Structural Divergence in Gender Wage Gap Distribution of Nepal

Central Department of Economics
Tribhuvan University.

February, 2, 2024

Structural Divergence in Gender Wage Gap Distribution of Nepal

Authors:
Manab Prakash, **Resham** Thapa-Parajuli,
Tilak Kshetri & **Sanjeet** Singh Thapa

Central Department of Economics
Tribhuvan University
Nepal

This year's Economics Nobel prize

Claudia Goldin,
Nobel prize winner in economics, 2023

- Goldin uncovered key drivers of gender differences in the labor market

- Provided the first comprehensive account of women's earnings and labor market participation through the centuries

- Highlighted role of access to the contraceptive pill on female's career planning

CEDECON
TRIBHUVAN UNIVERSITY

What does this paper do?

— Estimates wage gap between males and females across the entire wage distribution

— Examines the evolution of wage gap distribution over time

— Finding the nature of the wage gap by decomposing it into observable factors (Composition effect) and unobservable factors (Structural effect)

— Understanding why structural effect has started to dominate most of the gap by looking into (a) Difference in earning potential, and (b) Time allocation to home production.

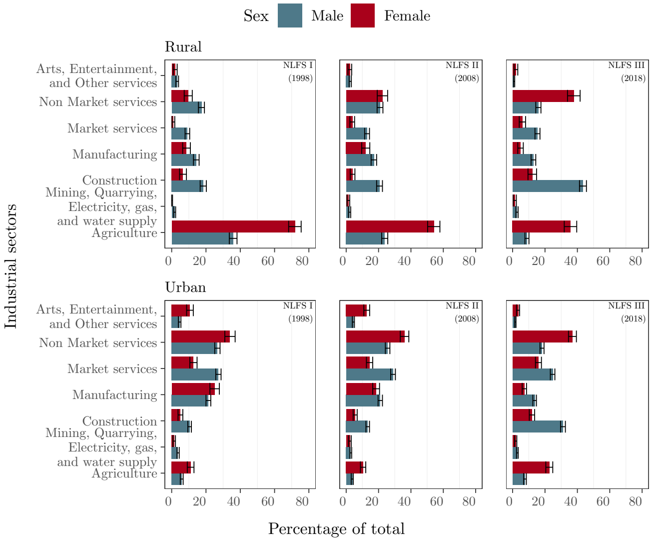
Why is this study necessary?

— Understanding the differential wage evolution across gender has key implications for national policy

— Few high quality literature are available, Mainali et. al (2017) looks into caste, and Yamamoto et. al (2019) looks into gender – substantial research gap

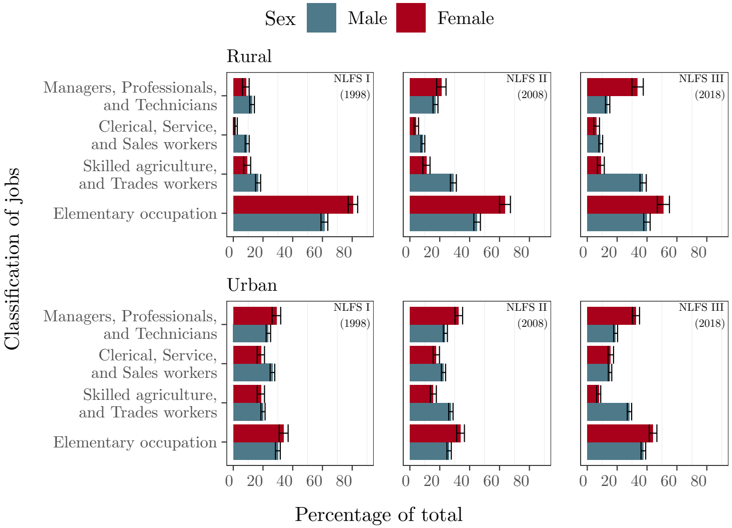
— Recent history – Nepal has gone through Maoist conflict, peak out-migration, and promulgation of new constitution. Knowing what happened in wage distribution and understanding the past helps formulating for future

Settings: Industry-wise employment

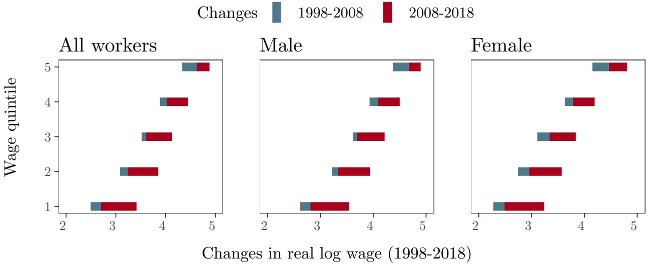


CEDECON
TRIBHUVAN UNIVERSITY

Settings: Occupation-wise employment



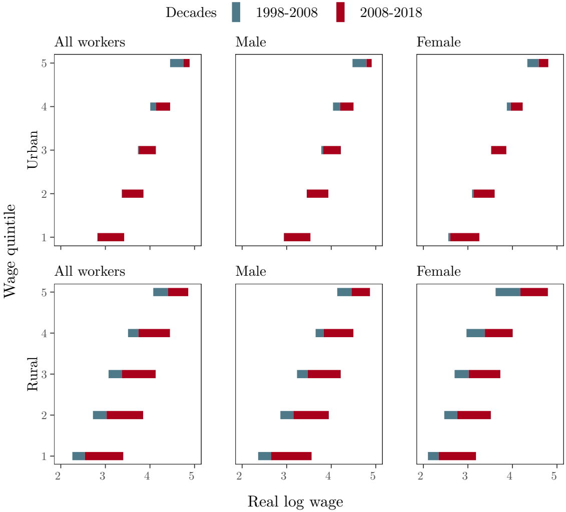
Settings: Changes in real wage distribution



	Overall		Male		Female	
Year	Q5–Q1	% change	Q5–Q1	% change	Q5–Q1	% change
1998	1.855	84.1 (-183.9)	1.767	82.6 (-149.0)	1.927	85.0 (-100.1)
2008	1.955	85.6 (-190.6)	1.895	84.7 (-159.5)	1.972	85.6 (-99.8)
2018	1.454	76.4 (-198.6)	1.342	73.5 (-153.1)	1.567	78.7 (-113.8)

Q1 & Q5 are first & fifth real wage(log) quintiles. The % change is real (non-log) wage spread between Q5 & Q1 relative to Q1; Differences between Q5 and Q1 are statistically significant (one-tailed t-test with all p-values ≤ 0.001). Figures in parentheses are t-values.

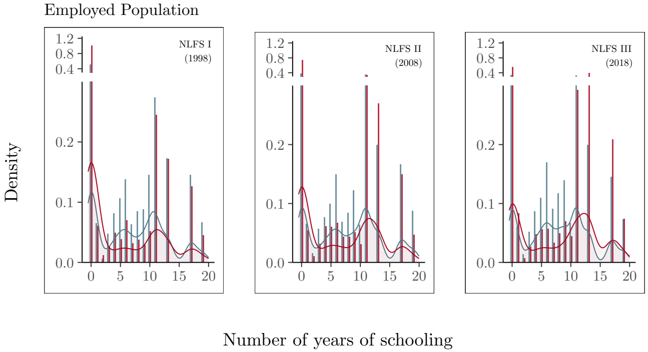
Settings: Where did the wage grow?



- 1^{st} decade: stagnant urban wage
- Decline of urban manufacturing
- Females catching up
- 2^{nd} decade: most of wage growth
- Rural-Urban convergence

CEDECON
TRIBHUVAN UNIVERSITY

Settings: Growth of education



– Community colleges have class cohorts with 2/3 females in addition to having gender parity in other degree granting institutions

Settings: Decomposition Literature 1

— Started with seminal works of Oaxaca (1973) & Blinder (1973), Decomposition has been refined and extended beyond the single point estimate of the wage distribution over the past half-century (Fortin, 2011).

— 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 (Machado,2005).

Settings: Decomposition Literature 2

— A major hurdle in distributional decomposition is to construct a counterfactual wage distribution – what will be wage of women if she was paid like men across the wage distribution – which can not be directly observed

— As a result, significant effort devoted to develop methods for constructing counterfactual e.g., Kernel density reweighing (DiNardo et al, 1996), Quantile regression to estimate inverse conditional distribution function (Machado & Mata 2005) , Recentered influence function (Firpo et al, 2009) etc.

— Recent innovation is Chernozhukov et.al (2013)'s technique of estimating conditional distributional regression model using quantile regression

— Women who are in jobs are different than general female population. How to address this differential selection? Any naive difference will be between special group of women and working men

— This is a Nobel prize awarded problem (2000), first seriously studied by Heckman (1974) and Gronau (1974)

— 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

— We correct for selection viá parametric approach in the quantile framework

Settings: Selection in wage differential 2

— We use Arellano & Bonhomme (2017)'s quantile-copula based technique to model the joint-distribution of error terms in outcome and selection models

— It overcomes Huber (2015)'s critique concerning the conditional independence assumption in sample selection models, particularly its implication of identical slopes across all quantile regressions

— 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.

— Recent cutting-edge method; very few empirical applications, one being Maasoumi & Wang (2019)

Standard employment and wage generating model with selection is:

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

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

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

Selection issue, females less likely to be in jobs, is addressed via Quantile-copula approach of Arellano and Bonhomme (2017)

Using law of iterated probabilities, we expand the wage cumulative distribution function conditional of gender $F_{Y_g|D_g}$ as

$$F_{Y_g|D_g}(y) = \int F_{Y_g|X,D_g}(y|X = x) \cdot dF_{X|D_g}(x), \qquad g \in (m, f). \tag{4}$$

We constructed counterfactual (female's returns being like male's) by swapping selection-corrected conditional quantile regression coefficients as Chernozhukov et al. (2013)

$$F_{Y_m^C:X=X|D_f}(y) = \int F_{Y_m|X,D_m}(y|X=x) \cdot dF_{X|D_f}(x). \quad (5)$$

With counterfactual, we can apportion the total wage distribution difference into structural effect (SE) and composition effect (CE) as

$$\begin{aligned} TE &= \left[F_{Y_f:X=X|D_f} - F_{Y_m^C:X=X|D_f}\right] + \left[F_{Y_m^C:X=X|D_f} - F_{Y_m:X=X|D_m}\right] \\ &= SE + CE. \end{aligned} \quad (6)$$

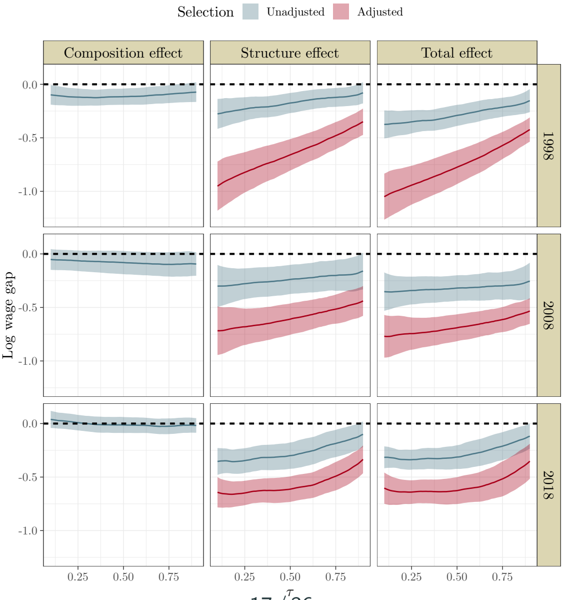
Datasets for decomposition results

- We used three rounds of Nepal labor Force Survey (NLFS) produced by National Statistics Office (formerly, CBS)

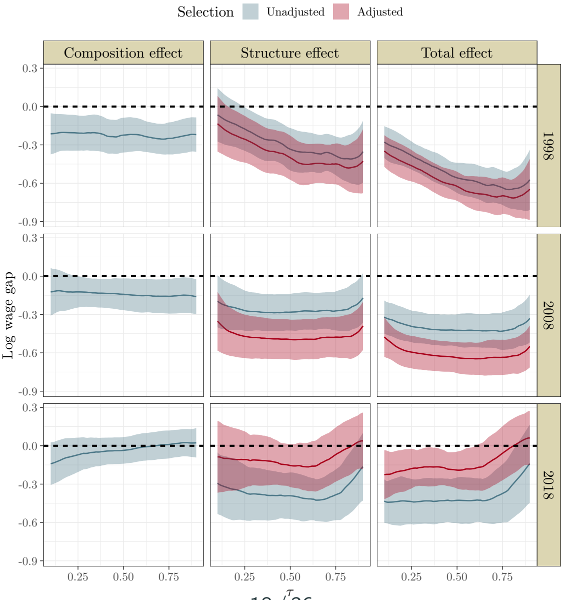
	NLFS I	NLFS II	NLFS III
Households	14,400	16,000	18,000
Working population (15-65 years)	38,535	44,734	47,905
Employed population	6,477	7,565	7,838

- In all three rounds, approximately 75% of the employed population are males.

Urban wage decomposition



Rural wage decomposition



Sources of structural effect

— Structure effect dominates the gender wage gap while composition effect has been nearly eliminated over years

— Improving human capital strategy has been exhausted

— Structural effect stems from two sources: Differing returns to observed characteristics; and unobserved labor market characteristics

— We look into household level dynamics: Differential earning potential and time allocation into home production to examine increasing relevance of structural effect on gender wage gap

Differential earning potential

— Using Census 2011, we examine effect of earning potentiality on job participation

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

Where,

GAP_h is male minus female average years of schooling in household h

X_f is a vector of the individual characteristics of women f

Z_h is a vector of household characteristics

ψ_u is urban dummy; π_d is district dummy; and

$\epsilon_{f,h}$ is the stochastic error term

Female participation and 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)
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)

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.

Time spent on home production

— We examine gender gap in time allocated for home production using NLFS II, NLFS III, and NLSS III

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

Where,

F is a female dummy; E is employed dummy; $F \times E$ is an interaction term

X_i is a vector of the individual characteristics

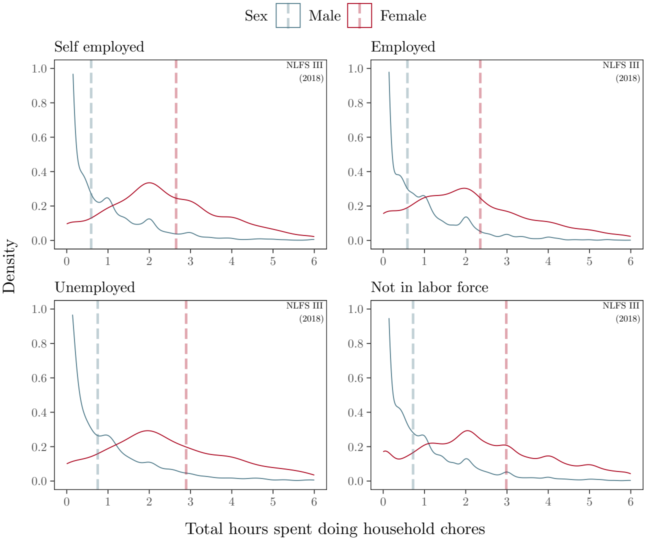
Z_h is a vector of household characteristics

ψ_u is urban dummy; and $\epsilon_{f,h}$ is the stochastic error term

	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
Adjusted R^2	0.385	0.346	0.353	0.334	0.335	0.303

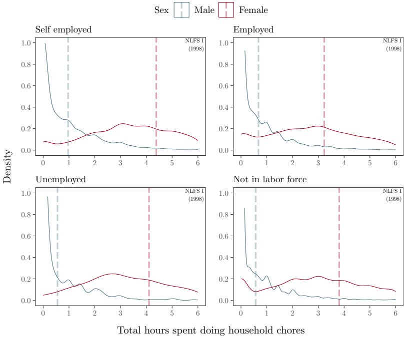
Model 1, 3 & 5 are unmatched, whereas model 2, 4 & 6 are matched with generalized full matching; Error bands in unmatched and matched models are HC1 robust standard errors and matched-subgroup-wise clustered standard errors respectively; Signif. Codes: ***: 0.01, **: 0.05, *: 0.1; Controls included are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

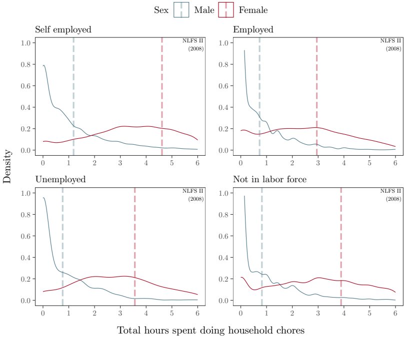
Labor market status and time use in 2018



CEDECON
TRIBHUVAN UNIVERSITY

Similar trend in the past





Conclusion 1

— Gender wage gap trajectory across rural and urban areas.

— Quantile-wise decomposed gender wage gap into CE and SE (Chernozhukov et al. (2013) & Arellano and Bonhomme (2017): tools + selection correction).

— Wage gap is converging for the higher quantile groups, widening or stagnating among lower-earners.

— SE mirrors the slope of TE, CE amplifies the uniformly.

— Notable trend of improvement in CE throughout the time with education progressing beyond gender-parity.

Conclusion 2

— The improvement is overshadowed by the aggravation of the structural effect, which persists even after adjusting for selection.

— 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.

— "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.

— We were unable to incorporating psychological attributes and consequences of policy changes.

— Q& A —

Instrument for Selection

- Majority of literature uses two instruments: Spousal income, and number of children
- Our data could not generate spousal pairs and their income; Nepali society differs from Western society in terms of family arrangement. People live in extended family where there are people to rear child
- 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.

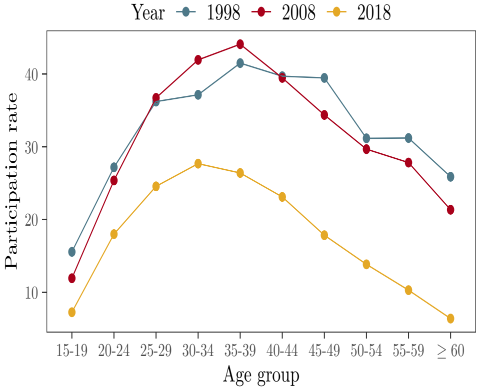


Figure 1: Female labor force participation with age group

- Majority of participation can be observed in child bearing age of women
- Low but child bearing age group(s) into work
- Employed number of family member could be one of the instruments

Table 1: Huber-Mellace instrument validity test

	Overall			Urban			Rural		
Round	Diff	p (prob)	p (mean)	Diff	p (prob)	p (mean)	Diff	p (prob)	p (mean)
PANEL A:	Instrument: Employed member IV								
I	-1.165	1	1.00	-0.781	1	1.000	-1.457	1	0.957
II	-1.164	1	1.00	-0.882	1	1.000	-1.320	1	0.962
III	-0.853	1	0.83	-0.854	1	0.989	-0.378	1	0.180
PANEL B:	Instrument: Child presence IV								
I	–	0.020	–	–	0.006	–	0.258	0.128	0.004
II	–	–	–	–	–	–	–	–	–
III	–	–	–	–	–	–	0.092	–	0.326

Table 2: Rural

τ	1998	2008	2018
0.10	-0.348	-0.476	-0.227
	-0.471 ; -0.224	-0.631 ; -0.321	-0.419 ; -0.035
0.25	-0.463	-0.594	-0.179
	-0.586 ; -0.34	-0.721 ; -0.467	-0.334 ; -0.023
0.50	-0.624	-0.638	-0.191
	-0.738 ; -0.51	-0.759 ; -0.517	-0.335 ; -0.046
0.75	-0.698	-0.635	-0.059
	-0.842 ; -0.554	-0.772 ; -0.497	-0.27 ; 0.153
0.90	-0.647	-0.550	0.061
	-0.886 ; -0.408	-0.714 ; -0.386	-0.15 ; 0.273

Table 3: Urban

τ	1998	2008	2018
0.10	-1.050	-0.769	-0.604
	-1.265 ; -0.834	-0.969 ; -0.57	-0.75 ; -0.458
0.25	-0.942	-0.745	-0.640
	-1.124 ; -0.761	-0.895 ; -0.594	-0.75 ; -0.53
0.50	-0.774	-0.690	-0.626
	-0.932 ; -0.617	-0.815 ; -0.564	-0.752 ; -0.501
0.75	-0.571	-0.613	-0.517
	-0.698 ; -0.445	-0.73 ; -0.495	-0.68 ; -0.353
0.90	-0.423	-0.533	-0.352
	-0.536 ; -0.309	-0.653 ; -0.413	-0.516 ; -0.188

Table 4: Rural

τ	1998	2008	2018
0.10	-0.134	-0.353	-0.087
	-0.352 ; 0.083	-0.583 ; -0.123	-0.368 ; 0.195
0.25	-0.256	-0.471	-0.108
	-0.439 ; -0.073	-0.641 ; -0.301	-0.328 ; 0.112
0.50	-0.401	-0.496	-0.155
	-0.574 ; -0.228	-0.652 ; -0.34	-0.323 ; 0.014
0.75	-0.449	-0.477	-0.069
	-0.608 ; -0.289	-0.636 ; -0.318	-0.281 ; 0.144
0.90	-0.428	-0.389	0.038
	-0.678 ; -0.177	-0.578 ; -0.2	-0.184 ; 0.26

Table 5: Urban

τ	1998	2008	2018
0.10	-0.951	-0.718	-0.642
	-1.181 ; -0.721	-0.944 ; -0.491	-0.783 ; -0.501
0.25	-0.822	-0.681	-0.648
	-1.011 ; -0.634	-0.851 ; -0.511	-0.763 ; -0.534
0.50	-0.659	-0.609	-0.613
	-0.805 ; -0.512	-0.755 ; -0.463	-0.732 ; -0.494
0.75	-0.479	-0.516	-0.492
	-0.606 ; -0.353	-0.652 ; -0.38	-0.624 ; -0.359
0.90	-0.350	-0.439	-0.335
	-0.473 ; -0.227	-0.578 ; -0.3	-0.464 ; -0.205

Result table: Unadjusted total effect

Table 6: Rural

τ	1998	2008	2018
0.10	-0.279	-0.320	-0.433
	-0.404 ; -0.154	-0.449 ; -0.19	-0.603 ; -0.263
0.25	-0.383	-0.393	-0.437
	-0.494 ; -0.273	-0.517 ; -0.269	-0.613 ; -0.26
0.50	-0.558	-0.424	-0.427
	-0.676 ; -0.44	-0.549 ; -0.298	-0.605 ; -0.248
0.75	-0.635	-0.430	-0.373
	-0.77 ; -0.501	-0.576 ; -0.283	-0.601 ; -0.145
0.90	-0.572	-0.331	-0.141
	-0.808 ; -0.337	-0.518 ; -0.144	-0.447 ; 0.166

Table 7: Urban

τ	1998	2008	2018
0.10	-0.375	-0.352	-0.315
	-0.506 ; -0.244	-0.532 ; -0.172	-0.418 ; -0.213
0.25	-0.351	-0.342	-0.338
	-0.459 ; -0.243	-0.472 ; -0.212	-0.43 ; -0.245
0.50	-0.291	-0.319	-0.313
	-0.389 ; -0.192	-0.438 ; -0.199	-0.424 ; -0.202
0.75	-0.214	-0.299	-0.211
	-0.303 ; -0.125	-0.428 ; -0.169	-0.342 ; -0.08
0.90	-0.153	-0.254	-0.118
	-0.26 ; -0.045	-0.427 ; -0.082	-0.235 ; -0.001

Table 8: Rural

τ	1998	2008	2018
0.10	-0.214	-0.123	-0.140
	-0.374 ; -0.053	-0.309 ; 0.063	-0.306 ; 0.026
0.25	-0.207	-0.123	-0.071
	-0.345 ; -0.07	-0.246 ; -0.001	-0.205 ; 0.064
0.50	-0.224	-0.142	-0.036
	-0.36 ; -0.088	-0.266 ; -0.018	-0.14 ; 0.068
0.75	-0.249	-0.158	0.010
	-0.375 ; -0.124	-0.293 ; -0.023	-0.099 ; 0.119
0.90	-0.220	-0.161	0.023
	-0.354 ; -0.085	-0.297 ; -0.024	-0.092 ; 0.139

Table 9: Urban

τ	1998	2008	2018
0.10	-0.099	-0.052	0.039
	-0.19 ; -0.007	-0.149 ; 0.045	-0.041 ; 0.118
0.25	-0.120	-0.064	0.008
	-0.2 ; -0.04	-0.16 ; 0.032	-0.064 ; 0.081
0.50	-0.116	-0.081	-0.014
	-0.192 ; -0.04	-0.189 ; 0.028	-0.088 ; 0.061
0.75	-0.092	-0.097	-0.025
	-0.176 ; -0.008	-0.211 ; 0.017	-0.098 ; 0.048
0.90	-0.073	-0.094	-0.017
	-0.165 ; 0.019	-0.204 ; 0.016	-0.086 ; 0.051

Result table: Unadjusted composition effect

Table 10: Rural

τ	1998	2008	2018
0.10	-0.065	-0.197	-0.293
	-0.273 ; 0.144	-0.4 ; 0.007	-0.533 ; -0.052
0.25	-0.176	-0.270	-0.366
	-0.346 ; -0.006	-0.427 ; -0.113	-0.582 ; -0.149
0.50	-0.334	-0.282	-0.391
	-0.5 ; -0.168	-0.425 ; -0.138	-0.573 ; -0.209
0.75	-0.386	-0.272	-0.383
	-0.537 ; -0.234	-0.425 ; -0.119	-0.582 ; -0.185
0.90	-0.353	-0.170	-0.164
	-0.595 ; -0.111	-0.363 ; 0.023	-0.429 ; 0.101

Table 11: Urban

τ	1998	2008	2018
0.10	-0.276	-0.301	-0.354
	-0.416 ; -0.136	-0.498 ; -0.103	-0.48 ; -0.229
0.25	-0.231	-0.278	-0.346
	-0.341 ; -0.121	-0.421 ; -0.135	-0.461 ; -0.231
0.50	-0.175	-0.238	-0.299
	-0.269 ; -0.081	-0.374 ; -0.102	-0.422 ; -0.177
0.75	-0.122	-0.201	-0.186
	-0.211 ; -0.034	-0.345 ; -0.057	-0.313 ; -0.059
0.90	-0.080	-0.160	-0.100
	-0.179 ; 0.019	-0.332 ; 0.012	-0.22 ; 0.019