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The gender wage gap in Myanmar: Adding insult to injury?

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Abstract

Gender wage inequality has been studied for decades, applying highly standardized regression decomposition techniques. It is common to find that education and experience explain small parts of the wage gap while differences in occupation and sector are important. Using three different surveys, all from 2017, we analyse the gender wage gap for urban workers in Myanmar. We start from a standard Mincer-type wage equation in which we condition on the workers level of education and years of experience. Subsequently we control for differences in occupational choice and sector of employment. Finally, we compare wages for men and women with similar characteristics, working in the exact same manufacturing enterprises. Our results show that the urban labour markets in Myanmar stand out as remarkable. In Myanmar, selection into wage work leads to an urban workforce in which the female wage-workers have higher levels of education than their male counterparts. Thus, female workers should, on average, have higher wages than male workers. Even so, the observed gender wage gap is 14-35 percent, depending on the survey analysed. Differences in educational attainment and selection into occupations and sectors cannot account for this wage gap. Instead, it is associated with a lower base wage for women and lower remuneration of women's experience. Digging deeper, we go beyond the traditional standardized methods and utilize a matched employer-employee dataset to generate one-to-one comparisons of female and male production workers with the same level of education and experience who are employed in the same manufacturing enterprises. Even in this setting, in which the male and female workers are closely matched, we find an average wage gap of 13 percent. Our analysis thus indicates substantial discrimination against women in Myanmar's urban labour markets, with the situation being worst for uneducated women in low wage jobs.

Keywords: discrimination, gender, labour market, Mincer earnings function, Myanmar, wage gap

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> Women shall be entitled to the same rights and salaries as that received by men in respect of similar work.
>
> *Article 350, Constitution of Myanmar, 2008*

> Related to income, men get 3000 Kyat, women get 2500 Kyat. It doesn't depend on status. It depends on strength. It is not discrimination.
>
> [Focus group discussion with Kayan Takhundaing, men aged 26-40, Demoso Township] *(GEN, 2015, p. 76)*

1. Introduction

Article 350 of Myanmar's constitution guarantees gender equality, and progress has been made in many areas in recent years. Among the improvements are gender parity in enrolment of girls and boys in primary and secondary school and increased participation of women in the labour force and in wage employment. The improvements have given rise to a view that gender equality is not a matter of concern in Myanmar. This common view is contradicted in several reports by a range of different institutions (JICA, 2013; GEN, 2015; ADB et al., 2016; Minoletti, 2016) and recent large scale surveys of workers, households and enterprises in Myanmar, which all find gender inequalities and substantial differences in average wages for female and male workers (ILO, 2016; Berkel et al., 2018; CSO et al., 2020; Hansen et al., 2020).

In this paper we use three recent surveys to analyse the gender wage gap in Myanmar.[1] Two of the surveys (the LFS and MLCS) have broad coverage in the sense of being nationally representative of all workers and households in Myanmar. We use the two surveys to break down the gender wage gap for workers in urban areas using standard Blinder-Oaxaca decompositions (Blinder, 1973; Oaxaca, 1973) of Mincer-type wage regressions in which we condition on the workers' human capital, selection into wage work, occupational choice and sector of employment. The third survey (MEMS) is a matched employer-employee survey covering workers in micro, small and medium size manufacturing enterprises in urban areas. This survey gives us the unique opportunity of comparing female and male production workers with similar attributes in terms of human capital and occupation within firms, whereby we can test if the women actually receive the same salaries as that received by men in respect of similar work, as stipulated in Article 350 of the Constitution. To our knowledge, we are the first in a developing country context to use such within-firm matching to identify pure gender wage gaps.

The gender wage gap in Myanmar is substantial. Using the household survey (MCLS) we find that the average wage for female workers is only 71 percent of the average wage for male workers, while the fraction is estimated to be 87 percent based on data from the labour force survey (LFS). Adjusting for the bias in the estimated average wages arising from the selection into wage work, we find that the adjusted average female wage is 70 percent of the adjusted average male wage in both surveys. Moreover, Blinder-Oaxaca decompositions show that, in practice, the wage gap can be fully attributed to the wage structure (the so-called unexplained part in the decomposition). Even so, there are some countervailing forces in the composition of Myanmar's labour market. Occupational and sectoral segregation have small and opposite influences in the sense that women should be expected to receive higher wages than men given their occupations while the sector composition points to lower wages for women. However, the main driver is a substantially lower return to experience for women compared to men. Conditional on occupation and sector, a female and a male worker with the same level of education and age can expect to see a substantially widening wage gap as they get older. There are also signs of different returns to education, and the returns are relatively higher for female workers such that the wage gap is lower for educated women than for uneducated women. However, the effect, though substantial, is not precisely determined.

When we decompose the wage gap along the female and male wage distributions a pattern of very large gaps in the low end of the distributions emerge, confirming the *sticky floor* result observed in many other

[1] The three surveys are the 2017 Myanmar labour force, child labour and school to work transition survey (LFS) (Deparment of Labour, 2017), the 2017 Myanmar Living Conditions Survey (MLCS) (CSO et al., 2020) and the 2017 Myanmar Enterprise Monitoring System (MEMS) (Berkel et al., 2018).

East Asian countries (World Bank, 2011). However, in Myanmar the pattern is closely associated with the wage structure while it is not associated with the labour market composition, in terms of human capital, occupation and sector of employment. In this sense, low wage female workers are truly disadvantaged in the urban labour market in Myanmar.

A more detailed analysis of wage workers in the manufacturing sector shows that within this sector there is segregation into high and low wage firms. However, there are again countervailing factors. Larger firms pay higher wages and female workers are working in large (higher paying) firms more frequently than men. But, conditional in firm size, firms with high shares of female workers pay lower wages and relatively more women are employed in such firms. The net result is a gender wage gap in the manufacturing sector of about 12 percent which is fully accounted for by the wage structure. Focusing next on firms for which we have respondents of both sexes, such that we know for certain that the firms employ both female and male production workers, a regression analysis using this restricted sample will show if female and male production workers within firms, conditional on education, are paid the same. We find that they are not–as the gap only decreases slightly (to 10 percent), and this is a within firm wage difference, which is not related to firm size or the share of female workers in the firms.

Finally, we confirm the size of the pure wage gap by matching female and male workers within each firm, based on educational level, experience, tenure and the way they are paid. Such a strict matching requirement leaves us with a sample of only 122 female workers. The gain is that we know that each of the 122 women have a male counterpart, with the exact same observable attributes, working in the same firm. The estimated average gender wage gap for the matched female workers is 13 percent. A brief analysis of the individual wage gaps reveal that the gaps are slightly increasing in wage work experience and the wage level, thus supporting the regression based results using the LFS and MLCS surveys.

The remainder of the paper is organized as follows. Section 2 provides a selective literature review with relevance for the Myanmar context. Section 3 presets the data giving both detailed statistics of the wage distributions and more succinct summaries of the background characteristics of the wage workers in the three surveys. In Section 4 we start with Blinder-Oaxaca decompositions at the mean based on the two broad surveys and a brief illustration of the wage gaps along the wage distributions. Subsequently, we move to the analysis of the matched employer-employee manufacturing sector data, which we analyse using both standard Blinder-Oaxaca decompositions and nearest neighbour matching estimates. Section 5 has our concluding remarks.

2. Related Literature

Researchers from almost all branches of the social sciences have for decades investigated the reasons for earnings inequalities between women and men and many longitudinal and comparative studies find that the gender wage gap narrows with improvements in socio-economic development and average income. Many different reasons for this trend have been explored.[2]

First, differences in human capital endowments between men and women are important for explaining gender wage gaps in both developed and developing countries. Over time, we have seen significant absolute and relative improvements in women's education and experience and Blau and Kahn (2017) report that 40 percent of the reduction in the gender wage gap in developed countries is due to women catching up in terms of relative human capital improvements. The same order of magnitude is found in Oostendorp (2009) in his analysis of several developing countries. Similarly, Ahmed and McGillivray (2015) find significant reductions in the gender wage gap over time in Bangladesh and attribute most of this decline to women's improved educational attainment. Moreover, although gender wage gaps are found to be larger at the lower end of the wage distribution, the dynamics show that changes in the gap at lower wage levels contribute relatively more to the decline in the average wage gap over time. Duraisamy and Duraisamy (2016), for example, find that the wage gap in India has declined over time, across the wage distribution, and that relative human capital improvements was an important contributing factor.

Differences in labour force attachment giving rise to differences in wage work experience is rooted in cultural norms (Jayachandran, 2015). This will in turn affect gender wage gaps as expected returns to human

[2]See *e.g.*, Weichselbaumer and Winter-Ebmer (2005) for a meta-analysis of 263 papers with wage gap regressions.

capital investments are influenced by decisions to participate in the labour market. Similar gendered norms are expected to be at play in the case of Myanmar (GEN, 2015). Women have more family responsibilities and need temporal flexibility more than men. Internalising this knowledge, employers will have less incentives to invest in on-the-job training for women than for men. This has been documented as a worldwide phenomenon (Mitsakis, 2019). Women themselves may also avoid jobs requiring large investments in firm-specific skills because the returns from such an engagement are relatively lower for workers requiring higher flexibility and mobility. This results in the classic compensating differential where workers sort across workplaces. If employers place a high penalty on flexibility in some high-wage occupations, this will contribute to the average gender wage gap. As stated in Blau and Kahn (2017), there is considerable empirical evidence illustrating that women receive less on-the-job training than men. Several papers also document substantial penalties for flexibility, such as shorter hours and temporary workforce interruptions. Thus, norms and employer preferences may give rise to lower returns to both eduction and experience for women relative to men.

Second, although there have been significant reductions in gender gaps in education, differences in occupation and sector choices continue to be striking in Myanmar. According to the World Bank (2011) such occupational and sectoral segregation by gender is persistent over time, and occupation and sector differences are said to account for almost half of the gender wage gap in both developed and developing countries (Oostendorp, 2009; Blau and Kahn, 2017). Borrowman and Klasen (2020) study the determinants of occupational and sectoral segregation and conclude that high levels of female labour force participation are not generally associated with improvements in sectoral and occupational segregation. Especially, they find that higher levels of female labour force participation do not improve occupational quality for women relative to men. Within sectors, male workers remain more likely to occupy managerial positions than their female counterparts (for given education, experience and skills). Moreover, relative improvements (catch-up) in educational attainment is found to *increase* segregation, thereby questioning whether gender differences in occupation and sector choice is a result of educational differences between female and male workers.

Gender gaps along the wage distribution are reported in several recent studies, even within sectors and occupations. In developed countries a "glass ceiling" effect dominates as a barrier that prevents women from advancing in their careers at the top end of the income distribution and this contributes significantly to the average gender wage gap (Blau and Kahn, 2017). For developing countries, studies predominately find a "sticky floor" effect.[3] Fang and Sakellariou (2015) conclude that countries in East Asia to a larger extent are characterized by a sticky floor pattern than in other regions of the World and they argue that differences in occupational and sector segregation are likely to be the main factors contributing to the larger gap at the bottom of the wage distributions in many East Asian countries.

Finally, selection into labour force participation and into wage work is also important for understanding the roots of the gender wage gap. Since data on market incomes are available only for a self-selected group of labour-force participants, selection bias is likely to be an issue in Myanmar where labour force participation is much lower for women than for men (the ratio of female to male labour force participation is 61 percent). Moreover, wages are often only recorded for wage-workers giving rise to additional selection concerns because of the large fraction of own account workers. The direction of these biases are however not obvious. Culture and norms influence female labour market participation decisions in ways where only the most empowered women in society are part of the labour force (Jayachandran, 2015). Xiao and Asadullah (2020) document that such norms account for almost half of the unexplained portion of the gender gap in labour force participation in China. Thus female wage workers are a select group of women who are likely to be from the higher end of the (unobserved) skills distribution. As such, we expect that differences in labour force participation may lead to an underestimation of the "true" average gender wage gap. On the other hand, the most vulnerable families, i.e., households in which the adults have low education, may be forced to have higher than average female labour supply in order to secure as many income generating sources as possible for the family. Such effects would tend to result n an overestimation of the average gender wage gap. Mahajan and Ramaswami (2017) find that greater female workforce participation in the agricultural sector in India has had a sizeable effect on female wages but not on male wages. Identifying the effect of female labour supply on wages by utilizing the variation in cultural and societal norms across

[3] See Chi and Li (2008) for China, Deshpande et al. (2018) for India, Pham and Reilly (2007) for Vietnam, Fang and Sakellariou (2011) for Thailand, and Sakellariou (2004) for the Philippines.

Table 1: Daily wage rates (Kyat)

	Obs.	Sum of weights	Geometric mean	Percentile 10	25	50	75	90
				LFS				
Female	3,223	1,175,142	5,892	3,000	4,000	6,154	7,555	11,364
Male	4,640	1,589,693	6,803	4,000	5,000	6,818	8,333	12,000
Gap (%)			86.6	75.0	80.0	90.3	95.5	94.7
				MLCS				
Female	1,722	1,131,893	5,180	2,143	3,600	5,357	6,786	10,714
Male	2,535	1,552,492	7,337	4,000	5,357	7,000	10,000	14,786
Gap (%)			70.6	53.6	67.2	76.5	67.9	72.5
				MEMS				
Female	1,616	333,108	5,382	3,488	4,186	5,039	6,977	8,915
Male	3,262	411,432	6,101	4,000	5,000	6,000	7,752	9,109
Gap (%)			88.2	87.2	83.7	84.0	90.0	97.9

Note: Weighted estimates using survey weights.
Source: Authors' calculations based on LFS, MLCS and MEMS.

regions, they conclude that failing to control for changing patterns in female labour force participation will lead to a misinterpretation of gender wage differentials, and to a too large attribution of the gender wage gap to discrimination. Lee and Wie (2017) focusing on a broader, representative, sample in India from 1988 to 2010 confirm this result by documenting that labour force participation selection corrected gender wage gap estimates are much smaller than the raw gender wage gap estimates. The same authors, however, find no evidence of labour force selection bias when focusing on a comparable representative sample of Chinese workers. As such, the impact of selection into labour force participation on the gender wage gap appears to be context specific.

In the analysis below of the average gender wage gap in Myanmar we seek to take account of the above mentioned factors that have been shown to affect the gap in other (developing) countries.

3. Data and Descriptive Statistics

We use data from three different surveys with information about wages and worker attributes in 2016/2017. The largest survey is the 2017 Myanmar labour force, child labour and school to work transition survey (LFS), the second is the 2017 Myanmar Living Conditions Survey (MLCS) and the third is the 2017 Myanmar Enterprise Monitoring System (MEMS). The sampling designs for the three surveys are aimed at creating a nationally representative sample of either workers, households or micro, small and medium size manufacturing firms in Myanmar, respectively. The surveys use stratified, two-stage area sampling designs with the 7 States, 7 regions and the Union Territory as strata and administrative areas within townships as primary sampling units. The LFS and MLCS surveys further stratify rural and urban areas within the States and Regions while the MEMS survey only cover urban areas.[4] Following a large part of the earlier literature (Appleton et al., 1999; Nordman et al., 2011; Appleton et al., 2014; Yahmed, 2018), we focus on the urban population to avoid confounding arising from differences in wage structures across the rural and urban areas. Therefore, we will only use observations from the urban strata in the three surveys. Thus, our analysis only cover the gender wage gap for urban wage workers and in some cases only urban wage workers in the manufacturing sector.

3.1. Wages

Table 1 presents summary statistics for the daily wage rates as they can be computed from the three surveys using the survey weights. We use daily wage rates as this is the most common wage period observed in all

[4] More detailed information about each of the three surveys can be found in Deparment of Labour (2017), CSO et al. (2020) and Berkel et al. (2018), respectively.

three surveys. According to the LFS, some 37 percent of the urban workers refer to a daily period when they report wages while in the MLCS survey, the share is 35 percent and as much as 48 percent in the MEMS survey. For workers reporting other wage periods (hourly, weekly, monthly or yearly) we compute daily wage equivalents based on information about the total wage and the number of hours or days worked. The first and second columns in Table 1 report the sample sizes and estimated population sizes (the sum of the weights) of the male and female wage workers in the urban areas, respectively. The population of wage workers covered in the MEMS survey is only about a quarter of the populations in the two other surveys. As explained above, the MEMS survey is representative for micro, small and medium size enterprises in the urban manufacturing sector, thus it is not designed to cover the population of urban wage workers. For the LFS and MLCS surveys we find good correspondence between the estimated number of urban wage workers.

The third column in the table gives the geometric means of the daily wage rates for female and male workers. In addition, we report the female to male wage ratio (the Gap (%)). The average daily female wage rate is around 5,300 Kyats in all three surveys while the average male wage rate varies more across the surveys, in particular because of much larger wages in the high end in the MLCS survey compared to the LFS and MEMS surveys. These averages should be evaluated in context where the statutory daily minimum wage level is 4,800 Kyats.[5] The gender wage gap at the average is substantial, as the average female wage rate is estimated to be only 71 percent of the average male rate using the MLCS survey and about 87 percent using the LFS survey. The higher ratio estimated from the MEMS survey is to be expected as it is for workers in micro, small and medium size manufacturing enterprises. Thus, a female-to-male wage ratio of 88 percent in this sub-population is also substantial.

The percentiles of the wage distributions, given in Table 1, show a tendency of smaller gender wage gaps at the high end of the wage distribution compared to the low end. Thus, for the workers included in these surveys, we do not find a (strong) glass ceiling effect but a very sticky female wage floor. However, detailed comparisons of the wage distributions are complex because of substantial rounding of wage rates for both men and women. Wage rounding, in the sense of daily wage rates that are integer multiples of 1,000 Kyat, is practically the norm for workers with a daily wage period (see Table A1 in Appendix A). The rounding is also clearly visible in Figure 1, which shows the empirical cumulative density functions of the wages for female and male workers in the three surveys. As seen, the wages, and thus the gender wage gap, makes substantial discrete jumps at almost all "round" wage rates.

Price levels vary substantially across Myanmar's regions and states and this influences the wage levels.[6] The regional variation in both the levels and dispersion is substantial. Because of the considerable regional variation, we condition on regional fixed effects in all regressions and decompositions in the following.

3.2. Workers' human capital, occupation and sectors of employment

Table 2 presents summary statistics for the wage workers' human capital, their occupation and the sector of employment. We have information about the completed level of schooling for each worker in all three surveys. Again, it is reassuring to note the correspondence between the LFS and MLCS survey estimates. Comparing female and male workers, we find a much higher prevalence of highly educated female workers, in particular the highest level, which includes workers having bachelor's degrees, master's degrees and PhDs. More than a third of the female wage workers have a higher education, a stark contrast to male workers where only 15-16 percent have higher education. Unfortunately, we do not have information about the actual working experience, so we resort to computing potential experience, given as the individual worker's age less the age at which s/he is expected to have finished her/his education. Unsurprisingly, given the difference in educational levels for female and male workers, we find that male workers, on average, are more experienced–by about 2.5 to 4 years. This matches well the difference in education. As we only include workers in the age range 15-65 years, the highest potential experience a worker can have is 50 years. As seen from Table 2, we have both female and male workers with both the highest and lowest possible experience in all three surveys.

[5] The PPP conversion factor for private consumption (Kyat per international US dollar) was 367.489 in 2016, hence, the average daily wage rate for female wage earners is about PPP$ 14.5 while the average for male wage earners is about PPP$ 17.7 (6500 Kyat).

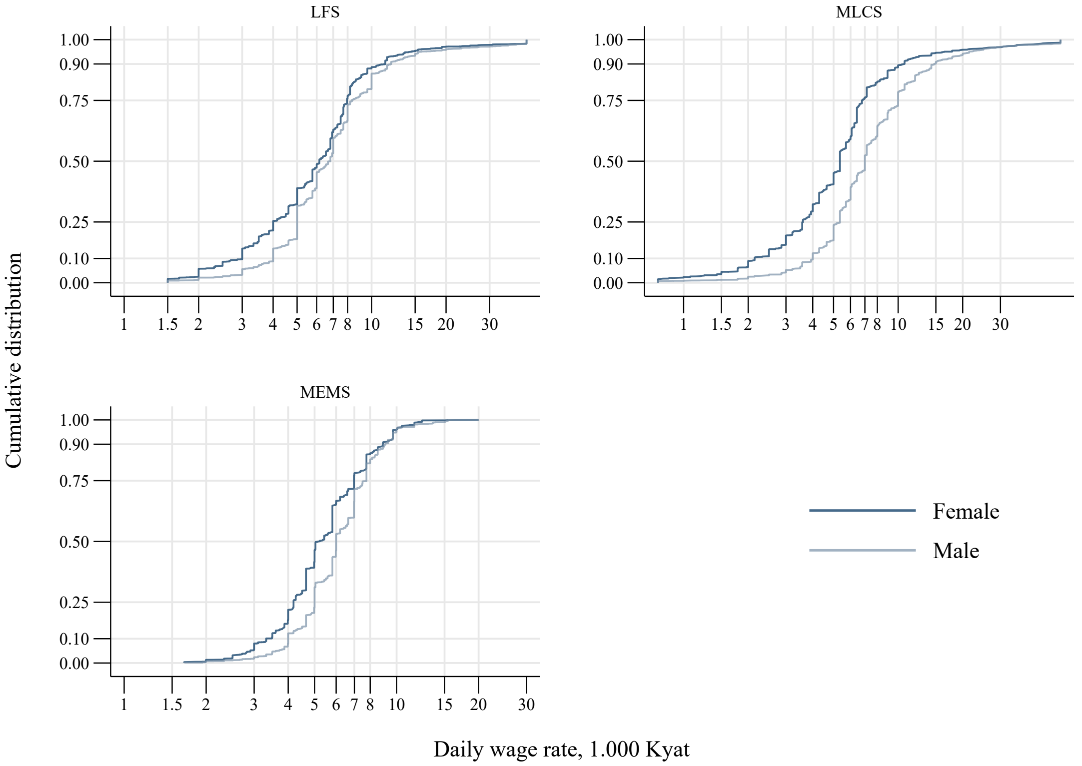
[6] The extent of regional variation in wage levels is illustrated in Figure A in Appendix A in which we present box plots of the wages for female and male workers in each State/Region.

Table 2: Summary statistics for the wage earners in each survey

	LFS		MLCS		MEMS	
	Female	Male	Female	Male	Female	Male
Potential experience						
Mean	14.400	18.195	16.064	18.650	12.696	16.908
Sd	11.671	11.994	11.981	11.998	10.812	10.831
Min.	0	0	0	0	0	0
Max.	50	50	50	50	50	50
Education						
Less than primary	0.090	0.129	0.077	0.061	0.051	0.089
Primary school	0.172	0.233	0.150	0.188	0.198	0.247
Middle school	0.206	0.301	0.178	0.319	0.195	0.246
High school	0.163	0.191	0.224	0.277	0.330	0.284
Higher education	0.368	0.146	0.371	0.155	0.226	0.134
Occupation						
Armed forces	0.000	0.009	0.000	0.012		
Manager	0.035	0.037	0.025	0.042		
Professional	0.202	0.038	0.161	0.040		
Technician	0.051	0.051	0.043	0.052		
Clerk	0.146	0.070	0.180	0.063		
Service and sales worker	0.148	0.110	0.145	0.094		
Skilled agricultural	0.014	0.027	0.001	0.005		
Craft worker	0.192	0.297	0.181	0.159		
Machine operators	0.024	0.125	0.009	0.139		
Elementary occupations	0.189	0.237	0.254	0.393		
Sector						
Agriculture	0.033	0.047	0.026	0.046		
Industry	0.342	0.415	0.319	0.431		
Mining	0.005	0.015	0.003	0.013		
Manufacturing	0.287	0.183	0.274	0.167		
Public Utilities	0.009	0.013	0.002	0.009		
Construction	0.041	0.204	0.040	0.242		
Services	0.625	0.538	0.656	0.523		
Commerce	0.142	0.114	0.211	0.135		
Transport and communications	0.045	0.162	0.024	0.143		
Financial and business-oriented services	0.102	0.104	0.049	0.045		
Public administration and defence	0.020	0.034	0.061	0.066		
Education, health, social work	0.231	0.050	0.162	0.028		
Other Service	0.084	0.074	0.149	0.107		
Legal structure						
Private company			0.236	0.192		
HH/family business			0.518	0.650		
Government/SOE			0.229	0.144		
Other			0.018	0.013		
Index of Dissimilarity						
Occupation	0.279		0.311			
Sector	0.324		0.363			
Observations	3,223	4,640	1,722	2,535	1,616	3,262

Note: Weighted means using survey weights. Middle school includes vocational training, high school includes undergraudate diploma, higher education is bachelor's degree and above.

Source: Authors' calculations based on LFS, MLCS and MEMS.



Note: Weighted estimates using sampling weights.
Source: Authors' calculations based on LFS, MLCS and MEMS.

Figure 1: Emprical cumulative density functions of wages for female and male workers

The surveys also have information about the workers' occupations. The majority of the female workers are in five occupations; as professionals, clerks, service & sales workers, craft workers and elementary occupations. The five occupations make up for an estimated 88 and 92 percent of all urban female wage workers according to the LFS and MLCS surveys. In contrast, male workers are predominantly service & sales workers, craft workers, machine operators or in elementary occupations. However, the concentration is lower as these five occupations only account for 77 and 79 percent of the urban male workers. The large share of male workers in elementary occupations in the MLCS is noticeable, in particular because it is one of the few estimates where we find large discrepancies between the LFS and the MLCS. The bottom part of Table 2 reports the Duncan index of dissimilarity for female and male occupations (Duncan and Duncan, 1955).[7] The index indicates that about 30 percent of the women or men would have to change occupation (without replacement) to obtain equal gender distributions across sectors. This order of magnitude is slightly above the average for a large set of developing countries as reported in Borrowman and Klasen (2020) but well within one standard deviation from the mean.[8] Hence, the occupational segregation is high but not extreme in Myanmar, compared to other developing countries.

Female and male workers are also employed in different sectors in much the same way as we observe in other countries. Two-thirds of the female workers are in services, and many of them are in education, health and social work or commerce. Among the one-third of the female workers employed in the industry, the bulk are in manufacturing. For male workers the split between industry and services is closer to fifty-fifty

[7]The index is computed as $D = \frac{1}{2}\sum_i \left|\frac{M_i}{M} - \frac{F_i}{F}\right|$, where M_i and F_i are the numbers of men and women working in sector i, respectively and the denominators are the total male and female wage earners.

[8]Based on harmonized household survey data from 69 developing countries Borrowman and Klasen (2020) find an average index of dissimilarity for occupation of 0.24 with a standard deviation of 0.12 and a range of 0.08-0.50. For the sectoral dissimilarity index the authors report a mean of 0.27 with a standard deviation of 0.11 and range 0.07-0.50.

(with about 5 percent in agriculture). Transportation and communication is the largest individual sector for male workers in services, while construction and manufacturing are the large sectors in industry. The index of dissimilarity for sectors of employment is also above the mean reported in Borrowman and Klasen (2020), but it is less than one standard error above the mean. Thus, the sectoral segregation is also large but not exceptional relative to other developing countries.

4. Results

4.1. Blinder-Oaxca decompositions of the gender wage gap in LFS and MLCS

We start the analysis of the gender wage gap by looking at Blinder-Oaxaca decompositions evaluated at the mean of the male and female wages. In brief, we estimate separate regression models for female (f) and male (m) workers using ordinary least squares or selection regressions. The two regressions have the same specifications for the observed (log-) wages, where the regressors include a constant term (and the inverse mills ratio in the heckit regressions):

$$Y_f = X_f\beta_f + u_f \tag{1}$$

$$Y_m = X_m\beta_m + u_m \tag{2}$$

Using estimated parameters $(\hat{\beta}_f, \hat{\beta}_m)$ and the means of the variables (indicated by a bar), the Blinder-Oaxaca decomposition at the mean can be expressed as

$$\bar{Y}_f - \bar{Y}_m = \bar{X}_f\hat{\beta}_f - \bar{X}_m\hat{\beta}_m = \underbrace{\hat{\beta}_m\left(\bar{X}_f - \bar{X}_m\right)}_{\text{Composition}} + \underbrace{\bar{X}_f\left(\hat{\beta}_f - \hat{\beta}_m\right)}_{\text{Wage structure}} \tag{3}$$

We denote the two terms in the decomposition “composition” and “wage structure”. The composition effects are the part of the wage gap that can be explained by differences in attributes and occupation or sector segregation between female and male workers while the wage structure is the part of the gap that is explained by differences in the returns to the attributes and choices of female and male workers. We consistently use the parameters from the male worker equation as weights when computing the composition effects and the average female attributes when computing the wage structure effects.[9]

We estimate four different wage equations using data from each of the LFS and MLCS surveys. In all regressions we control for regional variation in wage levels by including indicators for the States/Regions and we control for (some of) the wage rounding effects by including a wage period indicator, taking the value 1 if the wage period is not daily. Apart from these controls for possible confounders, in the first regression, we only include education and potential experience, denoted the Human Capital specification following Blau and Kahn (2017). In the second regression we seek to control for selection into wage work by estimating sample selection models (Heckman, 1979). We allow for sample selection for both female and male workers as they may (self-) select into wage work from outside the labour force as well as from own account work. In the LFS survey we have very limited information about the individuals' background, which is why we only add the size of the household (in logs) to the selection equation as an additional regressor to identify the wage equation. In addition, we only have information about whether they are wage-employed or not. As such, the selection equation groups together individuals outside the labour force and own account workers. We have more detailed information in the MLCS survey so we include information about marital status (married or not), association with the household head within the household (head, spouse, child, parent etc.) and the individual's religion (Buddhist, Christian, Islam, Hindu or other).[10] Moreover, with the MLCS data we are able to distinguish between selection into workforce participation and being self-employed. It should therefore be noted that the results reported for the selection models in Table 3 and Table 4 are not directly comparable.[11] In the third regression, we add controls for

[9] There has been much research on the index value problem in Blinder-Oaxaca decompositions. We follow Blau and Kahn (2017) and simply note that the weights we use corresponds to an experiment in which a female worker's actual wage is compared to her predicted wage in case we made a small intervention that transformed her to a male worker with the same attributes. In that sense we are estimating the average treatment effect of the treated (transforming a female worker to a male worker).

[10] Summary statistics for these selection variables are given in Table A2 in Appendix A.

[11] In Table A3 in Appendix A we report results using MLCS data for specifications directly comparable to the selection models reported in 3 in columns 1 and 2. In columns 3 and 4 of Table A3 we show results allowing for selection between wage work and own account work, conditional on being in the labour force.

Table 3: Decomposition of the gender wage gap at the mean (LFS)

Model	Human Capital		Human Capital w. selection		Full model		Full model w. selection	
	log points	% of gap	log points	% of gap	log points	% of gap	log points	% of gap
Female wage	8.681		7.984		8.681		8.012	
Male wage	8.825		8.299		8.825		8.364	
Difference	−0.144***	100.0	−0.316***	100.0	−0.144***	100.0	−0.352***	100.0
Composition	0.064***	−44.4	0.072***	−22.9	0.021	−14.9	0.033*	−9.3
Structure	−0.208***	144.4	−0.388***	122.9	−0.165***	114.9	−0.385***	109.3
Composition Effects								
Education	0.128***	−89.2	0.132***	−41.8	0.080***	−55.9	0.089***	−25.2
Experience	−0.047***	32.7	−0.048***	15.2	−0.034***	23.8	−0.036***	10.3
State/Region	0.002	−1.3	0.009	−2.9	0.002	−1.5	0.008	−2.4
Wage period	−0.019***	13.4	−0.021***	6.6	−0.025***	17.4	−0.023***	6.6
Occupation					0.035***	−24.6	0.026**	−7.5
Sector					−0.037***	26.0	−0.032**	9.0
Wage Structure Effects								
Education	0.110**	−76.2	0.235***	−74.2	0.077	−53.8	0.178***	−50.5
Experience	−0.130***	90.1	−0.270***	85.6	−0.114***	79.3	−0.253***	71.9
State/Region	0.009	−6.0	0.012	−3.7	0.012	−8.2	0.020	−5.6
Wage period	0.072*	−50.4	0.150***	−47.6	0.052	−35.8	0.139***	−39.6
Occupation					0.023	−16.2	0.014	−3.9
Sector					−0.019	13.3	−0.011	3.1
Constant	−0.269***	186.9	−0.514***	162.9	−0.196***	136.3	−0.471***	133.8
N Female	3,223		3,223		3,223		3,223	
N Male	4,640		4,640		4,640		4,640	

Note: The reference worker has no education and no experience. S/he works as an average across States/Regions, Occupations and Industries and is paid by a daily wage rate. Weighted estimates using survey weights. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
Source: Authors' calculations based on LFS.

occupation and sector choices (10 occupations, 27 sectors) to analyse the impact of segregation in the labour market on the wage gap. As seen in Table 2 we also have information about legal ownership of the work place and we include fixed factors for this (6 types) as additional controls for segregation. We denote this "the full model". Finally, the fourth decomposition is based on the full model in which we take account of selection into wage work using the same selection model as in the human capital specification. The results using the LFS survey are given in Table 3 while those for the MLCS are in Table 4.

First, we note that selection corrected estimates of the gender wage gap are relatively consistent across the two data sources (between 0.314 and 0.352 log-points). But, whereas the wage gap increases when allowing for self-selection (but not distinguishing between being out of the workforce and being self-employed) using the LFS data, the wage gap declines slightly in the MLCS data when allowing for selection into wage work. Second, in most regressions, the estimated composition effects indicate that women should have *higher* wages than men, on average, in the absence of wage structure effects. In the four regressions based on the LFS data, the composition effect is consistently positive, and it is significant even in the full model with occupation and sector controls when we also control for selection into wage work. In the full regressions using MLCS (Table 4) the composition effect is negative, marginally significant and explaining about 13 percent of the wage gap. Moreover, using either data set, we find very large differences in the reference worker wages (the constant).[12] This base difference accounts for more than the total wage gap in all regressions using the LFS data and a substantial fraction (87 percent) in the full model with selection, using the MLCS data.

We consistently find a positive composition effect of education (women have higher education) and a

[12]The reference worker (for both women and men) has no education and no experience. S/he works as an average across States/Regions, occupations, sectors and legal structures and is paid by a daily wage rate.

Table 4: Decomposition of the gender wage gap at the mean (MLCS)

Model	Human Capital		Human Capital w. selection		Full model		Full model w. selection	
	log points	% of gap	log points	% of gap	log points	% of gap	log points	% of gap
Female wage	8.553***		8.645***		8.553***		8.627***	
Male wage	8.901***		8.959***		8.901***		8.962***	
Difference	−0.348***	100.0	−0.314***	100.0	−0.348***	100.0	−0.335***	100.0
Composition	0.048***	−13.8	0.051***	−16.2	−0.046*	13.3	−0.041	12.1
Structure	−0.396***	113.8	−0.365***	116.2	−0.302***	86.7	−0.295***	87.9
Composition Effects								
Education	0.076***	−22.0	0.074***	−23.7	0.049***	−14.1	0.047***	−14.0
Experience	−0.029***	8.3	−0.024***	7.8	−0.028***	8.1	−0.024***	7.0
State/Region	0.000	0.0	0.000	−0.1	−0.001	0.3	−0.001	0.3
Wage period	0.001	−0.2	0.001	−0.2	0.001	−0.2	0.001	−0.2
Occupation					0.011	−3.1	0.012	−3.7
Sector					−0.052**	14.9	−0.050**	14.9
Legal structure					−0.025**	7.3	−0.026***	7.8
Wage Structure Effects								
Education	0.160**	−46.0	0.162**	−51.6	0.097	−27.9	0.104	−31.0
Experience	−0.164***	47.1	−0.085	27.1	−0.151***	43.5	−0.070	20.9
State/Region	0.005	−1.5	0.003	−1.1	0.006	−1.8	0.006	−1.9
Wage period	0.006*	−1.9	0.006*	−2.0	0.006*	−1.9	0.006*	−1.9
Occupation					−0.030	8.6	−0.033	9.7
Sector					−0.077*	22.2	−0.081**	24.3
Legal structure					−0.022	6.2	−0.026	7.7
Constant	−0.404***	116.1	−0.451***	143.9	−0.131	37.7	−0.202	60.2
N Female	1,722		1,722		1,722		1,722	
N Male	2,535		2,535		2,535		2,535	

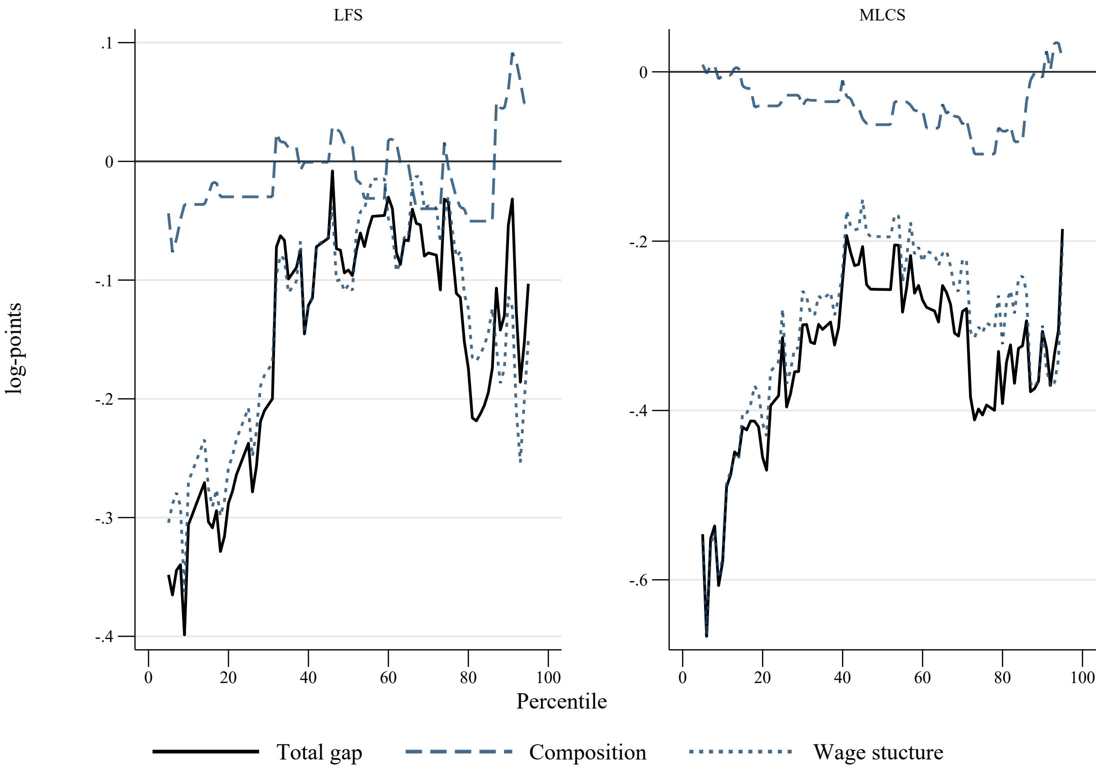
Note: The reference worker has no education and no experience. S/he works as an average across States/Regions, occupations, sectors and legal structures and is paid by a daily wage rate. Weighted estimates using survey weights. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Authors' calculations based on MLCS.

negative composition effect of experience (as women are younger). Moreover, we find significant positive, and substantial, wage structure effects of education, indicating that female workers get higher returns on education than male workers. As the base wage is lower for women compared to men, this difference indicates that female wages are relatively closer to male wages for higher educated workers, it does not indicate that highly educated women get higher wages than equally well educated men. The education effect is counter balanced, completely, by much lower returns on potential experience, even when we control for segregation. The difference in returns to potential experience is substantial, accounting for 70-90 percent of the wage gap. For the MLCS in Table 4, we find the same pattern but the relative size of the human capital effects are much smaller.

The composition effect of sectoral segregation is in line with findings in other countries in that women are relatively more frequently than men working in low wage sectors, but the relative importance of sectoral segregation is much lower than found elsewhere (Oostendorp, 2009). In contrast, the effect of occupational segregation is different from findings in most other countries, as the results in Table 3 indicate that women gain more form employment in high wage occupations (when assessed by the male returns). Using the MLCS data, occupational segregation is both materially and statistically insignificant for the gender wage gap.

The decompositions suggest that the main reason for the decrease in the wage gap across the wage distributions, as observed in Table 1, is that the wage structure is such that the gap is larger for women with no schooling, working in low-wage occupations, while it narrows for more educated women working in high wage occupations. Such a wage structure is confirmed in Figure 2, in which we plot the wage gap alongside the composition and wage structure effects for all percentiles in the range 5-95 percent of the



Note: Weighted estimates using sampling weights.
Source: Authors calculations based on MLCS

Figure 2: Decomposition of the gender wage gap along the wage distributions

distributions, based on the full model specification without selection.[13] As seen, the composition effect is small and generally unrelated to the gap until the top 20 percent of the wage distributions. In the high end we observe positive composition effects, but the wage structure effect is closely correlated (and on level) with the wage gap across the whole distribution in both data sets.

4.2. The gender wage gap in manufacturing firms

To get a more in-depth picture of the magnitude of the wage structure effects we turn to the MEMS data, which only covers micro, small and medium size firms in the manufacturing sector.[14] As seen in Table 2 the manufacturing sector employs large fractions of both the female and male wage workers in Myanmar, so by zooming in on this sector we focus on a reasonably large share of the wage workers. More importantly, MEMS is a matched employer-employee data set in which up to five production workers in each firm were interviewed about their educational and work experience background in addition to the information about their wage levels. Hence, we are able to make very precise comparisons of female and male workers with regards to equal pay for equal work–or at least equal worker attributes.

Table 5 presents Blinder-Oaxaca decompositions of the wages in the MEMS data, using the survey weights. The first regression is the human capital specification which is comparable to the corresponding specifications in Tables 3 and 4. The difference in average log-wages is -0.125 log-points, which is the same as the

[13]We estimate the percentile decompositions using recentered influence function (RIF) regressions as suggested by Firpo et al. (2009, 2018). Specifically we apply the user-written Stata command `oaxaca_rif` (see Rios-Avila, 2019). The RIF-regressions use kernel estimates of the data. Because of the wage rounding, we use a Gaussian kernel estimator with a band-with of 0.05. This narrow bandwidth preserves (most of) the bunching and this is the reason for the very erratic wage gaps in Figure 2.

[14]Micro firms have up to 9 employees, small firms have 10-49 employees while medium (and large) firms have 50 or more employees. In our MEMS data, 60 percent of the full time workers are employed in micro firms, 30 percent are in small firms and only 10 percent are employed in medium and large firms.

Table 5: Decomposition of the gender wage gap at the mean (MEMS)

Model	Human Capital		Full model		Firm model		Firm model w. mixed employees	
	log points	% of gap	log points	% of gap	log points	% of gap	log points	% of gap
Female wage	8.591		8.591		8.591		8.618	
Male wage	8.716		8.716		8.716		8.722	
Difference	−0.125***	100.0	−0.125***	100.0	−0.125***	100.0	−0.103***	100.0
Composition	0.025	−19.9	0.020	−16.3	0.043	−34.1	0.022	−20.9
Structure	−0.150***	119.9	−0.146***	116.3	−0.168***	134.1	−0.125***	120.9
Composition Effects								
Education	0.022**	−17.3	0.020**	−16.2	0.005	−4.0	0.000	0.0
Experience	−0.033***	26.1	−0.032***	25.2	−0.020**	15.9	0.003	−3.3
State/Region	0.032**	−25.7	0.039***	−30.8				
Wage period	0.004	−3.0	0.005	−3.9	−0.012	9.3	−0.001	1.0
Sector			−0.012	9.3				
Firm size					0.270***	−215.8	−0.006	6.3
Female share					0.272**	−217.5	0.002	−2.0
All male					−0.155	123.7		
All female					0.013	−10.3		
Firm					−0.331***	264.5	0.024	−22.9
Wage Structure Effects								
Education	−0.070	55.6	−0.091	72.9	0.054	−43.4	−0.027	25.6
Experience	−0.047	37.9	−0.044	35.0	0.059	−47.1	0.004	−3.6
State/Region	0.058*	−46.2	0.035	−28.0				
Wage period	0.086*	−68.7	0.077*	−61.8	0.090	−71.6	0.166	−160.1
Sector			−0.026	21.0				
Firm size					0.172***	−137.5	0.033	−32.0
Female share					−0.097**	77.2	0.000	−0.1
All male					−0.028	22.1		
All female					−0.059**	47.0		
Firm					−0.096	77.0	−0.155*	149.9
Constant	−0.177*	141.3	−0.097	77.2	−0.263	210.5	−0.146	141.2
N Female	1,616		1,616		1,616		756	
N Male	3,262		3,262		3,262		695	

Note: The reference worker has no education and no experience. S/he works as an average across States/Regions and is paid by a daily wage rate. In the regressions with firm fixed effects both the female and male worker are in an enterprise with 100 workers and 50 percent of each gender. Weighted estimates using survey weights. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Authors' calculations based on MEMS.

88.2 percent gap given in Table 2. In this survey we do find both composition and wage structure effects of location. This is caused by the sampling design as large firms are located in the main cities, Yangon and Mandalay, and, as we show later, such firms have different female-male wage gap ratios compared to smaller firms. Apart from this, the regression results are in accordance with the human capital regressions in Tables 3 and 4. In the second regression we add sector indicators (eight sectors) to test if sector segregation within manufacturing has a significant influence on the average wage gap. As seen, this does not appear to be the case. Thus, the comparison confirms the overall result that the gender wage gap is due to differences in remuneration of female and male workers.

The final two specifications in Table 5 are very different in that we include detailed worker and firm information. For the workers, we have information about their experience (number of years as wage workers) and their tenure (years working in current firm). Therefore, we replace the potential experience with this, more precise, information. We include both experience and tenure using the common specification with linear and squared terms. As for the firm information, we include firm size (the log of the number of full time employees) and the share of the full time employees that are women, including indicators for the end-points (all male and all female employee firms) to allow for special characteristics of such firms. Finally, we include firm fixed effects to account for the possibility that the wage gap is primarily caused by segregation into high and low wage firms (Blau, 1977; Groshen, 1991; Petersen and Morgan, 1995; Bayard et al., 2003).

Overall, the individual composition effects cancel out, whereby the total composition effect is small and insignificant, while the wage structure effect accounts for the full gender wage gap. The individual wage structure effects must be interpreted with caution in this model because of the many firm fixed factors. Even so, we find that education is no longer significant, neither statistically nor the order of magnitude when compared to the other effects. Moreover, even though differences in experience still explain a small fraction of the wage gap, this effect is also dwarfed by the effects of the firm characteristics.

The composition effects of both firm size and the share of female workers within the firm works to decrease the wage gap. However, this is countered by the effect of the firm fixed factors. This indicates a sorting of female and male workers. We have chosen a comparison firm that has 100 employees and equally many female and male workers. This normalization means that the average firm size for the female wages is negative (-3) and the average female share is also negative (-0.359 log-points). Thus the wage composition effects of firm size shows that the return to male workers of working in a larger firm is lower than the return to female workers. In that sense the wage structure effect of larger firms points to a smaller wage gap as shown in the table. In contrast, male workers have larger gains from working in firms with a higher share of female workers, conditional on firms size, whereby the wage structure effect is negative. Finally, on average, firms with 100 percent female employees pay lower wages than other firms conditional on firm size. Given these structural properties, the wage structure effect of the firm fixed effects is insignificant.

Within-firm gender wage differences are difficult to detect from the first of the firm model regressions because 60 percent of the sample of workers are employed in firms with only female or male workers. Therefore, in the second firm model we restrict the sample to workers who are employed in a firm in which the MEMS survey has interviewed both a female and a male worker. With this restriction we focus on firms for which we have both female and male wage information. As seen from the last rows of Table 5 this severely restricts our sample. But the gain is that the wage difference of -0.103 log-points (a female-male wage ratio of 90 percent) is the average wage gap in firms for which we are sure they employ both women and men. The small and statistically insignificant composition effect of the firm fixed effects shows that sorting into high and low wage firms is not a substantial explanation for the remaining gap. In contrast, the wage structure effect of the firm fixed factors is the estimated average pure wage gap in these firms, conditional on wage period effects, the employees' human capital endowments, firm size effects and worker composition effects. The estimate shows that female workers, on average, get 14 percent lower wages than men, for reasons not accounted for by other attributes in the regression.

Another way of estimating the average wage structure effect is to match female and male workers on observable attributes and estimate the average wage gap using only these matched workers. This estimator is based on the same assumptions as the Blinder-Oaxaca decomposition, but it does not require linearity and we can impose a common support requirement such that the thought experiment of what the wage rate would be if the woman was a man is meaningful in the sense that a man with identical observable attributes actually exists. Therefore, the nearest neighbour matching estimator is an interesting supplement to the regression models in Table 5.

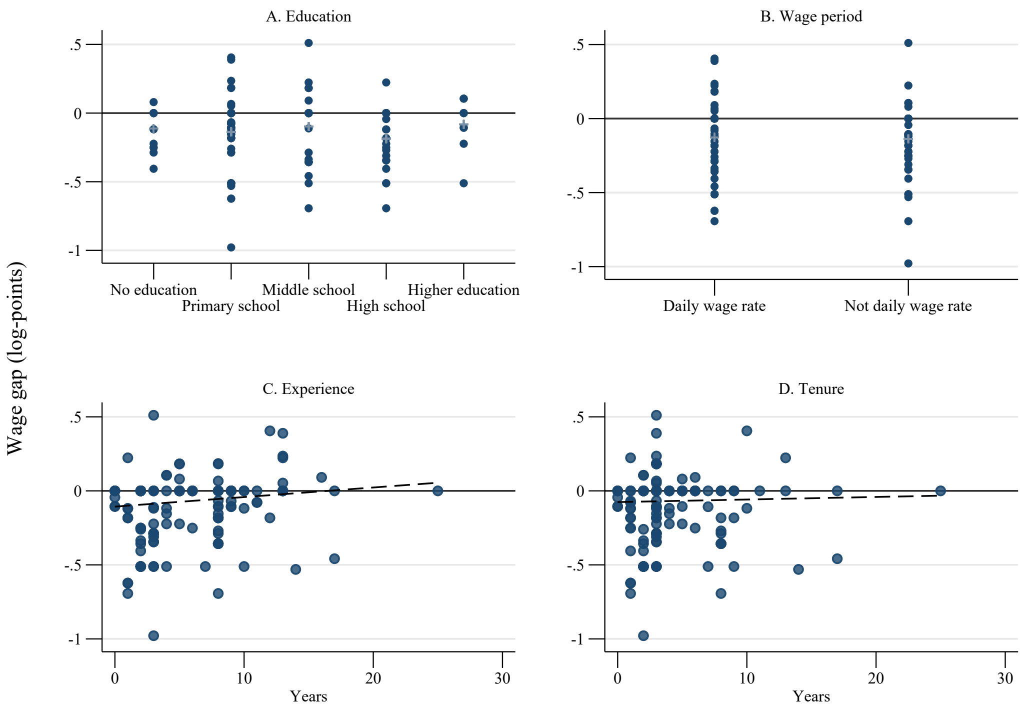
Table 6 reports results of two matching estimators. For the first, denoted broad match, we have matched female and male workers based on the Region/State, wage period, education, age (in bins of 5 years), manufacturing sector and firm size category (micro, small, medium-large). Thus, all matches of female and male workers are equal in these dimensions. To find nearest neighbours within these strata we minimize the squared difference in the firm size in which the workers are employed. This estimator has slightly more restrictive requirements than the full model specification in Table 5 but it should be a close equivalent. As seen, the estimated gap is -0.186 log-points, which is in good accordance with the regression result (-0.125 log-points), and it is statistically significant. The matching estimator illustrates the very small fraction of the sample that actually fulfils a requirement of being an exact match in the specified dimensions. We only have 293 female workers out of the full sample of 1,616 (18 percent).

To estimate the matching analogue of the within-firm conditional wage gap given in the final regression in Table 5 we find exact matches on wage period, education, experience and tenure within a given firm. This strict matching reduces the sample of female workers to 128 and we estimate the wage gap using at least a single male match based on 118 male workers (the matching is with replacement such that one male

Table 6: Nearest neighbour matching results for the gender wage gap

	Broad match		Firm, experience and tenure	
	mean	sd/se	mean	sd/se
Female wage	8.442	0.356	8.355	0.331
Predicted wage	8.610	0.224	8.486	0.276
Difference (ATET)	-0.186	0.026	-0.131	0.024
Distribution of the individual differences				
Share of negative differences	0.648		0.508	
Share of equal wages	0.010		0.367	
Share of positive difference	0.341		0.125	
N Female	293		128	
N Male	310		118	

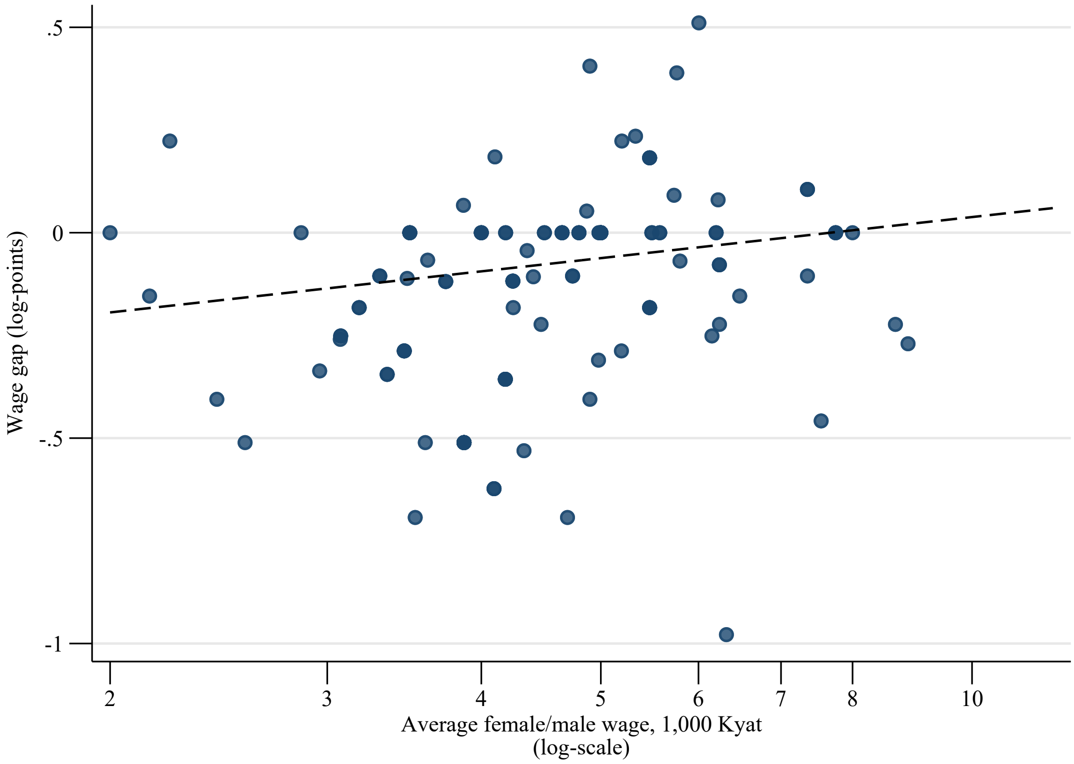
Note: The broad match has three male neighbour matches per female wage observations with exact match on Region/State, wage period, education, age (5 year bins) and firm size category. Selection on nearest neighbours within the categories is based on the squared distance between firm sizes (number of full time employees). The within firm match has one male match per female wage observation and exact match on firm, wage period, education, experience (years as wage worker) and tenure (years in firm).
Source: Authors' calculations based on MEMS.



Note: The dots are the estimated differences between the predicted and the actual wage for the 128 female workers. The '+'s in Panels A and B are the group averages. The regression line in Panel C has a slope of 0.013 (t = 2.66). The regression line in Panel D has a slope of 0.002 (t = 0.42).
Source: Authors' calculations based on MEMS.

Figure 3: Wage gaps for the matched workers along the matched attributes

worker can be a match for more than one female worker). The matched difference is -0.131 log-points (an 88 percent gap). Thus, our most strict estimate of the effect of being a woman compared to being a man endowed with the same wage contract in terms of wage period, the same level of education, the same years as wage worker and the same number of years in the same firm is a 13 percent lower wage. The estimated pure firm effect of -0.155 log-points and the "raw" difference of -0.103 log-points in Table 5 are both within a narrow confidence bound around the matching estimate.



Note: The dots are the estimated differences between the predicted and the actual wage for the 128 female workers. The regression line has a slope of 0.213 (t = 2.71).
Source: Authors' calculations based on MEMS.

Figure 4: Wage gaps for the matched workers and the average wage level for the pairs

The individual observations from the nearest neighbour match can be used to examine if the firm effect results in the Blinder-Oaxaca decomposition carries over to the smaller matched sample. We start by showing that the small sample of 128 female workers include women at all levels of education and wage period contracts as well as good variation in experience and tenure (Figure 3). The distribution across educational levels is not statistically different from the full sample of female workers (at the 5 percent level of significance), even though the matched sample is slightly tilted towards lower levels of education, and the wage differences in the matched sample do not vary systematically with the level of education. With regards to the wage period, the matched sample is different from the full sample in that a larger fraction of the women in the matched sample have a daily wage rate (63 percent) compared to the full sample (45 percent). But the average wage gaps are equal for the two groups of workers, so the bias in the sample may not be important. For experience and tenure, we find that women in the matched sample have about one year lower experience and tenure compared to the excluded women and, as seen from Figure 3 the wage gap is positively correlated with experience (i.e., the gap is smaller for women with more experience) while it is not correlated with tenure. Thus, the results we found for human capital endowments in the Blinder-Oaxaca decompositions are also present in this small matched sample.

Finally, using the individual observations we can also sketch how the wage gap vary with the wage level. Figure 4 is a cross plot of the wage difference against the average of the two wage rates (the female and the matched male wage rates). The average wage rate varies from 2,000 to just below 9,000 Kyat and there is a statistically significant positive association with the wage difference showing that the pronounced gap at the low end of the wage distribution in Figure 2 is also visible in this small sample of manufacturing workers.

5. Conclusion

We use three different nationally representative surveys to examine the gender wage gap in the urban areas of Myanmar. Two of the data sets cover workers from all sectors and occupations across all of Myanmar's Regions, States and the Union Territory while the third data set is a matched employer-employee data set with detailed information about production wage workers in micro, small and medium size firms in the manufacturing sector. We use the three data sets to estimate the relative contributions to the overall gender wage gap of (i) differences in educational levels and the return to education for female and male workers, (ii) gender segregation versus wage structure differences within occupations and sectors and (iii) gender segregation versus wage differences within firms in the manufacturing sector.

On a background of decades of research using labour market data covering all developed countries and many developing countries, applying highly standardized regression decomposition techniques, our results for Myanmar stand out as remarkable. In Myanmar, selection into wage work leads to an urban workforce in which the female wage workers have higher levels of education than their male counterparts. Thus, according to the Mincerian human capital approach to wage formation, female workers should, on average, have higher wages than male workers, unless female workers have lower returns to education. However, women appear to have higher returns to education, whereby both the composition effect and the wage structure effect suggest that female workers should have higher wages than male workers. The two results are remarkable compared to the labour markets in many other countries.

But, all along the wage distribution, female wage workers in Myanmar have substantially lower wages than male workers. Two explanations with empirical support in many other countries are segregation into different occupations and sectors. Also here Myanmar is unusual. The composition effects of occupational segregation are statistically significant and the order of magnitude is as in many other countries, but they point to higher female wages compared to male wages. The segregation into different sectors is also statistically significant and on par with findings in other countries, explaining about 25 percent of the gender wage gap. However, the sum of the composition effects is close to zero, such that the wage structure fully accounts for the observed wage gap. As such a balance of effects must be accidental, we should expect to see changes in the gender wage gap in coming years. Unfortunately, if Myanmar converges towards the structure in many other East Asian countries regarding occupational effects, we should expect an increasing wage gap.

Two effects dominate in the current wage structure. First, there are signs of gender wage differences within sectors. Second, female workers have a lower base wage and they get a lower return on experience compared to male workers. Overall, the decompositions thus points to discrimination as the main explanation of the wage gap, and the discrimination is more severe for older women with less education, who are expected to be among the lowest paid wage workers.

The signs of discrimination are reinforced by our analysis of the matched employer-employee data. When we apply the Blinder-Oaxaca decomposition on a restricted sample of firms for which we have responses from workers of both sexes and subsequently when we estimate the pure gender wage gap by nearest neighbour matching with strict requirements of the matches being for production workers in the same firms, having the same level of education, the same years of experience and the same tenure within the firm, we find estimates indicating that the average pure wage gap is about 13 percent in the manufacturing sector. As such, gender norms appear to outbalance the constitution in present day Myanmar.

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Appendix A. Supplementary tables and figures

Table A1: The shares of workers with rounded daily wage rates in the three surveys (percent)

	Rounded daily wage					
	LFS		MLCS		MEMS	
Daily wage rate	No	Yes	No	Yes	No	Yes
No	93.5	6.5	92.0	8.0	99.4	0.6
Yes	3.3	96.7	6.6	93.4	0.5	99.5
Total	59.8	40.2	62.1	37.9	51.9	48.1

Note: Weighted estimates using survey weights.

Source: Authors' calculations based on LFS, MLCS, MEMS.

Table A2: Summary statistics for variables in the selection models

	LFS				MLCS			
	Female		Male		Female		Male	
Wage worker	Yes	No	Yes	No	Yes	No	Yes	No
Potential experience								
Mean	14.400	21.541	18.195	19.871	16.064	22.870	18.650	20.875
Standard dev.	14.548	14.548	14.105	14.105	14.407	14.407	13.924	13.924
Minimum	0	0	0	0	0	0	0	0
Maximum	50	50	50	50	50	50	50	50
Education								
Less than primary	0.090	0.155	0.129	0.113	0.077	0.116	0.061	0.073
Primary school	0.172	0.243	0.233	0.193	0.150	0.199	0.188	0.129
Middle school	0.206	0.277	0.301	0.335	0.178	0.255	0.319	0.315
High school	0.163	0.218	0.191	0.262	0.224	0.285	0.277	0.361
Higher education	0.368	0.107	0.146	0.097	0.371	0.145	0.155	0.122
Household size								
Mean	5.016	5.023	5.205	5.077	4.826	5.109	4.986	5.199
Standard dev.	2.124	2.124	2.139	2.139	2.376	2.376	2.359	2.359
Minimum	1	1	1	1	1	1	1	1
Maximum	19	19	19	19	20	20	20	20
Household characteristics								
Married					0.416	0.586	0.641	0.581
Head					0.084	0.102	0.496	0.465
Spouse					0.264	0.428	0.003	0.005
Child (in-law)					0.493	0.344	0.398	0.413
Parent (in-law)					0.001	0.013	0.001	0.004
Sibling (in law)					0.056	0.041	0.020	0.035
Other relative					0.077	0.066	0.066	0.065
Unrelated					0.023	0.006	0.016	0.012
Religion								
Buddhist					0.921	0.882	0.912	0.884
Christian					0.051	0.063	0.049	0.059
Islam					0.021	0.045	0.034	0.043
Hindu					0.004	0.007	0.004	0.007
Other					0.003	0.003	0.000	0.007
Observations	3,223	12,822	4,640	8,789	1,722	6,785	2,535	4,630

Note: Weighted means using survey weights. Middle school includes vocational training, high school includes undergraduate diploma, higher education is bachelor's degree and above.

Source: Source: Authors' calculations based on LFS and MLCS.

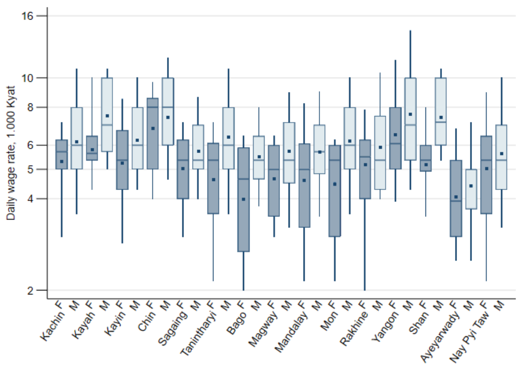
Table A3: Decomposition of the gender wage gap at the mean (MLCS): Two alternative selection models

Model	Human Capital Wage work/ Non-wage work		Human Capital Wage work/ Self-employed		Full model Wage work/ Non-wage work		Full model Wage work/ Self-employed	
	log points	% of gap	log points	% of gap	log points	% of gap	log points	% of gap
Female wage	8.661***		8.588***		8.650***		8.594***	
Male wage	9.221***		8.979***		9.331***		9.253***	
Difference	−0.560***	100.0	−0.391*	100.0	−0.681***	100.0	−0.659***	100.0
Composition	0.044**	−7.9	0.045**	−11.5	−0.052*	7.7	−0.060**	9.2
Structure	−0.604***	107.9	−0.436**	111.5	−0.629***	92.3	−0.598***	90.8
Composition Effects								
Education	0.075***	−13.4	0.076***	−19.6	0.047***	−6.9	0.049***	−7.5
Experience	−0.031***	5.5	−0.032***	8.1	−0.031***	4.5	−0.041***	6.2
State/Region	−0.001	0.1	0.000	0.1	−0.002	0.3	−0.002	0.4
Wage period	0.001	−0.1	0.001	−0.2	0.001	−0.1	0.001	−0.1
Occupation					0.013	−1.9	0.012	−1.8
Sector					−0.051**	7.5	−0.051**	7.8
Legal structure					−0.028***	4.2	−0.028***	4.2
Wage Structure Effects								
Education	0.170**	−30.4	0.162**	−41.5	0.112	−16.4	0.103	−15.7
Experience	−0.103	18.4	−0.163	41.6	−0.078	11.5	−0.204***	31.0
State/Region	0.013	−2.4	0.006	−1.5	0.024	−3.5	0.022	−3.4
Wage period	0.006*	−1.1	0.006*	−1.6	0.006*	−0.9	0.006*	−0.9
Occupation					−0.032	4.6	−0.030	4.6
Sector					−0.084**	12.3	−0.082**	12.4
Legal structure					−0.018	2.6	−0.013	2.0
Constant	−0.691***	123.4	−0.448**	114.6	−0.559***	82.1	−0.401**	60.8
N Female	1,722		1,722		1,722		1,722	
N Male	2,535		2,535		2,535		2,535	

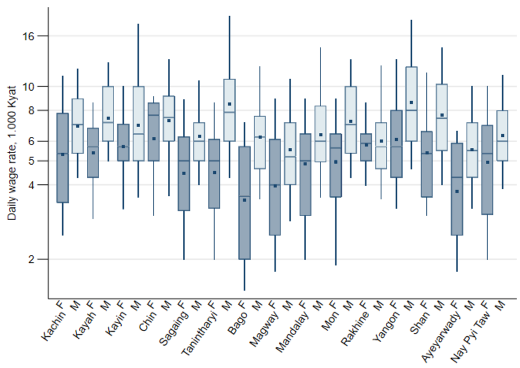
Note: The reference worker has no education and no experience. S/he works as an average across States/Regions, occupations, sectors and legal structures and is paid by a daily wage rate. Weighted estimates using survey weights. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Source: Authors' calculations based on MLCS.

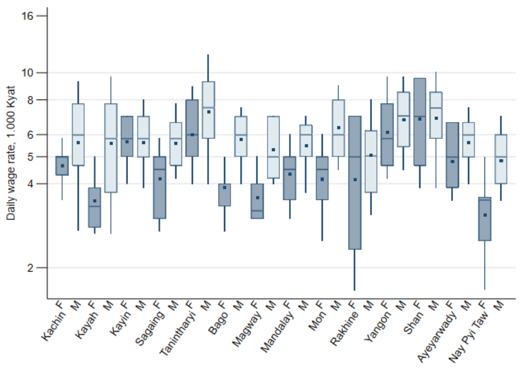
(a) LFS



(b) MLCS



(c) MEMS



Note: Weighted estimates using the sampling weights. The boxes are the interquartile range (p25-p75), the whiskers are at p10 and p90 while the lines in the boxes are the medians (p50) and the dots in the boxes are the geometric averages.
Source: Authors' calculations based on LFS, MLCS and MEMS.

Figure A: Box plots of wage distributions across states and regions