumption in Sri Lanka (Gunatilaka and Chotikapanich, 2009; De Silva, 2016). This helps explain why sustained economic growth and falling unemployment have failed to alleviate social tensions in the country. Per- sistent inequities along highly visible, well-defined markers of social status such as education and occupation can heighten perceptions of social exclusion during times of rapid economic change, even if inequality does not worsen. In a diverse society like Sri Lanka, such tensions risk escalating into violent confrontation, sometimes along ethnic and cultural divisions unre- lated to the underlying source of inequality (Dunham and Jayasuriya, 2000). That economic inequality can engender such dire social externalities within specific historical contexts reaf- firms the need for more detailed, micro-level analyses of distributional change.

The government, therefore, urgently needs to capitalize on the gains made from liberal economic reforms. Expanding access to education and good jobs should be of top priority. Despite universal free public education in Sri Lanka, inequities in school quality and ac- cess remain a serious problem (World Bank, 2005), with recent evidence showing worsen-ing gaps between rich and poor in secondary and tertiary school attendance (Newhouse et al., 2016). No doubt, well-conceived public infrastructure investment is essential. Beyond building schools and roads, the focus must also be on developing regional hubs outside the established metropolises, increasing urban-rural connectivity, and reducing the monetary and time costs of accessing education and market work. Attention should also be given to attracting more women into the labor force, for example, by increasing childcare facilities, improving public transport, and loosening legal restrictions on part-time work. Unless all segments of society are able to fully participate in the development process, the risk of social upheaval can intensify with further structural change, with costly repercussions for economic growth and political stability.

Notes

[1]The other is Kumara (2015a) who examines wage differentials by education level using data from 2013.

[2]In contrast, the conditional quantile regression of Koenker and Bassett (1978) generates *total* effects of a change in the explanatory variables on the outcome variable's unconditional distribution. This technique is used in the decomposition methods developed by Machado and Mata (2005) and Melly (2005).

[3]The self-employed are excluded because the LFS does not report self-employment incomes except in 2013 and 2014. Imputing them from observationally similar wage employees could lead to biased results if self-employment incomes are determined differently to wage incomes. Part-time workers bring another source of potential bias: their self-reported hours usually suffer from measurement error, causing a spurious negative relationship between wages and hours worked (Juhn, 2003). Moreover, including self-employed and part-time workers raises selection issues as their employment choices are not random. Because wage data is available for part-time workers, however, they are included later as a robustness check.

[4]Real wages were computed using the GDP deflator (2013=100) reported by the Central Bank of Sri Lanka. The GDP deflator was used in lieu of a consumer price index (CPI) because the only consistent CPI series calculated by the Central Bank covers just the Western Province. Whether using the GDP deflator or the CPI, the results are nearly identical.

[5]The other five educational categories are primary, lower secondary, middle secondary, Ordinary level (grade 11), and Advanced level (grade 13). 'Ordinary level' and 'Advanced level' refer to qualifying examinations administered by the central government. The Advanced level exam determines entrance to the public university system.

[6]This U-shaped relationship between women's education and participation is documented in other studies for Sri Lanka (Gunatilaka, 2013) and India (Olsen and Mehta, 2006; Klasen and Pieters, 2015).

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Tables

Table 1: Decomposition Results for Men, 1992-2014

	Mean	Q10	Q25	Q50	Q75	Q90
Wage 1992	3.863	3.119	3.555	3.868	4.295	4.609
Wage 2014	4.469	3.846	4.151	4.448	4.793	5.143
Difference	**0.606**	**0.727**	**0.597**	**0.579**	**0.499**	**0.535**
	(0.012)	(0.022)	(0.018)	(0.020)	(0.017)	(0.018)
Endowment effects:						
Age	0.008	0.005	0.004	0.008	0.011	0.012
Education	0.071	0.051	0.037	0.057	0.083	0.094
Govt	−0.023	−0.039	−0.024	−0.026	−0.023	−0.006
Occupation	0.035	0.009	0.025	0.036	0.050	0.044
Total endowment effect	**0.104**	**0.054**	**0.052**	**0.092**	**0.131**	**0.150**
	(0.020)	(0.025)	(0.016)	(0.017)	(0.025)	(0.031)
Coefficient effects:						
Age	−0.095	0.091	−0.389	0.013	−0.263	−0.121
Education	−0.001	0.190	0.111	0.030	−0.081	−0.033
Govt	0.001	−0.029	−0.016	0.002	0.027	0.061
Occupation	−0.130	−0.081	−0.213	−0.163	−0.103	−0.068
Constant	0.647	0.473	0.865	0.538	0.750	0.477
Total coefficient effect	**0.524**	**0.679**	**0.553**	**0.496**	**0.432**	**0.404**
	(0.012)	(0.028)	(0.022)	(0.015)	(0.022)	(0.026)
Error 1	−0.006	0.001	0.002	0.006	−0.042	0.014
Error 2	−0.017	−0.007	−0.010	−0.015	−0.022	−0.033

Notes: a. Bootstrap standard errors in parentheses based on 200 bootstrap replications.
b. For the sake of brevity, results for marital status, children, ethno-religious group and district controls are not shown. *Source*: Sri Lanka Labour Force Survey.

Table 2: Decomposition Results for Women, 1992-2014

	Mean	Q10	Q25	Q50	Q75	Q90
Wage 1992	3.640	2.705	3.226	3.694	4.127	4.487
Wage 2014	4.301	3.509	3.853	4.249	4.820	5.130
Difference	**0.661**	**0.804**	**0.627**	**0.554**	**0.692**	**0.643**
	(0.020)	(0.042)	(0.029)	(0.029)	(0.024)	(0.025)
Endowment effects:						
Age	0.003	−0.066	−0.027	−0.004	0.035	0.062
Education	0.153	0.149	0.138	0.098	0.116	0.240
Govt	−0.001	−0.003	−0.003	−0.001	−0.001	−0.000
Occupation	0.119	−0.006	0.044	0.122	0.232	0.206
Total endowment effect	**0.252**	**0.011**	**0.125**	**0.230**	**0.383**	**0.495**
	(0.067)	(0.123)	(0.070)	(0.060)	(0.085)	(0.118)
Coefficient effects:						
Age	−0.020	0.188	0.166	0.240	0.059	−0.216
Education	−0.002	−0.107	0.151	0.114	0.015	0.012
Govt	0.055	0.020	0.020	0.078	0.099	0.043
Occupation	−0.240	−0.404	−0.663	−0.129	−0.044	0.025
Constant	0.680	1.250	0.892	0.025	0.015	0.292
Total coefficient effect	**0.441**	**0.668**	**0.489**	**0.330**	**0.367**	**0.295**
	(0.028)	(0.093)	(0.096)	(0.089)	(0.106)	(0.110)
Error 1	0.023	0.213	0.104	−0.010	−0.007	−0.064
Error 2	−0.055	−0.087	−0.091	0.005	−0.051	−0.084

Notes: a. Bootstrap standard errors in parentheses based on 200 bootstrap replications.
b. For the sake of brevity, results for marital status, children, ethno-religious group and district controls are not shown. *Source*: Sri Lanka Labour Force Survey.

Table 3: Decomposition Results for Men, with Imputed Sample, 1992-2014

	Mean	Q10	Q25	Q50	Q75	Q90
Worker Sample						
Wage 1992	3.863	3.119	3.555	3.868	4.295	4.609
Wage 2014	4.469	3.846	4.151	4.448	4.793	5.143
Difference	**0.606**	**0.727**	**0.597**	**0.579**	**0.499**	**0.535**
	(0.012)	(0.022)	(0.018)	(0.020)	(0.017)	(0.018)
Total endowment effect	**0.143**	**0.122**	**0.089**	**0.133**	**0.171**	**0.165**
	(0.017)	(0.021)	(0.014)	(0.014)	(0.023)	(0.029)
Total coefficient effect	**0.478**	**0.611**	**0.532**	**0.438**	**0.382**	**0.399**
	(0.012)	(0.021)	(0.016)	(0.018)	(0.023)	(0.028)
Sample with Selection Correction						
Wage 1992	3.827	2.902	3.492	3.840	4.255	4.675
Wage 2014	4.437	3.719	4.128	4.442	4.774	5.149
Difference	**0.610**	**0.816**	**0.636**	**0.602**	**0.520**	**0.474**
	(0.014)	(0.038)	(0.024)	(0.010)	(0.017)	(0.021)
Total endowment effect	**0.156**	**0.168**	**0.123**	**0.132**	**0.192**	**0.207**
	(0.014)	(0.026)	(0.016)	(0.011)	(0.019)	(0.028)
Total coefficient effect	**0.463**	**0.621**	**0.527**	**0.469**	**0.345**	**0.314**
	(0.014)	(0.036)	(0.017)	(0.018)	(0.024)	(0.034)

Notes: Bootstrap standard errors in parentheses based on 200 bootstrap replications.
Source: Sri Lanka Labour Force Survey.

Table 4: Decomposition Results for Women, with Imputed Sample, 1992-2014

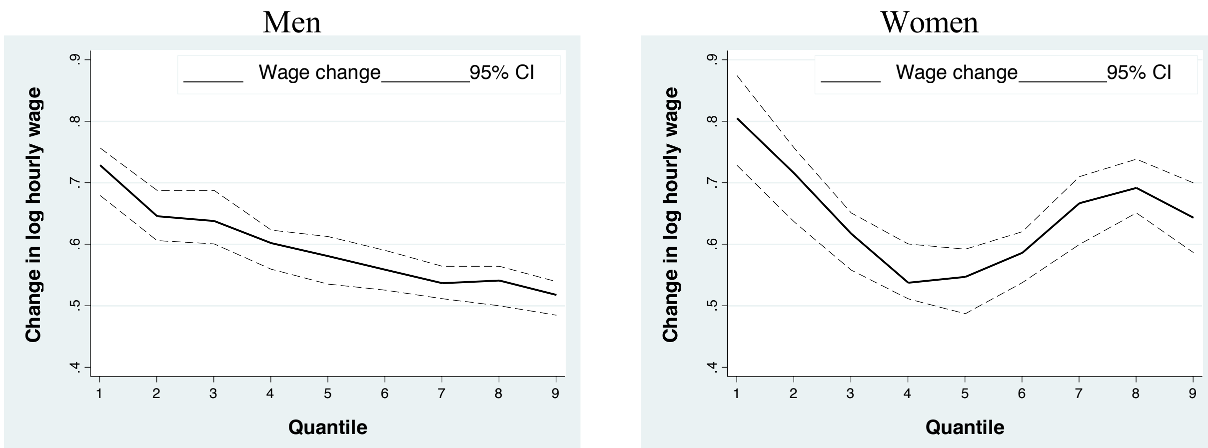
	Mean	Q10	Q25	Q50	Q75	Q90
Worker Sample						
Wage 1992	3.640	2.705	3.226	3.694	4.127	4.487
Wage 2014	4.301	3.509	3.853	4.249	4.820	5.130
Difference	**0.661**	**0.804**	**0.627**	**0.554**	**0.692**	**0.643**
	(0.020)	(0.042)	(0.029)	(0.029)	(0.024)	(0.025)
Total endowment effect	**0.297**	**0.141**	**0.200**	**0.260**	**0.369**	**0.460**
	(0.050)	(0.083)	(0.053)	(0.045)	(0.059)	(0.091)
Total coefficient effect	**0.387**	**0.580**	**0.428**	**0.293**	**0.341**	**0.310**
	(0.026)	(0.079)	(0.046)	(0.039)	(0.068)	(0.078)
Sample with Selection Correction						
Wage 1992	3.580	2.293	3.161	3.660	4.065	4.697
Wage 2014	4.208	3.169	3.779	4.175	4.679	5.213
Difference	**0.628**	**0.877**	**0.619**	**0.515**	**0.613**	**0.516**
	(0.031)	(0.047)	(0.070)	(0.027)	(0.020)	(0.041)
Total endowment effect	**0.225**	**0.198**	**0.268**	**0.207**	**0.226**	**0.305**
	(0.019)	(0.034)	(0.048)	(0.018)	(0.023)	(0.048)
Total coefficient effect	**0.413**	**0.618**	**0.413**	**0.330**	**0.317**	**0.309**
	(0.037)	(0.081)	(0.045)	(0.030)	(0.050)	(0.042)

Notes: Bootstrap standard errors in parentheses based on 200 bootstrap replications.
Source: Sri Lanka Labour Force Survey.

Figures

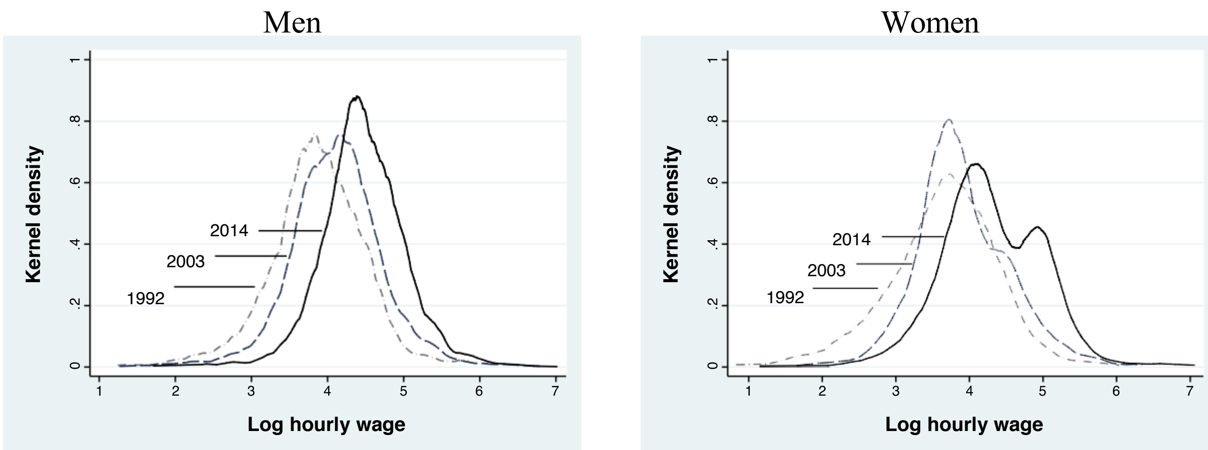
List of figure captions:

Figure 1: Change in Log Hourly Wages by Quantile, 1992-2014



Source: Sri Lanka Labour Force Survey

Figure 2: Wage Distribution, 1992-2014



Source: Sri Lanka Labour Force Survey