Structural divergence in gender wage gap distribution of Nepal*

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Abstract

This paper studies the evolution of the gender wage gap and looks at its source arising from the household-level dynamics. First, we decompose the selection-adjusted gender wage gap distribution over three rounds of Nepal Labor Force Surveys (1998-2018) and discuss disparities over time. Despite achieving parity in human capital, the gap stagnates for below-median earners but converges at higher wage tiers in urban and rural areas, showing a "sticky floor" nature. Moreover, by 2018, the source of the gap diverged - almost all of the gap was due to unobserved characteristics. Second, we test the implications of the household decision-making model on female labor force participation using the 2011 national census. We find that a higher spousal potential earning gap hinders women from being employed. Also, females allocate substantially more time to household chores, indifferent to the employment status, and effectively experience a "double burden" of work when employed. These results point out that improving human capital is an exhausted strategy. As long as females' participation is a derivative of males' earning potential and time allocations are skewed against females, the convergence of the gap remains challenging.

Keywords: Labor participation, Quantile-Copula, Distributional decomposition, Selection bias, Gendered Labor market outcomes, Education gap.
JEL Codes: J31, J51, C21

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1 Introduction

Understanding the outcome that females face when they participate in the labor market is key in designing gender-equitable labor policy, especially in the global south, where females still face myriad of challenges when they want to join or are in the labor market. Globally, there has been a convergence in female participation and wage rates (OECD, 2023; WEF, 2020). However the pace of convergence has been stagnating in advanced economies (Blau & Kahn, 2017). This stagnation begs the question of whether the low-hanging fruits have largely been exhausted in developed economies, leaving only politically sensitive or economically costly gender parity policy measures. If developed economies, with their greater financial strength and better institution qualities, struggle to sustain progress, it is imperative for developing countries to book-keep the factors driving the wage gap and critically examine which aspects to be addressed for avoiding the similar fate. Our contribution to this extensive literature is twofold. The first contribution of this paper is to decompose the selection-adjusted wage distribution over two decades in a developing country, Nepal. The second is to understand important channels of structural bias, differential time allocation in home production and intra-household gender education gap, against females.

Generally, women, either out of societal expectations or personal choice, allocate a larger share of time in home production, which increases women's reservation wage and makes them less likely to participate in the job market. As a result, female participation in the job market invariably suffers from the sample selection issue which was first identified and addressed by Heckman (1974) and Gronau (1974). Thus, women who participate in the job market may not represent the overall female working age population as only females with a certain set of characteristics may join the job market. Several approaches have been developed in the literature to address the selection bias (Arellano & Bonhomme, 2017; Bar et al., 2015; Blau & Kahn, 2006; Blundell et al., 2007; Buchinsky, 1998; Huber & Melly, 2015; Maasoumi & Wang, 2017; Mulligan & Rubinstein, 2008). We opt for a quantile-coupula approach of Arellano and Bonhomme (2017) and jointly estimate wage and participation equations after explicitly modeling correlation between unobservables of both equations. Methodologically, this is less restrictive compared to available alternatives and use of quantile regression helps to extract the entire wage distribution. Afterwards, we employ Chernozhukov et al. (2013) to decompose the net difference between male and female wage distributions into composition and structure effects. Prior is the wage gap resulting from the difference in individual characteristics of males and females, and latter is the difference due to varying returns of those characteristics.

The three rounds of Nepal Labor Force Surveys (1998-2018) cover some of the major events that reshaped the Nepalese labor market. The decade-long armed conflict, starting in 1996 and claiming 14,242 lives (Joshi & Pyakurel, 2015), stagnated economic growth of the country. As a result, during the conflict and the post-conflict transition, the national economy struggled to accommodate the growing youth population, which fueled the rise of international labor migration (Libois, 2016). The out migration rate surged post-conflict, peaking in 2013/14 and slightly declining thereafter (MoFESS/GoN, 2020; MoLE/GoN, 2013), and continues to provide a sizable remittance inflow up to a quarter of gross domestic product. Immediately after the conflict, interim constitution of 2007 introduced a reservation system in public institutions for women and marginalized segment of the society(Mainali et al., 2017; Subedi et al., 2022). In the mean time, economic structure transformed from subsistence agriculture to service sector, without developing a significant industrial base (Sapkota, 2013). This change led to proliferation of service sector jobs in the newly liberalized parts of economy, mainly in education, health, and finance. Thus in the two decades of data coverage, the initial one exhibits armed conflict and minimal job market changes, whereas the second entails peak out migration, rapid growth of service sector, and the implementation of reservation system.

We find notable trends of gender wage convergence between high-earners, while a widening or stagnated gap among low-earners. The “sticky floor”, rather than “glass ceiling” phenomenon seems to be a more apt characterization of this change. The female labor force participation declined from 30.2% during agriculture led job market of 1998 to 16.9% in 2018, when service sector dominated available jobs. This change in the available jobs’ nature along with affirmative action policies, mandating 33% women participation, selectively benefited educated women at the upper end of the wage distribution. The educational advantage in service sector led to a significant influx of educated women into the labor force over the course of two decades. As a result, contribution of composition effect in the wage gap grossly vanished by 2018 across the entire wage distribution. Overall in these two decades, wage disparities remarkably shifted towards being mostly structurally driven rather than compositional one.

The qualitative change in the nature of gap, i.e., very meager compositional gap but almost all structural gap, imply improving human capital alone won’t budge the gap. The culprit, structural effect, comes from two sources: first, differing returns to observed characteristics and second, unobserved characteristics in the wage equation. The second part, unobserved characteristics can be any of myriad of variables that have been studied in the literature like personal preferences(Le Barbanchon et al., 2020; Wiswall & Zafar, 2017), household dynamics (Bertrand et al., 2015; Goldin et al., 2017), job characteristics (Card et al., 2015), and societal structures (Becker et al., 2019; Givord & Marbot, 2015; Goldin, 2006; Lippmann et al., 2020) over others that effect female job market participation and outcome. To understand the increasing trend of structural effects especially in urban areas, we look at the household level dynamics and check how they suppress women from participating in gainful employment. The stylized household decision-making model of Cortés and Pan (2020) makes some interesting predictions. If wives have or are presumed to have advantage in household tasks, they are less likely to participate in job market vis-a-vis their husbands. On top of it, if husbands have larger advantage in job market, this advantage skews wives more so towards household chores.

We test this prediction in national census (2011) by looking into the relation between differential earning potential and employment status. We find spousal education gap, the proxy for difference in earning potential, hinders female job market participation and promotes sorting of female into home production especially after marriage. The negative effect of spousal education gap increasingly overshadows gains from years of schooling when single women first marries and later becomes spouse of household head. Interestingly, the spousal education gap does not hinder female participation in own account work, but only employment in labor market.

Further, we find this observed gendered sorting to be consistent with the time allocation in home production. Females allocate a similar amount of time doing household chores in three data sets: a living standard and two labor force surveys covering 2008 to 2018. In this decadal time frame, women's time declined by 40 minutes from previous 142 minutes, which when examined along side the employment status looks hollow. Men, regardless of employment status, contribute very little. But, females consistently work almost at the same level. The observed decline does not seem to originate from substitution across gender, but could have been through widespread adoption of home appliances and infrastructure development, like increased access to piped drinking water, that is beyond the scope of this paper. These results in combination confirm that household dynamics are important part of increasing structural effect when considering selection.

The paper is organized in the following fashion. In section 2, methodology, we review selection adjustment methods and describe estimation strategy used in this paper. In section 3, we describe nature and sources of data along with changes in the work force characteristics. Section 4 presents results and discussions of decomposition, selection, time use, and earning potential sequentially. In section 5, we conclude with possible extensions.

2 Methodology

2.1 Existing approaches and related literature

The measurement of the gender-based wage gap can be traced back to the seminal work of Oaxaca (1973) and Blinder (1973), wherein the mean wage gap was decomposed into composition and structure effects. This methodological development has spurred a substantial body of research aimed at refining and extending the Oaxaca-Blinder decomposition beyond the single point estimate of the wage distribution over the past half-century

(Fortin et al., 2011). Methodological extensions towards whole of the wage distribution allows for the identification of gender gaps specific to particular wage groups, facilitating a deeper understanding of differences both between and within groups (J. Machado & Mata, 2005). Recent applications of distributional decomposition include study of wage gap (Maasoumi & Wang, 2019), educational achievements (Le & Nguyen, 2018), and regional inequalities (Jemmali, 2023) over others.

A major hurdle in distributional decomposition is to construct a counterfactual distribution, which can not be directly observed. As a result, significant amount of effort in decomposition literature has been devoted to develop methods for constructing counterfactual. DiNardo et al. (1996) use kernel density reweighing, whereas, Firpo et al. (2009) utilize recentered influence function. J. Machado and Mata (2005) deploy quantile regression to estimate the inverse conditional distribution function. In contrast, Chernozhukov et al. (2013) tackle the problem directly by estimating the conditional distributional regression model using quantile regression.

In addition to going beyond mean, addressing the selection concern has been an important agenda in studying gender wage differentials. Four major strategies in the literature have been developed, namely: (a) imputation, (b) identification at infinity, (c) parametric modeling of selection, and (d) the bounding approach (C. Machado, 2017). The imputation method involves utilizing observed covariates and economic model-based restrictions to impute values for the missing part of the data, i.e., those who do not participate in the work. A recent application, Blau et al. (2021), searches backward and forward in the panel data and proxies missing wage by the observation in the nearest wave. In contrast, identification at infinity circumvents the selection by limiting itself only to a much-smaller segment of labor force where participation rates are very high and selection is considered negligible (Heckman, 1990; C. Machado, 2017; Mulligan & Rubinstein, 2008).

The parametric approach to selection correction is bolder; it aims to explicitly model the selection process, either at the mean (Heckman, 1974, 1979; Newey, 2009) or at quantiles (Buchinsky, 1998). In these models, the outcome and the latent selection equations exhibit linearity with respect to covariates and error terms are assumed to be independent of covariates conditional on the selection probability. In comparison, the bounding approach has a lesser ambition as it only seeks to tighten the worst-case scenario bounds on the gender wage gap viá restrictions motivated by the economic theory (Blundell et al., 2007). But, these restrictions – availability of instrument to tighten the bound, pre-suppositions on the selection's sign, or both – being weaker than parametric modeling impose wider bounds.

In the spirit of Buchinsky (1998), we correct for selection viá parametric approach in the quantile framework. However, we use Arellano and Bonhomme (2017)'s copula based technique to model the joint-distribution of error terms in outcome and selection models. This approach overcomes Huber and Melly (2015)'s critique concerning the conditional independence assumption in sample selection models, particularly its implication of identical slopes across all quantile regressions. With additional restrictions compared to the bounding approach, our methodology provides more tighter bounds and greater flexibility in capturing the direction of sample selection from the observed data, rather than relying solely on theoretical priors.

2.2 Selection in a distributional decomposition

We consider a standard employment and wage generating model with

$$Y^* = q(U, X), \tag{1}$$

$$E = \mathbb{1}\{V \leq p(Z)\}, \tag{2}$$

$$Y = Y^* \text{ if } E = 1, \tag{3}$$

where the latent wage Y^* is a function of wage determining observables X and unobservables U. The V is the difference in unobservables of the reservation and market wage equations, which jointly with $Z = (B, X)$ defines the employment status E. Since we can only observe wage Y of employed, we are left with a sample selection bias dictated by the dependence structure between two sets of unobservables, U and V. Further, the Z strictly contains X and the instrument B influences employment status but not the wage.

Given the availability of (a) exclusion restriction ($(U, V) \perp\!\!\!\perp Z|X$), (b) continuous joint distribution of (U, V), defined as $C_x(u, v)$, strictly increasing in u, (c) continuous outcome such that $\tau \mapsto q(\tau, x)$ is strictly increasing and continuous in τ, and (d) propensity score, $p(Z) \equiv \Pr(E = 1|Z)$, which is always greater than zero, Arellano and Bonhomme (2017) show that the observed rank for the τ^{th} quantile, $q(\tau, x)$, is no longer the τ in the selected sample, i.e.,

$$\begin{aligned} \Pr(Y^* \leq q(\tau, x)|E = 1, Z = z) = Pr(U \leq \tau|V \leq p(z), Z = z) = G_x(\tau, p(z)) \\ \equiv C_x(\tau, p)/p. \end{aligned} \tag{4}$$

Instead, the conditional copula G_x maps ranks τ in the distribution of Y^* conditional on $X = x$ to ranks $G_x(\tau, p(z))$ in the distribution of Y conditional on $Z = z$. Thus, for all $\tau \in (0, 1)$, the conditional τ-quantile of Y^* coincides with the conditional $G_x(\tau, p(z))$-quantile of Y given $E = 1$. As a result, knowing G_x map from latent to observed ranks mean we can recover $q(\tau, x)$ as a quantile of observed outcomes by shifting percentile ranks.

We work with linear quantile functions, which are selection corrected in three steps: first, propensity score $\hat{p}$ is computed using a probit model, second, copula parameter $\hat{\rho}$ is estimated, and third, given $\hat{p}$ and $\hat{\rho}$, τth quantile regression coefficient $\hat{\beta}_\tau$ is computed. Frank copula is used to model the dependence structure between U and V. The choice of the Frank copula is primarily motivated by its simplicity, as it relies on a single parameter ρ. Moreover, the Frank copula demonstrates considerable flexibility, allowing for a wide range of data-driven dependencies, including negative. Also, ρ has an useful interpretation; a negative ρ imply positive selection into employment and vice-versa. Additionally, we examine the robustness of results on copula-choice and provide Gaussian copula based estimates.

Using the law of iterated probabilities, the wage cumulative distribution function conditional on gender $F_{Y_g|D_g}$ can be expanded to an integral of conditional outcome over the observed characteristics as

$$F_{Y_g|D_g}(y) = \int F_{Y_g|X,D_g}(y|X=x) \cdot dF_{X|D_g}(x), \qquad g \in (m, f). \tag{5}$$

To construct counterfactuals, e.g., what would be females' wages if they were paid like men, we can either manipulate F_X as in DiNardo et al. (1996), or $F_{Y|X}$ as in Chernozhukov et al. (2013). The earlier approach uses re-weighting by propensity scores, which is not easily extended to address selection (Maasoumi & Wang, 2017), whereas, the latter estimates conditional distribution of the outcome employing the conditional quantile regression. We follow Chernozhukov et al. (2013) and swap selection corrected conditional quantile regression coefficients across groups to construct counterfactual scenario of when females' returns are like males' as

$$F_{Y_m^C:X=X|D_f}(y) = \int F_{Y_m|X,D_m}(y|X=x) \cdot dF_{X|D_f}(x). \tag{6}$$

With the counterfactual in hand, we can apportion the total difference between male and female wage distribution ($TE \equiv F_{Y_f:X=X|D_f} - F_{Y_m:X=X|D_m}$) into differences due to differing returns to labor market characteristics (structural effect or SE) and differential distribution of those characteristics (composition effect or CE) i.e.,

$$\begin{aligned} TE &= \left[F_{Y_f:X=X|D_f} - F_{Y_m^C:X=X|D_f}\right] + \left[F_{Y_m^C:X=X|D_f} - F_{Y_m:X=X|D_m}\right] \\ &= SE + CE. \end{aligned} \tag{7}$$

We assume male to be the baseline and do not model male's selection into the workforce. A lack of suitable instrument for male's workforce participation also led to this methodological decision. As a result, the selection adjusted and unadjusted results differ in SE and TE, but not in CE. The practical implementation of the wage equation include years of schooling, experience, experience squared, caste group, marital status, total hours spent on household chores, buildup density in the district, and average district level out-migration. These variables are similar to human capital specifications of Blau and Kahn (2017) and implementation found in Maasoumi and Wang (2019). Details on the variable construction are available in the annex.

2.3 IV and the exclusion restriction

In literature, spousal income and number of children are two popular instrumental variables (IV) used for the female selection into the labor force. The pioneering work of Heckman (1974) uses number of children in a shadow price function, where as, others use it as an instrument (Chang et al., 2011; Heckman, 1980; Lee, 2009; Maasoumi & Wang, 2019; Mulligan & Rubinstein, 2008). The underlying argument of the IV is increased cost of child rearing will hinder women participating in the labor force. The strength of this exclusionary assumption depends on socio-economic norm which can vary widely in developed and developing economies. In Nepal, families are multi-generational and often child rearing is shared with grandparents. Additionally, in labor force surveys, we can observe that most women's labor participation in figure 1 is after the childbearing age group which is typically around 20 years of age (GoN/MoH et al., 2017). The use of second style of IV, non-wife spousal income, used in Martins (2001) and Schafgans (1998) and Chang et al. (2011), requires richer data-set than available to us.

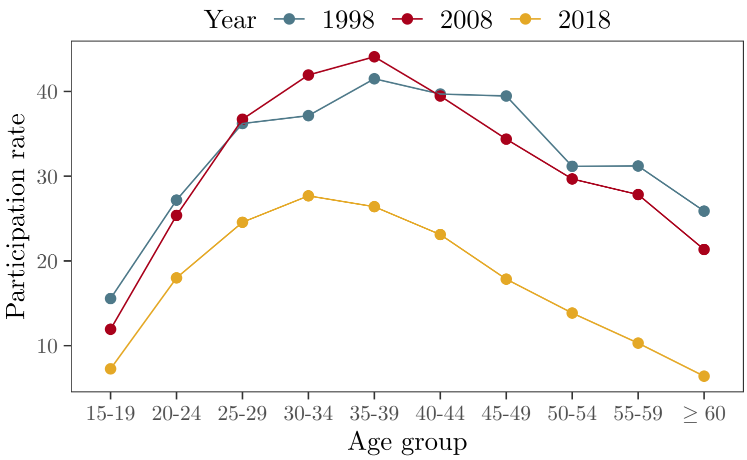

Figure 1: Female labor force participation with age group

In this context, we use the ratio of number of other wage earners to total working age population as an IV to determine female labor force participation. The key assumption being that it is plausible for females to specialize in home production and be excluded from the labor market if other family members are already earning. Also, the use of share instead of directly using non-wife wages, avoids the problem of using spousal income, i.e., high wage earners marry similarly earning mates. A similar exclusion restriction strategy in conjunction with other instruments is implemented by Yahmed (2018). Additionally, we exploit the test developed by Huber and Mellace (2014) to examine the validity of the instrument. They show that assumptions of exclusion restriction and positive monotonicity of selection instrument in the standard employment and wage generating model imply following two inequality constraints

$$\mathbb{E}(Y|B=1,E=1,Y\le y_{\mathrm{q}}) \le \mathbb{E}(Y|B=0,E=1) \le \mathbb{E}(Y|B=1,E=1,Y\ge y_{1-\mathrm{q}}), \quad (8)$$

where q is proportion of always selected in the mixed population, and y_{q} is the q-th conditional quantile in the conditional outcome distribution given $B=1$ and $E=1$. These twin inequalities can be jointly tested using following null hypothesis:

$$H_0 : \begin{pmatrix} \mathbb{E}(Y|B=1,E=1,Y\le y_{\mathrm{q}}) - \mathbb{E}(Y|B=0,E=1) \\ \mathbb{E}(Y|B=0,E=1) - \mathbb{E}(Y|B=1,E=1,Y\ge y_{1-\mathrm{q}}) \end{pmatrix} \le \begin{pmatrix} 0 \\ 0 \end{pmatrix} \quad (9)$$

We discretize the instrument by presence of any other wage earner in the household as one and zero otherwise and test the joint hypothesis using mean and probability constraints. We fail to reject the proposed IV in all of our data sets even when considering all types of data partitions. In contrast, number of children in the family as an instrument either fails to converge or is rejected by the test in most of the data sets. The test results are available in the annex.

2.4 Household dynamics in female participation

We check for role of the household dynamics in women's labor market outcomes vis-á-vis men through two ways. First, we look in to the effect of earning potentiality on job participation, and second, we examine gender gap in time allocated for home production. For the first, we explore how differential earning potential changes probability of female's engagement in employment using census (2011) data set. We proxy earning potential by male-female average years of schooling gap. The basic regression is a logit model for the probability that female f in household h participates in employment as an employee,

$$P(\text{Employee}_{f,h}) = GAP_h\beta + X_f\gamma + Z_h\delta + \psi_u + \pi_d + \epsilon_{f,h}, \quad (10)$$

where GAP_h is male minus female average years of schooling of household h, X_f is a vector of individual characteristics of female, Z_h is a vector of household characteristics, ψ_u is urban dummy, π_d are district dummies, and $\epsilon_{f,h}$ is the stochastic error term.

This GAP_h is a rough measure as it compares all working age female household members with male members. For a sharper measurement of earning potential difference, we look into spousal pairs, replacing GAP_h in equation 10 with GAP_f, which is the gap in years of schooling between female and her husband. We extract two types of spousal pairs from the census. The first type is son and daughter-in-law pair. The second type is household heads and their spouses. These two types of spousal gaps allow us to examine differences caused by degree of home production responsibility. For robustness of the specifications, we also check the probit versions of the discussed models. Further, we contrast the results of probability of female being employed against female engagement in the own account work.

For the second objective, we run a baseline OLS model of time spent on doing household chores by individual i of household h as

$$TimeSpent_i = F\beta_1 + E\beta_2 + (F \times E)\beta_3 + X_i\gamma + Z_h\delta + \psi_u + \epsilon_{i,h}, \tag{11}$$

where F is a female dummy, E is an employed dummy, $F \times E$ is an interaction term, X_i is a vector of individual characteristics, Z_h is a vector of household characteristics, ψ_u is urban dummy, and $\epsilon_{i,h}$ is the stochastic error term. Years of schooling, age, and age squared are included in X_i, whereas, house ownership, land ownership, household size, and caste group are included in Z_h. The time spent doing household chores is defined as total hours spent on home production and running household errands. Complete variable descriptions are available in the annex.

Coefficients of interest are $\hat{\beta}_1, \hat{\beta}_2$, and $\hat{\beta}_3$ which provide information on gender-wise differential time allocation. For robustness of coefficients, we use two strategies. First, we construct variables with same definition from Living standard survey (2011) and Labor force surveys (2008, 2018) to conduct baseline regressions. Second, we remove variation associated with personal and household characteristics using statistical matching followed by regression. We use Mahalanobis distance matching using generalized full matching approach that assigns every unit to subclass and minimizes the largest within-subclass distances in the matched sample (Sävje et al., 2021). Data balance, before and after matching, is reported in annex figure A5.

2.5 Data sources

We compute wage gap through three rounds of nationally representative Nepal Labor Force Survey (NLFS) produced by National Statistics Office (NSO), formerly known as Central Bureau of Statistics (CBS), dated 1998, 2008, and 2018. These are multistage stratified random sampling surveys that consider geographical domain, urban-rural heterogeneity, and seasonal variation, followed by probable oversampling adjustments. The first round interviewed 14,400 households, while the subsequent rounds interviewed 16,000 and 18,000 households, resulting in a working population (15 - 65 years) of 38,535, 44,734, and 47,905 individuals, respectively. These surveys provide information on cash earnings from which we extracted employed samples of 6,477 (76% males and 24% females), 7,565 (74% males and 26% females), and 7,838 (76% males and 24% females) across all rounds. In addition to wages, surveys report individual and household characteristics, including demographics, skills acquisition, and job market attributes.

For effects of earning potentiality on female labor market participation, we use Housing and Population Census 2011 of Nepal, also conducted by NSO. For this analysis we include all individuals in the working age (15-65 years). The census surveyed total of 5,427,302 households, out of which the available micro-data randomly samples approximately 15.5% of the total households to get the sample of 841,565 households. Additionally, we extract time use from the third round of Nepal Living Standard Survey (NLSS III) 2011. It was also conducted by NSO using two staged stratified random sampling with a population frame of census 2011. Six thousand households were interviewed across Nepal, leading to a working population sample size of 18,260 individuals, with 8,074 males and 10,186 females.

3 Labor market characteristics

Alongside political and social upheavals coming from the civil war and mass migration, the timeline 1998 to 2018 encapsulates major shift of economic activities from low productive agriculture sector to high productive service sector. In between, agriculture sector declined by 8 percentage point from 34% in 1998, whereas service sector thrived with the increase from 8% to 13% for market services [1] and 25% to 37% for non-market services [2]. This trend of transformation differed with geography. Earlier in 1998, women in rural areas were predominantly in agriculture whereas, women in urban areas were mostly in health, education, government and manufacturing sector. With time however, importance of manufacturing declined substantially in both urban and rural areas. These manufacturing jobs in urban areas were mostly in textile and garment industries, which went bust after the end of the Multifiber Arrangement in the early 2000s (Shakya, 2018). Industry wise, females in 2018 are engaged in health, education, and government jobs in both areas; see figure 2. Since 2008, these sectors have absorbed females at a large scale with the introduction of reservation system (Subedi et al., 2022). Another important employers of females are banking and private enterprises, primarily in urban areas.

The economic transformation also changed the nature of available work. In 1998,

[1] Market service includes trading considering both retail and wholesale services, transportation, financial sector including banking, financing and insurance, repair and maintenance, communication including broadcasting, information technology, and repairs and maintenance.

[2] Non-market services consists of public administration, defence, education, health and social services.

around 50 % of the jobs were elementary occupations, usually in agriculture. On the other hand, managers, professionals and technicians only held 21% of the jobs. In the period of two decades, elementary occupation reduced by 5 percentage points and managerial jobs increased by almost 12 percentage points. Females, in 1998, were mostly engaged in the elementary occupation; see figure 3. By 2018, jobs that employed females in rural areas were bifurcated into elementary occupation and newly growing white collar jobs.

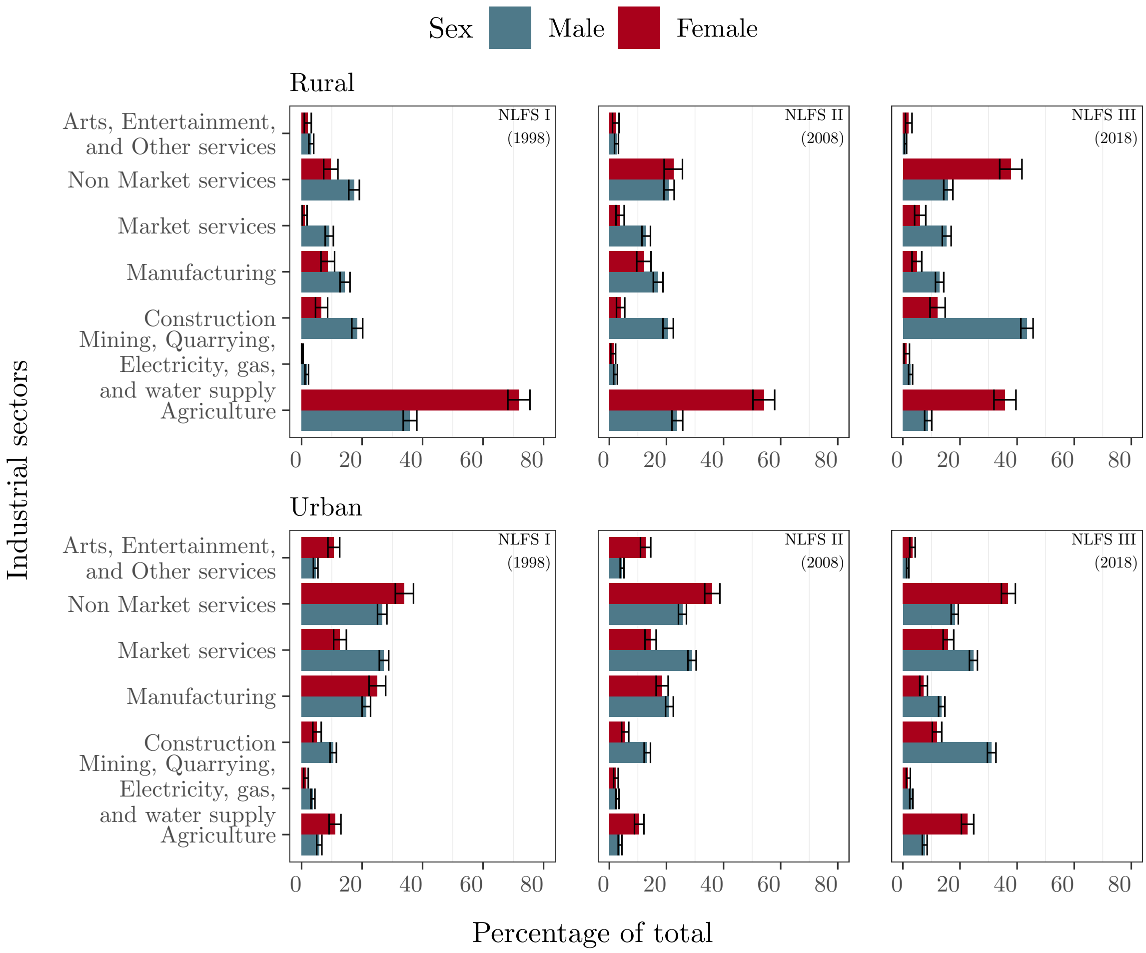

Figure 2: Industry-wise employment in rural and urban areas

After the restoration of democracy in 1990, the country went through the liberalization and decentralization of the education sector with a marked shift in attitude towards education. It was no longer just a social service but an investment with its own economic returns. This change fostered the growth of private education sector, particularly in urban areas, catering to burgeoning middle and higher-class families (Carney & Bista, 2009). The decentralization policies, too, were well-received, especially by rural communities, since they involved greater community participation in building and operating education institution, enrolling first generation graduates all over the Nepal. Also during this time, newly available jobs in service sector that paid more for an extra year of schooling created a strong aspirational case for the higher education, especially in females. Thus, the

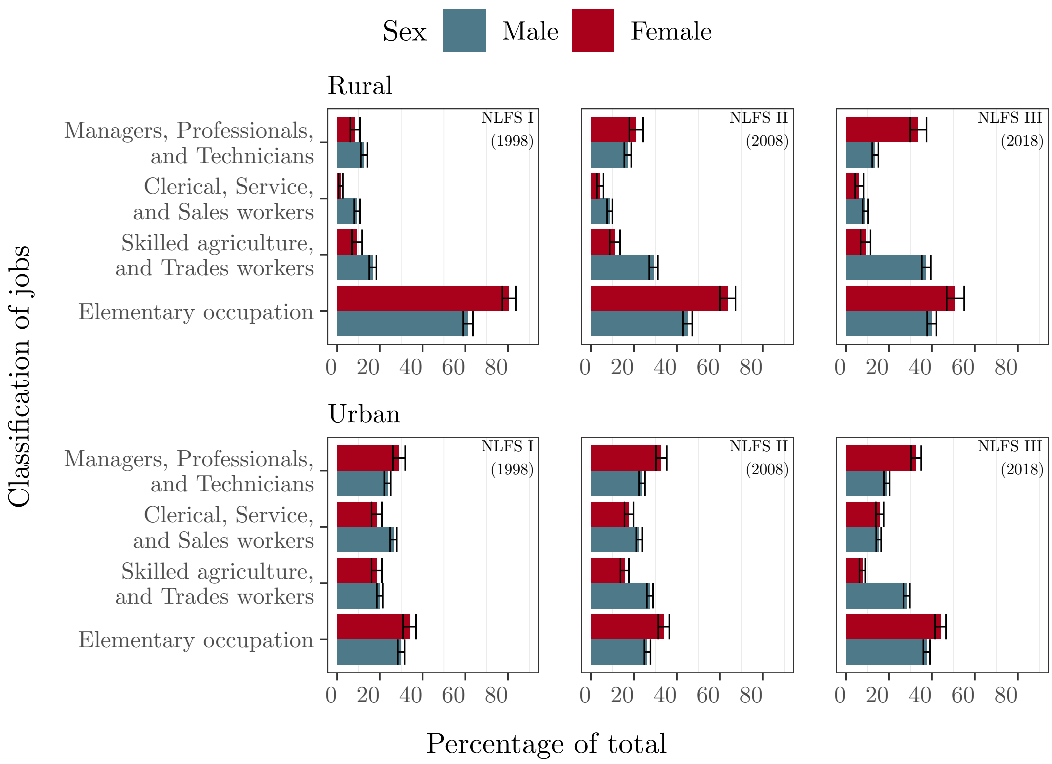

Figure 3: Classification of jobs in rural and urban areas

gender gap in education, see figure A2 in annex, has progressively narrowed over time, with both males and females attaining higher level of education. With time however, employed females have outpaced employed males in higher education. This educational surpass is not surprising since community collTab:WageSAIQeges have class cohorts with more than two third females in addition to having gender parity in other degree granting institutions (GoN/UGC, 2022).

The increase in the years of schooling also led young working age cohort to stay in educational institutions longer, delaying their job market entry. Moreover, the transition of the economy away from low yielding agriculture sector and this delay have caused the gradual decline in the labor force participation rate (LFPR) from 50.2% to 32.4% in two decades. By 2018, women's labor force participation stood 18.2% from earlier 31.3%, whereas, males saw even larger decline from 70.4% to 50.9%. Within those who are in the labor force, there has been the complete turn around in its composition. In 1998, majority of males and more than two thirds of women in labor force were self employed. This situation completely reversed by 2018, when majority of males and more number of women report to be engaged in wage jobs than self employment; see table A1 in annex. Overall, between 1998 and 2018, fewer people are in the labor force, but among those who are in the labor force, more are in wage jobs than being self employed.

In these decades, wage earners have seen their earning improve in real terms. The increase in the wage in the first decade was negligible and only the highest quintile group

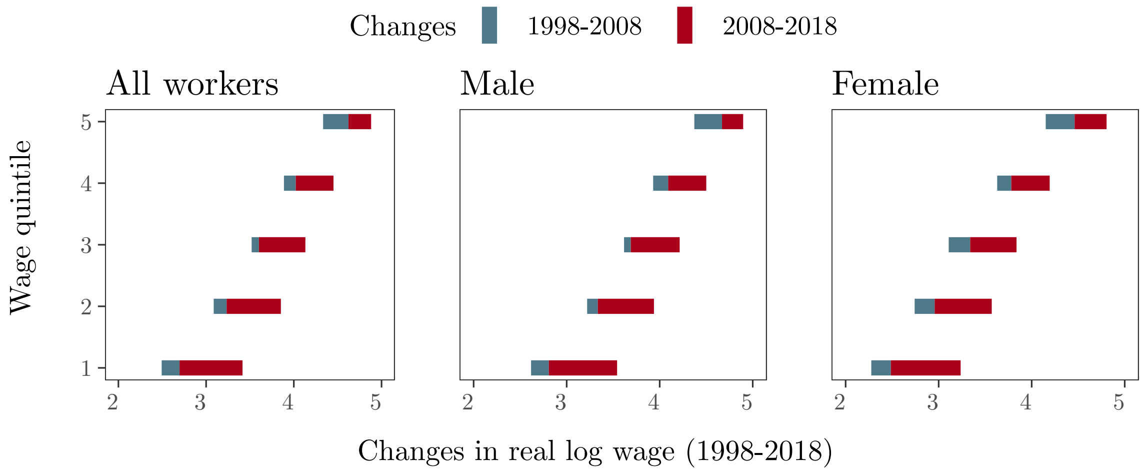

Figure 4: Changes in real wage throughout the wage distribution (1998-2018)

saw a sustained progress. This change worsened the inter-quintile wage spread, especially among males; see table A2 in annex. Genderwise, females were the greater beneficiary of changes in the first decade; see figure 4. In contrast, we witnessed substantial wage improvements for both group across all quintiles between 2008 and 2018. In this decade too, women saw larger gains and improved their position relative to the men. Females in the highest wage quintile experienced substantial improvements and came quite near to the highest earning males. As a consequence, gender wage gap decreased all around with sharpest decline in the highest quintile group. With time, the wage distributions have shifted rightward and the largest improvement came at the lower end of the distribution. This pro-poor shift has caused compression of real wages across both genders negating the increase in the wage spread of the first decade.

Wage evolutions were substantially different between rural and urban areas; see figure A1 in the annex. In the first decade, development in urban area was anti-poor, with people in bottom three quintiles either seeing eroding or stagnant real wage. At the same time, rural areas saw improvements across the board that brought them closer to the urban wages. In the second decade however, wages improved across both areas, but larger rural gains narrowed the urban-rural wage divide. A probable cause for this narrowing is the out migration, mostly of men, that largely happened in the second decade. This out migration decreased the rural labor supply, pushing rural wages up towards the urban parity. See table 3 for further details on observed characteristics across years.

4 Results and discussion

4.1 Genderwise wage gap decomposition

During the urban wage stagnation of the first decade, highest male wage quantiles saw larger improvements in their position compared to females. Overall, the total gender gap deteriorated above the median, whereas, there were slight improvements in the bottom quarter of the distribution; see figure 5. In the lowest wage group ($\tau = 0.1$), there was a slight convergence in the gap from -0.38 to -.35 units of log wage; see table 4. In the next decade, however, higher wage quantiles ($\tau = 0.9$) improved their position drastically, overcoming the decline of 2008 and improving upon 1998's gender gap. But, the situation was not so rosy for the rest. Median females saw slight slump in their position and lowest quantiles saw paltry improvements when considering both of the decades.

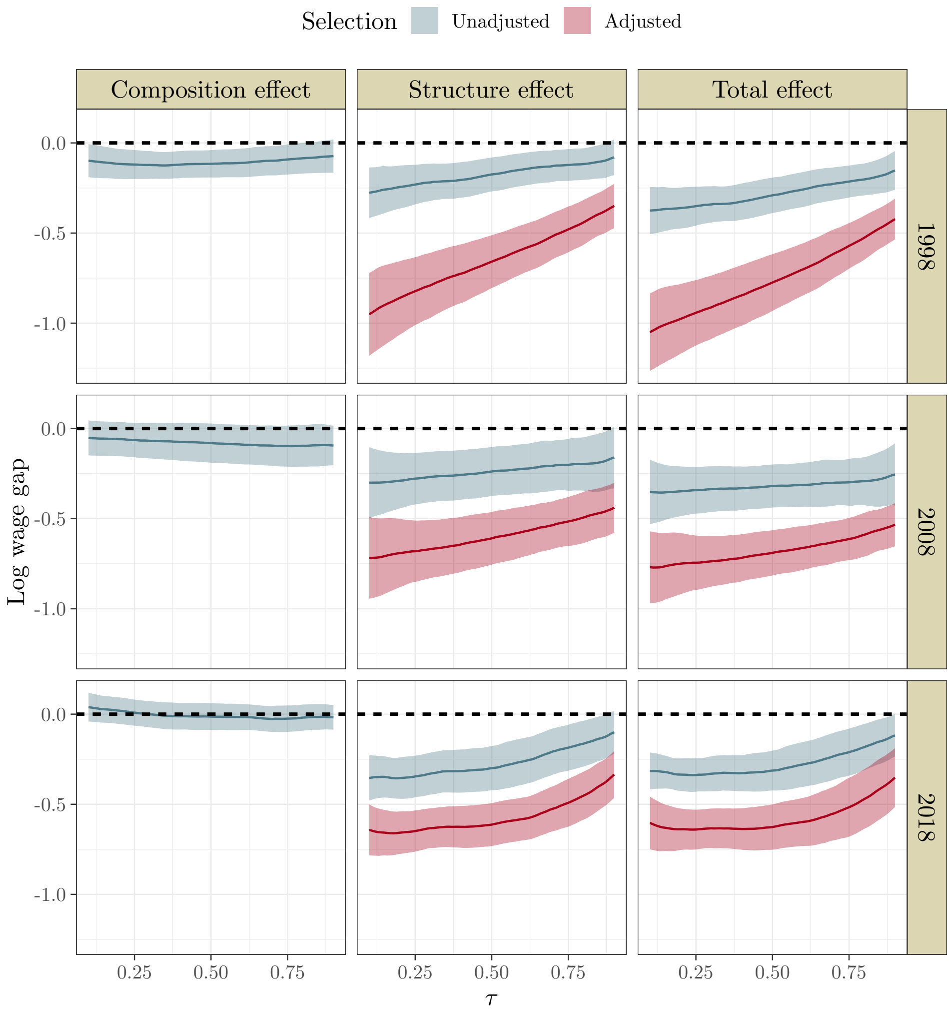

Figure 5: Urban wage decomposition

CE-wise, urban females improved their position in both of the decades. In the first decade, there was strong catching up in wage groups below median, but a slight divergence

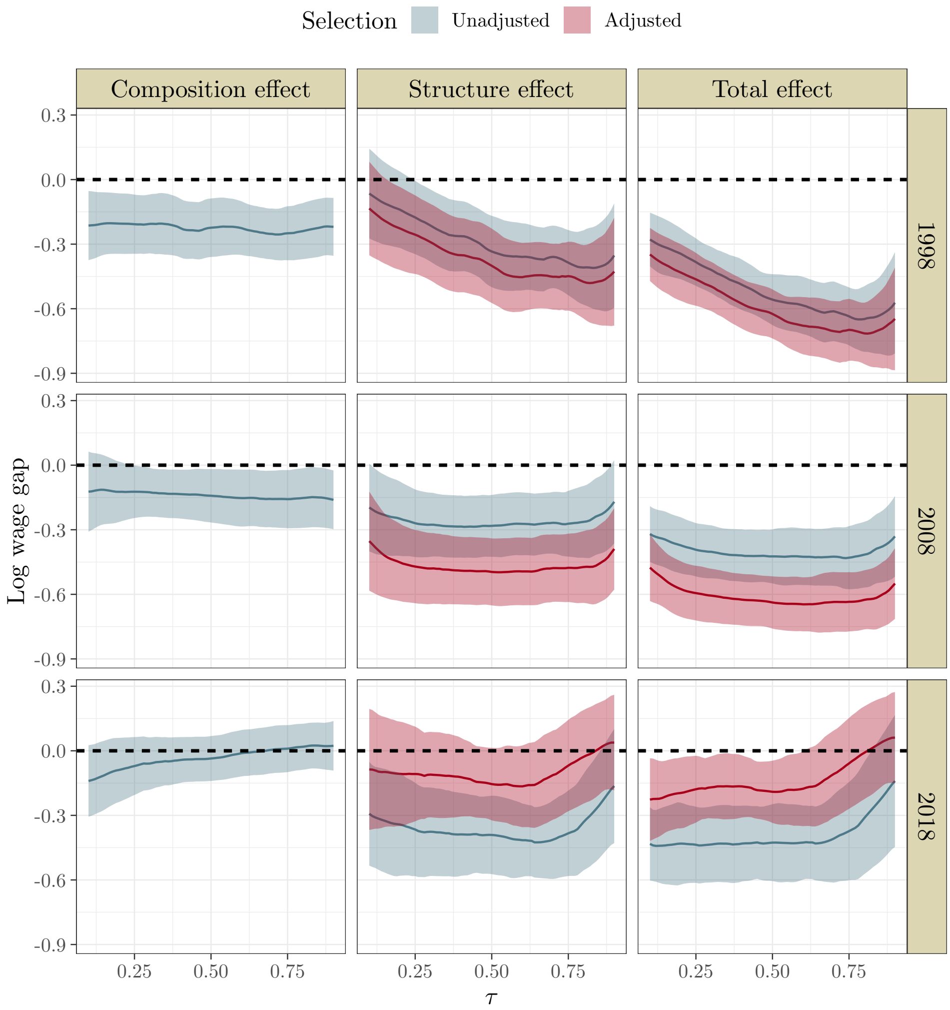

Figure 6: Rural wage decomposition

at higher wage groups. But, by 2018, women had all but surpassed men. At the 90th quantile, CE was only 14.4% of the total gap, whereas, at 10th quantile, women were ahead of males by 0.04 units of log wage. This improvement in the CE sits stark compared to changes in SE. In both 2008 and 2018, there was continued worsening off for all except the highest quantile groups. At median, SE increased from -0.18 to -0.30. As a result, declines caused by SE overshadowed improvement in CE, causing lack of convergence for most of the wage groups. It is worth noting that the overall gap in 2018 is no longer attributed to CE; the SE determines most of the total gap.

Rural areas saw remarkable improvements except for wage groups below first quartile between 1998 and 2008. In the 90th quantile, gap declined from -0.57 to -0.33, but the gap increased from -0.28 to -0.32 in the 10th quantile; see figure 6. Very large gaps at higher wage groups in 1998 was due to types of jobs that women were participating in. Majority of rural workers specially females held elementary occupation in agricultural sector but males dominated high paying skilled jobs. Moreover, there was also a vast difference in CE, about 40.1% of TE at median. With improving CE and increasing female's participation in high paying occupation and industry, gender wage gap shrank in the next decade among upper wage quantiles. The shrinkage was rapid after 2008, as female increased their involvement in high paying managerial and technical positions by almost two folds; see figures 2 and 3 .

After 1998, the gap continued to increase below the median when it was declining at median and higher wage groups. This dynamic reversed the shape of gender wage gap distribution. In 1998, low earning females earned closer to their male counter parts. But, with time, they gradually started to lose against males, whereas, high earning females began to reach parity with males by 2018. An important reason for this worsening at the bottom is types of jobs available in rural areas. Jobs in lower wage quantile are dominated by elementary occupation in agricultural sector, which are labor intensive physical works. Males, with their natural advantage, are more involved in the physically demanding tasks that are generally paid better. So, overtime, with more labor shifting their preferences towards other industries and lower availability of male in agricultural sector due to wide-spread out migration, the asking price of males have increased further than that of females, leading to wage gap divergence at the lower end.

Females in the rural areas too, have almost reached parity with males, when it comes to CE. In 1998, median CE was -0.23 points of log wage, which declined substantially in both decades to -0.04. By 2018, only at the lower end, females were behind males in distribution of observed wage characteristics. During the same time, 90th quantile females came slightly ahead of males from being markedly behind. When it comes to SE, it has changed its distributional shape over time similar to TE. Median and lower earning females have particularly suffered from exacerbating SE, overshadowing their gains in CE. Similar to urban areas, SE plays the dominant role in determining the overall gap.

4.2 Selection adjusted decomposition

In urban areas, upon adjusting for the selection bias, the gender wage gap aggravates further. It more than doubles throughout both decades, exhibiting an even greater disparity, especially in the lower wage quantiles. In all surveys, adjusted female wage distributions are lower than unadjusted indicating positive selection. That is women with higher level of observed wage determining characteristics are employed compared to the female working age population of the period. The degree of sample selection is higher in 1998 with the largest impact of adjustment in the lowest wage quantiles. Over time, adjusted total gap has declined across the distribution indicating reduction of difference in characteristics between employed and working age females. At median, adjusted total wage gap declined from -0.77 in 1998 to -0.63 in 2018, whereas the 90th percentile saw improvement to -0.35 from -0.42; see table 5.

Compared to urban area, rural area has a more nuanced selection results. In the first two survey year, there was a positive selection of the women in to the labor force, which caused adjusted wage gap to further increase. During these years, elementary occupation with few managerial jobs constituted the rural job market. The work force characteristics of females were poor and lagged substantially behind males. Whatever few higher wage paying jobs were there, they were taken by few educated females and rest of the low paying jobs were taken by females who were similar to rural working age population, leading to a situation of a slight positive selection into the labor force. But, by the last survey in 2018, rural jobs started to bifurcate towards service and elementary jobs. This time however, much of the women working age population had taken advantage of available educational opportunities made accessible by recently opened community colleges.

As a result, educated working-age female pool had job opportunities into two areas: growing service sector jobs and established elementary occupation. But service sector jobs did not grow fast enough in rural areas, especially market based service sectors, to absorb this new surplus of college educated young working females. And, those employed in elementary occupations pulled the average human capital of employed further down. This led to a strange situation, where a good chunk of women with higher human capital were not in jobs and those who were in wage jobs were either with low human capital or were not in the sufficient quantity. As a result, our analysis finds women in rural areas to be negatively selected into the labor force and adjusted wage gap distribution is lower than the raw wage gap.

4.3 Household dynamics and female participation

According to the model of home production, female members are less likely to join job market if their market potential is less than male household members. We test this hypothesis in 2011 census using four different logit regression models of engagement in employment with key explanatory variable being education gap. The education gap is a proxy for difference between market earning potential across males and females.

In the first model, we use gender education gap – difference of mean years of schooling of males and females in a household – to understand its effect on employment of females from that household. It is a rough measure as it aggregates both married and unmarried household members, among whom there may not be a marital relationship and gendered work division, e.g., father and teenage daughters. Despite this, the coefficient is negative with both statistical and economical significance. An additional year of schooling increase in males compared to women reduces the employee status of females by -0.02 in log odds; see table 1. We subsequently make the measurement more precise by including all types of husband and wife pairs in column 2. The coefficient increases in magnitude to -0.05 in log odds. We further partition the data set between two spousal pair types: (a) male head

Table 1: Female engagement in employment and gender education gap

	Gender-wise	Spousal pairs		
	All	All	Daughter-in-law	Spouse of HH
Panel A:	Engaged in any work as an employee			
Gender education gap	-0.021***	-	-	-
	(0.003)			
Spousal education gap	-	-0.054***	-0.029***	-0.055***
		(0.003)	(0.005)	(0.003)
Years of schooling	0.071***	0.053***	0.087***	0.053***
	(0.007)	(0.010)	(0.010)	(0.010)
Pseudo R^2	0.08099	0.08142	0.08941	0.08390
Panel B:	Engaged in own account work			
Gender education gap	-0.004**	-	-	-
	(0.002)			
Spousal education gap	-	0.010***	0.0001	0.012***
		(0.002)	(0.002)	(0.002)
Years of schooling	-0.045***	-0.041***	-0.081***	-0.032***
	(0.008)	(0.005)	(0.008)	(0.004)
Pseudo R^2	0.18033	0.22762	0.23328	0.22494
Observations	2,210,575	653,309	114,547	538,762

District-wise clustered standard-errors in parentheses; Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; Included control variables are age, age squared, caste groups, first component of dwelling characteristics' principal component analysis, urban dummy and districts; Spouse of HH include both wives of male household heads as well as female household heads; Source: authors' estimation.

and his wife or female head and her husband, and (b) son and daughter-in-law pair from a multi-generational family. In this sub-division across the spousal pair types, we find that there are differences in both spousal education gap's magnitude and its importance vis-a-vis years of schooling. Among head's wives, an additional year of spousal education gap penalizes employment probability by -0.05 in log odds, which is approximately same as gains from an additional year of schooling of the wife. But, among daughter-in-law pairs, effect of spousal education gap is approximately half compared to household head's wives and is overshadowed by the returns from years of schooling.

Continued increase in magnitude of coefficient of the education gap when moving from first column to the third and then to fourth reinforces the argument that burden on women increases when they move from being daughter to daughter-in-law and then finally being spouse of household head. The first coefficient is weighted down by the presence of daughters who face fewer occupational barriers compared to daughter-in-laws and wives of household head. Once daughter gets married, the hindrance from the education gap increases from -0.021 to -0.029. As a newly wed in her husband's family, she has a support of other family members in child rearing and household chores, but faces more stigma to join employment compared to when she was unmarried. Finally, when her family splits with her husband's parents, she no longer enjoys that additional support and now has to manage home production mostly by herself. As a result, at this stage, her improvement from additional years of schooling is completely offset by her spousal education gap.

We check this result against how spousal education gap affects engagement in own account work. Despite statistical significance, thanks to generous sample size, we no longer find economically significant negative coefficient in any of the models. The sign of the spousal education gap also changes to positive and magnitude decrease approximately by five times. Even more interesting is that the sign of years of schooling flips to negative, meaning more educated are now less likely to be involved in own account work. These results in panel B in conjunction with panel A imply that spousal education gap is important when women want to join job market, but is not a significant factor when engaging in own account work. In probit specifications, the results for both of the panels do not change, but have smaller coefficients; see **annex table A4**.

Next, we look into the time allocated towards home production and find that penalty of being women has hardly budged in a decadal time frame; see table 2. The coefficient of the matched results are similar to baseline regressions. In 2018, unemployed women, in general, spent 102 minutes more than unemployed men doing household chores, whereas if they were employed they did additional 89 minutes of work compared to unemployed men. This is in contrast to males, who hardly share the home production burden - figure 7 is even more explicit. Whatever the employment status of women, they work between 2 to 3 hours per day. But, men don't put in even an hour of work.

Table 2: Gendered evaluation of time spent doing household chores

	Total hours spent on household chores					
	NLFS II, 2008		NLSS III, 2011		NLFS III, 2018	
Variables	(1)	(2)	(3)	(4)	(5)	(6)
Female	2.37***	2.43***	2.47***	2.59***	1.71***	1.70***
	(0.025)	(0.039)	(0.050)	(0.081)	(0.020)	(0.028)
Employed	−0.497***	−0.474***	−0.135***	−0.143	−0.173***	−0.172***
	(0.027)	(0.043)	(0.051)	(0.093)	(0.024)	(0.040)
Female×Employed	−0.179**	−0.183**	−0.212**	−0.214*	−0.224***	−0.214***
	(0.070)	(0.078)	(0.085)	(0.117)	(0.054)	(0.061)
Observations	41,602	41,602	15,650	15,650	44,549	44,549
R^2	0.385	0.346	0.354	0.335	0.335	0.303
Adjusted R^2	0.385	0.346	0.353	0.334	0.335	0.303

Model 1, 3 & 5 are unmatched, whereas model 2, 4 & 6 are matched with generalized full matching; Error bands in unmatched and matched models are HC1 robust standard errors and matched-subgroup-wise clustered standard errors respectively; Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; Controls included are age, age squared, years of schooling, urban dummy, household size, caste groups, house ownership, & land ownership; Source: authors' estimation.

It is true that in earlier years, these male-female disparities were even larger; see **annex figure A2**. But, the same results also inform that 40 minutes decline observed between 2008 and 2018 among females has less to do with males increasing their share of

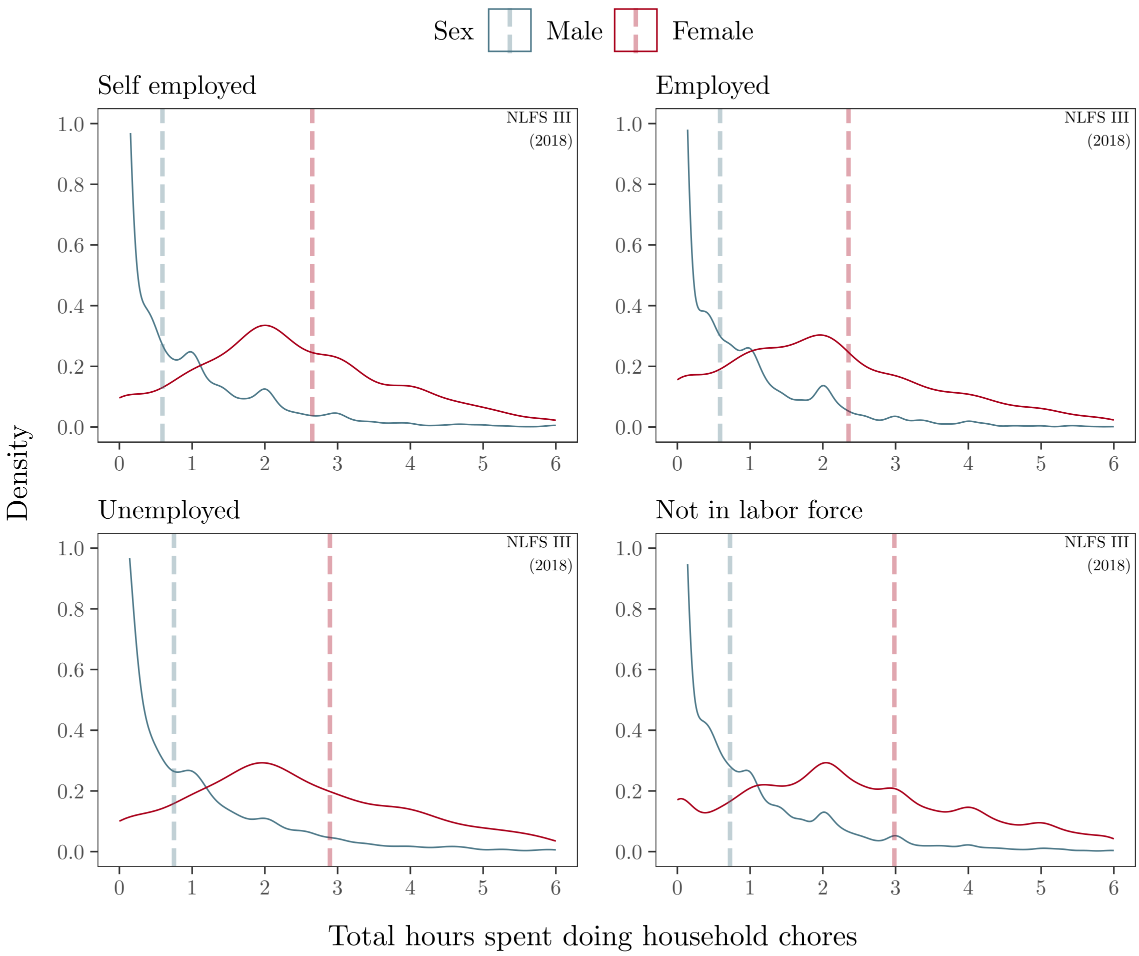

Figure 7: Employment status and gendered time allocation on household chores in 2018. Vertical dashed lines indicate group-wise means.

burden, i.e., substitution across gender is inelastic. Rather, this decline could have come from time saving technologies' adoption and infrastructure development. For example, two of the tasks included in household chores variable are time required to fetch firewood/dung and water. Widespread use of liquefied petroleum gas and electricity, as it has happened in the last decade, decreases fuel fetching time, whereas, increased access to tapped drinking water decreases water collecting time. Both of these, and other time saving changes have occurred and women have seen some improvements in their time allocation over the last two decades. But, similarly sized coefficients describing a large gap vis-á-vis men across different data sets and estimation procedures in table 2 point that women were and are consistently contributing to the home production in an unequal fashion.

4.4 Discussions

Our decomposition results are similar to what are being reported in the literature – wage convergence is slowing either by sticky floor or glass ceiling. For example in India, Nepal's south neighbor, Deshpande et al. (2018) reports persistent unexplained gender wage gap, despite women's wage-earning characteristics improving relative to men. They find, similar to us, "sticky floor" with increasing structure effect, with gap being more pronounced among low-wage earners. In a past study using a different Nepalese data set, Yamamoto et al. (2019) report a large wage gap and a strong structure effect. These studies do not fully account for the type of work, exact work-related experience and other finer work place characteristics. We, too, miss these variables due to both methodological and data deficiencies.

But, despite worker characteristics being significant in determining wage gaps, workplace characteristics are important. For example, Chatterji et al. (2011) verifies that only a tiny fraction of the gender earnings gap in Britain can be ascribed to employee characteristic differences, highlighting the substantial role of workplace characteristics in England. This partly explains why newer data sets which have more variance in the nature of work and its associated pay, when decomposed without sufficient details on the work, will have comparatively more SE. So, one portion of our increased SE can come from not capturing the work in the wage equation. Despite this shortcoming, human capital specifications have quite strong explanatory power. For example, in Blau and Kahn (2017), human capital specification alone puts female to male log wage ratio to 82.1% compared to 91.6% when adding industry and occupation variables. Thus, even when only looking at the human capital specifications, we can find change in their relative importance for the wage gap. In our results for rural area, there is a substantial convergence in CE between 1998 and 2008. It points out that Nepal has utilized a powerful source of convergence to a full effect in these two decades.

When considering selection, Maasoumi and Wang (2019) found different conclusions than without. We too find that positive selection of highly educated women into the labor force hides the true extent of the gender gap if selection is not accounted for, especially in urban areas. This along with differential outcomes - stagnation below median wages but convergence above - at different wage groups show the necessity of more literature with distributional decomposition considering selection. But, the selection can often depend on applied method; C. Machado (2017) reaches different conclusions with different methods in the same data. Despite this vagarity, selection remains a key issue as noted by Heckman (1974) and Gronau (1974) and provides a "truer" picture of the labor market than without.

Increasing SE and weakening role of gender-parity in human capital for improving the gap, means we have to look at structural factors affecting females' meaningful labor market outcomes. One of the important determinant of such is intra-spousal negotiation. Bertrand et al. (2015) reports a societal aversion towards wife earning more than the husband. These societal attitudes affect marriage formation, wives' labor force participation, income, marriage satisfaction, and household chores. For example, in developed countries, high skilled women tend to marry less often than their less skilled counterparts (Bertrand et al., 2020) - the marriage gap depends on societal attitudes towards working women. Similarly in Nepal, intra-spousal negotiation looks unfavorable for women. Our results show that higher spousal education gap makes it difficult for women to participate in labor market as an employee. The gap's effect increases with increase in the household stature of female from being daughter-in-law to wife of the household head. This style of female sorting to household work aligns with the prediction of stylized home production model of Cortés and Pan (2020).

In addition to the gendered sorting into the employment, the time devoted to the home production is also very gendered. We find men shrinking from contributing even when they are not employed, and this pattern has not changed in the last two decades. As a result, currently, women face "dual burden" of work when they want to be employed. If they are employed, they have to do job hours, but they also have to continue putting in hours at home as if they were not employed; the difference of being employed is mere 12.8 minutes in 2018. This type of "dual burden" is a norm among females in the labor market everywhere (Hochschild & Machung, 2012).

A similar result has been reported in the Southern Europe by Lichard et al. (2021). In a more specific setting, Álvarez and Miles-Touya (2019) study differential allocation of time in nonworking days between dual-earner couples. They too, find that during wives' nonworking days, wives take on most of the household tasks. These skewed home production responsibilities amplify the wage gap. For example in Europe, when mothers faced motherhood penalties after a child birth, fathers enjoyed wage premiums (Cukrowska-Torzewska & Lovasz, 2020). Similarly, Cortés and Pan (2020) report that two-thirds of remaining gender earnings gap in the US were due to child-rearing responsibilities imposed on women alone. These type of barriers can come in different forms too. In Italy, social norm of marriage within the community preserved social norms against working women, which discouraged women from participating into jobs, eventually increasing gender participation gaps (Righetto, 2023). As a consequence of non-participation in home production, men can often work inflexible jobs for longer hours, taking fewer leaves, and be in jobs that demand on-call availability, which provides structural advantages. On the other hand, employers often reward these same advantages, increasing males' earning potential in the labor market (Goldin, 2014).

Recently, the role of psychological factors for keeping females outside labor market participation have been started to be recognized. In the case of the US high-wage earning workers, Francis et al. (2023) found that gender-based pay gaps persisted due to career interruptions and differences in risk preferences, particularly at the executive level. Even among recent graduates, the preference might lead females to choose very different choices. For example in Piazzalunga (2018)'s study of recent graduates, childcare, part-time employment availability, and traditional gender norms were important in determining the gender wage gap.

5 Conclusion

In this paper we examined the trajectory of the gender wage gap across the rural and urban areas of Nepal. Using the decomposition tools developed by Chernozhukov et al. (2013) and selection correction approach of Arellano and Bonhomme (2017), we quantile-wise decomposed gender wage gap into composition and structural effects. We find that wage gap is converging for the higher quantile groups while it is widening or stagnating among lower-earners, i.e., "sticky floor" phenomenon. Structural effect mirrors the slope of the total effect, whereas, the composition effect amplifies the distribution uniformly across all the quantiles in both urban and rural Nepal. In addition, there is a notable trend of improvement in composition effect throughout the time with education progressing beyond gender-parity. However, this improvement is overshadowed by the aggravation of the structural effect, which persists even after adjusting for selection. Almost all of the wage gap is attributable to the differential returns to observed factors or simply the unobserved factors, which at the worst case can be the identity of being a woman in an unfriendly social construct. This situation differs from earlier times when composition effect used to explain considerable portion of the gap.

We investigated this divergence by looking at household dynamics that affect female labor force participation. We show that improvement of women's education does not guarantee female labor market participation. Women's success is linked with spousal education level - higher spousal education gap pushes females away from the job market as they climb the family hierarchy. Along with this gendered sorting into labor market, there is a substantial gender-wise discrepancy on time spent on household chores. Despite being employed or not, women always contribute substantially more on household chores and this trend has hardly changed in the last two decades. Whereas, males have put in similar time in home production consistently and there is almost zero substitution effect. This "dual burden" costs flexibility to participate in job market. To address these structural issues, it necessitates more than simply providing women with higher education and improved job skills.

An intriguing avenue for future research lies in incorporating the psychological attributes of workers and examining the impact and consequences of policy changes, such as affirmative actions implemented by the government. Investigating how these policies influence wage disparities and economic outcomes could offer valuable insights into the effectiveness of such initiatives and their implications for gender equity.

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Table 3: Summary statistics on selected variables for employed

		1998		2008		2018	
		Male	Female	Male	Female	Male	Female
Hourly wage		14.71	10.88	30.56	23.09	89.74	69.84
		(8.80)	(7.95)	(21.55)	(18.40)	(42.51)	(43.04)
Number of children aged ≤ 12		1.63	1.53	1.41	1.32	1.30	1.15
		(1.45)	(1.45)	(1.42)	(1.28)	(1.35)	(1.20)
Built up volume		232.10	270.93	284.44	314.57	110.94	146.51
		(391.77)	(409.17)	(424.26)	(435.90)	(258.61)	(299.47)
Years of schooling		7.14	5.11	7.94	6.59	7.89	8.02
		(5.75)	(6.15)	(5.72)	(6.21)	(5.42)	(6.35)
Head's years of schooling		6.01	5.35	6.71	6.22	6.10	6.66
		(5.96)	(6.29)	(5.91)	(6.26)	(5.60)	(6.07)
Age		33.29	30.96	34.34	31.62	35.41	32.74
		(11.18)	(10.91)	(11.44)	(10.69)	(11.95)	(10.31)
Daily hours spent on household chores		0.68	3.23	0.73	2.95	0.59	2.35
		(1.07)	(2.37)	(1.13)	(2.27)	(0.97)	(1.81)
Urban (in %)		64.4	61.9	64.9	66.3	64.5	71.1
Marital status (in %)	Never married	17.3	22.1	18.3	23.6	17	19.4
	Married	80.5	70.4	80.1	69.5	81.3	73.9
	Seperated, Divorced and Widowed	2.2	7.4	1.6	6.9	1.7	6.7
Caste (in %)	Khas	29.5	24	29.9	30.4	29	33.2
	Janajati	29.8	35.9	31.8	36.5	27.9	29.5
	Adhibasi	4.6	3.4	7.3	7.4	13.5	13.7
	Madhesi	2.1	0.8	13.5	7.8	11.5	6.6
	Dalit	6.4	8.7	10.9	13.8	14.4	15.1
	Others	27.6	27.3	6.5	4.1	3.7	1.9
Education (in %)	Illiterate	25.7	50.2	19.3	37.1	17	27.6
	Below primary	15.4	9.3	15.8	10.9	16.2	11
	Primary	26	11	24.5	11.8	29.3	12.7
	Tenth grade	13.7	12.3	17.8	16.8	16.6	14.6
	Secondary	8.6	8.6	10	13.5	10	19.8
	Bachelors	7.3	6.3	8.3	7.5	7.3	10.5
	Masters & above	3.3	2.3	4.4	2.3	3.6	3.7

Table 4: Decomposition of wage distribution in rural urban overall areas

	Total Effect			Composition Effect			Structure Effect		
τ	1998	2008	2018	1998	2008	2018	1998	2008	2018
PANEL A:				Decomposition of rural wage gap					
0.10	-0.279	-0.320	-0.433	-0.214	-0.123	-0.140	-0.065	-0.197	-0.293
	-0.404 ; -0.154	-0.449 ; -0.19	-0.603 ; -0.263	-0.374 ; -0.053	-0.309 ; 0.063	-0.306 ; 0.026	-0.273 ; 0.144	-0.4 ; 0.007	-0.533 ; -0.052
0.25	-0.383	-0.393	-0.437	-0.207	-0.123	-0.071	-0.176	-0.270	-0.366
	-0.494 ; -0.273	-0.517 ; -0.269	-0.613 ; -0.26	-0.345 ; -0.07	-0.246 ; -0.001	-0.205 ; 0.064	-0.346 ; -0.006	-0.427 ; -0.113	-0.582 ; -0.149
0.50	-0.558	-0.424	-0.427	-0.224	-0.142	-0.036	-0.334	-0.282	-0.391
	-0.676 ; -0.44	-0.549 ; -0.298	-0.605 ; -0.248	-0.36 ; -0.088	-0.266 ; -0.018	-0.14 ; 0.068	-0.5 ; -0.168	-0.425 ; -0.138	-0.573 ; -0.209
0.75	-0.635	-0.430	-0.373	-0.249	-0.158	0.010	-0.386	-0.272	-0.383
	-0.77 ; -0.501	-0.576 ; -0.283	-0.601 ; -0.145	-0.375 ; -0.124	-0.293 ; -0.023	-0.099 ; 0.119	-0.537 ; -0.234	-0.425 ; -0.119	-0.582 ; -0.185
0.90	-0.572	-0.331	-0.141	-0.220	-0.161	0.023	-0.353	-0.170	-0.164
	-0.808 ; -0.337	-0.518 ; -0.144	-0.447 ; 0.166	-0.354 ; -0.085	-0.297 ; -0.024	-0.092 ; 0.139	-0.595 ; -0.111	-0.363 ; 0.023	-0.429 ; 0.101
PANEL B:				Decomposition of urban wage gap					
0.10	-0.375	-0.352	-0.315	-0.099	-0.052	0.039	-0.276	-0.301	-0.354
	-0.506 ; -0.244	-0.532 ; -0.172	-0.418 ; -0.213	-0.19 ; -0.007	-0.149 ; 0.045	-0.041 ; 0.118	-0.416 ; -0.136	-0.498 ; -0.103	-0.48 ; -0.229
0.25	-0.351	-0.342	-0.338	-0.120	-0.064	0.008	-0.231	-0.278	-0.346
	-0.459 ; -0.243	-0.472 ; -0.212	-0.43 ; -0.245	-0.2 ; -0.04	-0.16 ; 0.032	-0.064 ; 0.081	-0.341 ; -0.121	-0.421 ; -0.135	-0.461 ; -0.231
0.50	-0.291	-0.319	-0.313	-0.116	-0.081	-0.014	-0.175	-0.238	-0.299
	-0.389 ; -0.192	-0.438 ; -0.199	-0.424 ; -0.202	-0.192 ; -0.04	-0.189 ; 0.028	-0.088 ; 0.061	-0.269 ; -0.081	-0.374 ; -0.102	-0.422 ; -0.177
0.75	-0.214	-0.299	-0.211	-0.092	-0.097	-0.025	-0.122	-0.201	-0.186
	-0.303 ; -0.125	-0.428 ; -0.169	-0.342 ; -0.08	-0.176 ; -0.008	-0.211 ; 0.017	-0.098 ; 0.048	-0.211 ; -0.034	-0.345 ; -0.057	-0.313 ; -0.059
0.90	-0.153	-0.254	-0.118	-0.073	-0.094	-0.017	-0.080	-0.160	-0.100
	-0.26 ; -0.045	-0.427 ; -0.082	-0.235 ; -0.001	-0.165 ; 0.019	-0.204 ; 0.016	-0.086 ; 0.051	-0.179 ; 0.019	-0.332 ; 0.012	-0.22 ; 0.019

Coefficients are in log wage. Bounds (95% confidence interval) are based on 100 bootstraps.

Table 5: Decomposition of wage distribution in rural urban overall areas

	Total Effect			Structure Effect		
τ	1998	2008	2018	1998	2008	2018
PANEL A:	Decomposition of rural wage gap					
0.10	-0.348	-0.476	-0.227	-0.134	-0.353	-0.087
	-0.471 ; -0.224	-0.631 ; -0.321	-0.419 ; -0.035	-0.352 ; 0.083	-0.583 ; -0.123	-0.368 ; 0.195
0.25	-0.463	-0.594	-0.179	-0.256	-0.471	-0.108
	-0.586 ; -0.34	-0.721 ; -0.467	-0.334 ; -0.023	-0.439 ; -0.073	-0.641 ; -0.301	-0.328 ; 0.112
0.50	-0.624	-0.638	-0.191	-0.401	-0.496	-0.155
	-0.738 ; -0.51	-0.759 ; -0.517	-0.335 ; -0.046	-0.574 ; -0.228	-0.652 ; -0.34	-0.323 ; 0.014
0.75	-0.698	-0.635	-0.059	-0.449	-0.477	-0.069
	-0.842 ; -0.554	-0.772 ; -0.497	-0.27 ; 0.153	-0.608 ; -0.289	-0.636 ; -0.318	-0.281 ; 0.144
0.90	-0.647	-0.550	0.061	-0.428	-0.389	0.038
	-0.886 ; -0.408	-0.714 ; -0.386	-0.15 ; 0.273	-0.678 ; -0.177	-0.578 ; -0.2	-0.184 ; 0.26
PANEL B:	Decomposition of urban wage gap					
0.10	-1.050	-0.769	-0.604	-0.951	-0.718	-0.642
	-1.265 ; -0.834	-0.969 ; -0.57	-0.75 ; -0.458	-1.181 ; -0.721	-0.944 ; -0.491	-0.783 ; -0.501
0.25	-0.942	-0.745	-0.640	-0.822	-0.681	-0.648
	-1.124 ; -0.761	-0.895 ; -0.594	-0.75 ; -0.53	-1.011 ; -0.634	-0.851 ; -0.511	-0.763 ; -0.534
0.50	-0.774	-0.690	-0.626	-0.659	-0.609	-0.613
	-0.932 ; -0.617	-0.815 ; -0.564	-0.752 ; -0.501	-0.805 ; -0.512	-0.755 ; -0.463	-0.732 ; -0.494
0.75	-0.571	-0.613	-0.517	-0.479	-0.516	-0.492
	-0.698 ; -0.445	-0.73 ; -0.495	-0.68 ; -0.353	-0.606 ; -0.353	-0.652 ; -0.38	-0.624 ; -0.359
0.90	-0.423	-0.533	-0.352	-0.350	-0.439	-0.335
	-0.536 ; -0.309	-0.653 ; -0.413	-0.516 ; -0.188	-0.473 ; -0.227	-0.578 ; -0.3	-0.464 ; -0.205

Coefficients are in log wage. Bounds (95% confidence interval) are based on 100 bootstraps.