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INFORMAL EMPLOYMENT AND THE STRUCTURE OF WAGES IN INDIA: A REVIEW OF TRENDS*

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The "alternative", "atypical" or "informal" workforce has grown in developed and developing countries alike. One of the more recent evolutions of informal employment has been of informal employment within formal enterprises. In the interest of flexibility and cost-reduction, many formal firms increasingly resort to hiring workers on a temporary or informal basis. Alongside, and perhaps, as a result of the persistence and pervasiveness of informal employment, issues relating to inequality have come to the fore. This paper is motivated by these two intertwining aspects of Indian labor market—informality and wage inequality. Using nationally representative sample data, the paper examines trends in wage inequality. Using a regression based inequality decomposition, the paper compares the sources of wage inequality across different employment groups and the reasons for differences in wage inequality.

JEL Codes: J46, J31, J21

Keywords: decomposition, formal sector, inequality, informal employment, wage structure

1. INTRODUCTION

In India, consumption inequality has risen since the 1990s alongside increases in income and wealth inequalities (Anand and Thampi, 2016; Banerjee and Piketty, 2010; Topalova, 2008). Since the 2000s, there is some evidence to suggest a decline in inequality in disposable incomes (Rani and Furrer, 2016). Wage inequality, on the other hand, has registered a marginal increase over the years (Cacciamali *et al.*, 2015). However, when disaggregated by regions (rural and urban), wage inequality is found to be declining in rural areas and increasing in urban (Cacciamali *et al.*, 2015). Labor income being the most important factor contributing to overall income inequality and to changes in income inequality (Rani and Furrer, 2016), it is pertinent to explore the contributions and trends in different forms of labor to overall labor income inequality.

In India, the structure of employment and the sources of labor income have changed over time. The majority of workers continue to work in the informal

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sector. In recent years, the formal sector has contributed to a rise in the number of informal workers through the hiring of workers in informal arrangements, a process referred to as "casualisation" or "informalization" of the workforce. Firms create a dual structure within their enterprises, preferring to hire unskilled workers as contract/temporary staff rather than as regular workers (Ramaswamy, 2008). Informal hiring allows firms to avoid stringent labor regulations which are applicable typically to directly employed formal workers. It also offers significant cost savings and allows firms to operate with a flexible production model (Goldar and Aggarwal, 2012; Kapoor, 2016).

Formal firms, having better access to financial capital and hence, more advanced technological processes, are likely to pay higher wages. At the same time, these firms in the formal sector are likely to resort to mechanization and automization, have preference for skilled workers, thus creating greater job polarization and hence tend to generate larger income disparities. Over time, with greater liberalization, wage inequality is expected to fall (Figini and Gorg, 2011) but some liberalization in its early phases leads to increase in capital intensity, increasing the skill premium and thereby increasing inequality if the distribution of skills is asymmetric, as is the case in India. Therefore, within these forms of workers, i.e. informal workers in the formal sector, it is likely that wage dispersion may have increased. The presence of informal workers in the formal enterprises can also diminish the bargaining power of the regular or formal workers (Kapoor, 2016). For instance, Kapoor (2016) and Banga (2005) find an increase in wage dispersion within the organized sector with an increase in contractualization. In particular, Kapoor (2016) identifies that contractualization of the workforce contributed *more* to wage inequality than an increase in capital intensity, i.e., the marginal impact of contractual hiring was larger than the marginal impact of rising capital intensity.

While all of the above studies are restricted to the organized manufacturing sector, studies that have considered the unorganized sector, typically use a regular-casual distinction between workers (Cacciamali *et al.*, 2015; Das, 2012; Dutta, 2005). This has its own limitations since most "regular" workers are also informal workers since they do not have basic employment/job security. This analysis seeks to address this gap by explicitly accounting for the informalization within formal sector and within "regular" jobs.

In the context of the increasing informalization of the labor force, this paper examines the implications for wage inequality. Firstly, it examines to what extent trends in wage inequality among different employment groups has differed from overall trends. Secondly, a regression-based decomposition is used to examine the relative contribution of various factors such as age, education and industrial affiliation to the extent of wage inequality in *each type of employment*. Finally, using Yun's (2006) extension of the regression-based decomposition, it examines the factors accounting for differences in wage inequality *between different categories* of employment.

Following a brief description of the definitions used, Section 2 describes broad trends in wage inequality across employment groups. Section 3 details the decomposition methodology used to identify sources of wage inequality. The sources of wage inequality within employment groups, and the factors accounting

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for differences in wage inequality across employment groups are presented in section 4. Section 5 concludes.

2. Informal Employment and Wage Structure in India – Definitions, Measurement and Trends

2.1. Defining Informal Employment

Informality may be defined in terms of the enterprise or employment. Informal *employment* is defined as any employment without the provision of employment-related social security benefits. For the purpose of this analysis, the provision of Provident Fund (PF)¹ is taken as a proxy for provision of social security benefits. Data limitations as well as considerable overlap between the provision of PF and other social security benefits motivate the adoption of PF as a proxy for social security benefits. For further discussion on the rationale and tenability of this assumption, see Abraham (2017).

Informal *enterprises* are defined as unincorporated proprietary or partnership enterprises, while formal enterprises are comprised of public/private limited companies, government/public sector units and cooperatives.

Juxtaposing the definition of employment alongside the definition of enterprises based on the conceptual framework provided by the International Conference of Labour Statisticians (Hussmanns, 2004), employment can be differentiated as being informal or formal, and within informal or formal enterprises. Accordingly, employment may be categorized into formal employment (FE), informal employment in informal enterprises (IIE), self-employment (SE) and informal employment in formal enterprises (IFE).

The nationally representative Employment and Unemployment Surveys (EUS) of the National Sample Survey Organisation (NSSO) form the primary source of data (NSSO 1999, 2004, 2011). These surveys, typically conducted quinquennially, are household-level surveys aggregating information on household attributes as well as individuals' demographic details including education and work status. Surveys for the year 1999–2000 (55th Round), 2004–2005 (61st Round) and 2011–2012 (68th Round) are used in this analysis.

2.2. Broad Trends in Informal Employment

Examining the changes in the share of each type of employment in the workforce reveals a huge growth in enterprise-based informal employment, i.e. IIE and IFE, a decline or stagnation in formal employment (FE) and a recent decline in self-employment, overall, and in rural and urban areas (Figures 1–3).

In terms of the demographic profile of workers in each type of employment, while SE and IIE are typically uneducated or undereducated, the IFE unlike their counterparts in informal enteprises, are comprised of a relatively larger share of

¹The Provident Fund (PF) is a fund contributed to by employers and employees. Any employer with 20 or more workers is required to register under the EPF scheme. A fixed proportion of employees' salaries accrue to this fund. In recent years, this contribution has been made optional for some employees. The employers are also mandated to contribute a fixed proportion to each employee's fund, and this has not been made optional.

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Figure 1. Trends in Forms of Employment, Overall, 1999–2000 to 2011–2012 *Note:* FE-formal employment, SE-self-employment, IIE-informal employment in informal enterprises, IFE-informal employment in formal enterprises.

Source: Author's computation using NSS EUS various rounds. [Colour figure can be viewed at wileyonlinelibrary.com]



Figure 2. Trends in Forms of Employment, Rural India, 1999–2000 to 2011–2012 Note: FE-formal employment, SE-self-employment, IIE-informal employment in informal enterprises, IFE-informal employment in formal enterprises.

Source: Abraham (2017). [Colour figure can be viewed at wileyonlinelibrary.com]

educated individuals (Abraham, 2017). The recent trend of informalization in formal enterprises has also seen a growing engagement of women, with an accompanying decline in self-employment among women.

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Figure 3. Trends in Forms of Employment, Urban India, 1999–2000 to 2011–2012 Note: FE-formal employment, SE-self-employment, IIE-informal employment in informal enterprises, IFE-informal employment in formal enterprises.

Source: Abraham (2017). [Colour figure can be viewed at wileyonlinelibrary.com]

2.3. Trends in Wage Inequality

There is a consistent ordering with respect to average weekly earnings (Table 1), with formally employed earning the highest, followed by IFE and then IIE. Weekly wages include wage/salary earnings in cash or in kind, received or receivable for work done during the reference week. Despite their higher mean earnings, IFE have highest variation in earnings.

Figure 4 shows the inequality in the distribution of earnings within employment types. Each bar represents the share of total earnings that accrues to a particular decile of that employment group. As would be expected, every successive decile account for a larger share in the total wage earnings than the previous decile. Among all three groups, the least paid 10 percent accounted for less than 5 percent of total wages, while the highest paid 10 percent accounted for more than a fifth (20 percent) of total wages paid. Among FE and IIE, although the distribution of

		2011–2012		, ,	2004–2005		1999–2000		
	Mean	Median	CV	Mean	Median	CV	Mean	Median	CV
All FE IFE IIE	1094 2231 774 548	629 1973 543 493	1.2 0.8 1.07 0.7	748 1638 605 362	415 1454 388 291	1.4 0.9 1.08 0.8	829 1439 556 405	500 1250 400 350	1.0 0.6 1.05 0.9

 TABLE 1

 Real Weekly Wages, Summary Statistics

Note: CV - coefficient of variation.

Source: Author's computation using NSS EUS Rounds. CPI-Industrial workers has been used to convert wages to real wages.



Figure 4. Share of Wages (%) Accounted for by each Decile Group, Overall 2011–2012 *Note*: FE–formal employment, SE–self-employment, IIE–informal employment in informal enterprises, IFE–informal employment in formal enterprise.

Source: Author's computations using NSS EUS Rounds. [Colour figure can be viewed at wileyonlinelibrary.com]



Figure 5. Changes in Wage Inequality (Gini), Overall 1999–2000 to 2011–2012 *Source*: Author's computations using NSS EUS Rounds.

wage earnings was not similar across decile groups, there were no disproportionately large shares accruing to any given decile. But in the IFE, the share of wages accruing to the top decile was much higher than other groups, as well as the same decile group in other employment types.

In 2011, the top 10 percent in IFE accounted for more than thirty percent of total IFE wage earnings. In comparison, among the FE and IIE, the top 10 percent received less than a quarter of the total wage earnings in that employment type.

The Gini coefficient provides an insight into the evolution of wage inequality across employment groups (Figures 5–7). Amongst the IFE, inequality increased initially followed by a decline. For the formal workers, on the other hand, there

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Figure 6. Changes in Wage Inequality (Gini), Rural 1999–2000 to 2011–2012 *Source*: Author's computations using NSS EUS Rounds.



Figure 7. Changes in Wage Inequality (Gini), Urban, 1999–2000 to 2011–2012 Source: Author's computations using NSS EUS Rounds.

has been an increase in wage inequality in both rural and urban areas, while the informal workers in informal enterprises (IIE) have seen a gradual decline in wage inequality. These results are most apparent in the urban areas, compared to the rural.

Among the FE and IIE, the estimates of inequality by different measures (Table 2) give similar conclusions, confirming the robustness of these results. Between 1999–2000 and 2011–2012, inequality levels rose among the FE, for all measures of inequality while it declined among the IIE. For IFE, wage inequality rose between 1999–2000 and 2004–2005, but declined by 2011–2012. The secular trends observed among the FE and IIE are not seen at the overall level suggesting that IFE dominates overall wage inequality trends.

The percentile dispersion ratios provide information on the extent of deviation between selected percentiles of the wage distribution. For instance, in 2011–2012, the 90th percentile wage was 5 to 6 times higher among the IFE and FE than the

			Meas	TABLE 2 URES OF WAGE]	[NEQUALITY					
					RURAL					
		FE			IFE			IIE		
	1999–2000	2004–2005	2011-2012	1999–2000	2004-2005	2011-2012	1999–2000	2004-2005	2011-2012	
MeanLogDeviation	0.22	0.20	0.24	0.30	0.37	0.25	0.21	0.22	0.18	
Theil index GE(1) Half of CV Squared	$0.18 \\ 0.19$	$0.17 \\ 0.19$	$0.20 \\ 0.23$	$0.32 \\ 0.49$	$0.39 \\ 0.56$	$0.27 \\ 0.41$	$0.21 \\ 0.31$	$0.22 \\ 0.30$	$0.17 \\ 0.24$	
Gini Gini	0.32	0.31	0.34	0.41	0.46	0.37	0.34	0.35	0.31	
Atkinson(0.5) Atkinson(1)	0.09 0.20	0.09 0.18	0.10 0.21	$\begin{array}{c} 0.14 \\ 0.26 \\ 0.2 \end{array}$	$\begin{array}{c} 0.17 \\ 0.31 \\ 0.31 \\ \end{array}$	$0.12 \\ 0.22 \\ 0.22$	0.10 0.19	$\begin{array}{c} 0.10\\ 0.20\\ 0.2\end{array}$	$\begin{array}{c} 0.08 \\ 0.16 \\ 0.16 \end{array}$	
Atkinson(2) p90/p10	0.43 7.21	0.42 5.52	0.46 6.67	0.47 6.33	$0.51 \\ 9.17$	0.41 5.25	0.36 4.62	0.38 4.8	0.34 4.29	
990/p50 p10/p50 p75/p25	$1.73 \\ 0.24 \\ 2.03$	$ \begin{array}{c} 1.79\\ 0.32\\ 2.02 \end{array} $	$ \begin{array}{c} 1.88 \\ 0.28 \\ 2.38 \end{array} $	2.44 0.38 2.38	3.67 0.4 2.56	2.1 9.6	2 0.43 2.1	2.06 0.43 2.08	$^{1.8}_{2.42}$	
					URBAN					
Mean Log Deviation	0.17	0.22	0.24	0.32	0.38	0.33	0.25	0.24	0.22	
GE(0) Theil index GE(1) Half of CV Squared	$0.16 \\ 0.20$	$0.23 \\ 0.51$	$0.22 \\ 0.30$	$0.34 \\ 0.54$	$0.39 \\ 0.55$	$0.36 \\ 0.57$	$0.26 \\ 0.43$	$0.24 \\ 0.35$	$0.22 \\ 0.32$	
GE(2) GE(2)	0.21	0.35	0.25	0.42		0.42	72.0	92.0	0.25	
Atkinson(0.5)	0.08	0.10	0.11	0.15	0.18	0.16	0.12	0.11	0.10	
Atkinson(1)	0.16	0.20	0.21	0.27	0.32	0.28	0.22	0.21	0.20	
p90/p10	4.37	5.32	6.16	6.67	9.52	6.58	5.15	5.33	5.33	
p90/p50	2.01	2.08	2.05	2.83	3.94	2.87	2.00	2.13	2.00	
p10/p50	0.46	0.39	0.33	0.42	0.41 2 00	0.44 2 50	0.27	0.40 2 33	0.38	
0171742	1.7.1	1.40	1-1-1	1.51	1.70	1.00		00.7	4.14	

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10th percentile. The 90–10 dispersion is highest among the IFE in urban areas, and among the FE in rural areas. On the other hand, in comparing the 90th percentile with the 50th percentile, i.e. the median group, the dispersion continued to be higher among the IFE in all the years. The high inequality is prominent in upper half of distribution in case of IFE. Wage inequality below the median (10–50) is lower. For IIE, all measures show gradual improvement in the direction of greater equity in wage earnings.

3. Methodology

3.1. *Identifying Sources of Wage Inequality (Fields approach)*

Income/wages may be described by a stochastic process, typically a regression, with specific explanatory factors including age, education. The inequality decomposition using the Fields method (2003) identifies the contribution of each factor to overall inequality.

Assuming a semi-log wage model,

(1)
$$\ln(Y_i) = \alpha + \sum_j \beta_j x_j + \varepsilon_i$$

where Y represents wages of individual *i*, X_j is a vector of *j* characteristics, β_j is a vector of coefficients, and ε_i is a vector of stochastic disturbance term.

Equation (1) is rewritten as,

(1a)
$$\ln(Y_i) = \sum_{j=1}^{J+2} a_j Z_j$$

where,

(1b)
$$a = \left[\alpha \beta_1 \beta_2 \dots \beta_j 1\right]$$

and,

(1c)
$$Z_i = \begin{bmatrix} 1x_1x_2 \dots x_j\varepsilon_i \end{bmatrix}$$

Adapting the methodology of Shorrocks (1982), Fields shows that

(2)
$$\sigma^2(\ln Y) = \sum_{j=1}^{J+2} \operatorname{cov}\left[a_j Z_j, \ln Y\right]$$

where σ^2 represents variance. Equation (2) may be modified to,

(3)
$$1.0 = \frac{\sum_{j=1}^{J+2} \operatorname{cov} \left[a_j Z_j, \ln Y \right]}{\sigma^2 \ln \left(Y \right)} = \sum_{j=1}^{J+2} S_j (\ln Y)$$

(4)
$$s_j = \frac{\operatorname{cov}\left[a_j Z_j, \ln Y\right]}{\sigma^2 \ln Y}$$

(5)
$$\sum s_j = 1.0$$

where each $S_j(\ln Y)$ represents the 'factor inequality weight' capturing the contribution of factor variable X_j to overall inequality of Y_i . This decomposition is applicable to virtually all inequality measures including the Gini, the Atkinson index, the GE measures and the coefficient of variation.

In most empirical applications of this regression-based decomposition method, the semi-log wage equation is not corrected for selection bias. Dutta (2005) is an exception and she uses the Lee (1983) method to correct for selection bias in a polychotomous choice model. Those unobserved factors that influence an individual's employment outcome may also influence his/her earnings. Additionally, if workers self-select into sectors, there is likely to be sample selection bias in estimating the wage equations. Those attributes that resulted in a worker being (in) formally employed may also influence her (in)formal wage earnings.

So, let wages (w) of individual *i* in *j* outcome be

(6)
$$w_{ji} = x_{ji}\beta_j + u_{ji}, j = (1, ..., P)$$

An individual has an unobservable utility from his employment choice, based on a set of attributes z_i . So,

(7)
$$I_{ij}^* = z_{ji}\gamma_j + \eta_{ji}$$

where, I_{ii}^{*} is the unobservable utility.

An outcome *j* is chosen iff

(8)
$$I_{ii}^* > \operatorname{Max} I_s^* (s = 1 \dots P), j \neq s$$

where I_s^* is the unobservable utility for the individual from any outcome other than *j*.

Define ε_{ii} such that,

(9)
$$\varepsilon_{ji} = \operatorname{Max} I_s^* - \eta_{ji} \, (s = 1 \dots P, j \neq s)$$

Although utility (I_{ij}^*) is not observable, the employment choice is, represented by an indicator function *I*. So,

I = j if and only if $I_{ii}^* > MaxI_s^*$ ($s = 1 \dots P$), $j \neq s$, or,

(10)
$$z_{ji}\gamma_j + \eta_{ji} > \varepsilon_{ji} + \eta_{ji}$$

So, I = j if and only if,

(11)
$$\varepsilon_{ji} < z_{ji} \gamma_j$$

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Then, assuming a type I extreme value distribution for ε_{ji} , the probability that sector *j* is chosen is

(12)
$$P(I=j) = P\left(\varepsilon_{ji} < z_{ji}\gamma_{j}\right) = F\left(z_{ji}\gamma_{j}\right)$$

This is the first stage multinomial choice selection model.

In the second stage, the wages are observed only for those who are working and on the basis of the sectoral choice. The conditional wage equation is

(13)
$$E(w_{ji}|I=j) = E(w_{ji}|\varepsilon_i < z_{ji}\gamma_j) = x_{ji}\beta_j + E\left(u_{ji}|\varepsilon_{ji} < z_{ji}\gamma_j\right)$$

The second term captures the selection bias in the wage equation. While Equation (12) forms the first stage polynomial choice selection model, the second stage model is an OLS wage equation. The selectivity bias is corrected using Lee (1983)'s analogue of the inverse Mill's ratio represented by the last two terms in Equation (14).

(14)
$$E(w_{ji}|I=j) = x_{ji}\beta_j + \delta_j\lambda_j + \vartheta_{ji}$$

where,

(15)
$$\lambda_{j} = -\phi \left[\Phi^{-1} \left[F_{j} \left(z_{j} \gamma_{j} \right) \right] \right] / F_{j} \left(z_{j} \gamma_{j} \right)$$

and, $\delta_j = \sigma_j \rho_j$ where, σ_j is the variance of u_{ji} , and ρ_j measures the correlation between u_i and ϵ_j .

Therefore, the semi log model used for the Fields decomposition will also contain a lambda term which is introduced to correct for the selection bias. However, while selection bias due to the nature of labor force participation is accounted for, the sampling bias created due to the non-availability of self-employed earnings and their exclusion from the estimation sample is not being accounted for here.

3.2. *Identifying Sources of Differences in Wage Inequality (Yun approach)*

While the Fields approach allows us to disentangle how various factors influence wage inequality for each type of employment, Yun's (2006) method allows to identify the factors that contribute to the *differences* in wage inequality between two employment types. Yun (2006) synthesizes the methods of Fields (2003) and John *et al.* (1991) to decompose the difference in log-earnings between two groups/time periods into coefficients (price) effects and characteristics (quantity effects). The coefficient/price effect captures the differences in inequality due to a difference in the returns to a factor between the two groups. The characteristics /quantity effect, on the hand, captures the differences in inequality due to a difference in the distribution of that particular factor between the two groups.

For any two wage distributions (A and B), the differences in inequality where inequality is measured as variance of log, is given by,

(16)
$$\sigma_A^2 - \sigma_B^2 = \sum_{k=1}^{K-1} \left(s_{k*} \sigma_*^2 - s_{kB} \sigma_B^2 \right) + \sum_{k=1}^{K-1} \left(s_{kA} \sigma_A^2 - s_{k*} \sigma_*^2 \right) + \left(\sigma_{\in A}^2 - \sigma_{\in B}^2 \right)$$

where s_{k^*} is the relative factor inequality weight associated with factor k in the auxiliary earnings equation. The auxiliary earnings equation is estimated by replacing the coefficients of group A with those of group B, while keeping individual characteristics and residuals unchanged. $\sigma_A^2, \sigma_B^2, \sigma_e^2, \sigma_*^2$ represent variances of A, B, residuals and of y in the auxiliary equation, respectively. σ_{ei} is the covariance of residual and i.

The first term on right hand side represents the characteristics (quantity) effects, second represents the coefficient (price) effects and last term captures the residuals effect.

4. Findings

4.1. How Different are Different Types of Workers Across the Wage Distribution?

Wage inequality may occur as a result of difference in workers' characteristics across wage earnings. Figures 8–11 describe the distribution of workers' gender, education, sector of work and age across the wage spectrum, by employment type. Each bar represents a decile group, with the bars going from 1st decile (lowest wage group) to 10th decile (highest wage group) in each employment type. Each bar is further divided into the share of a particular demographic—gender, age group, industry of employment, in that decile group.

As wage levels increases, the share of women declines, although the trend is less obvious among the FE and IFE (Figure 8). The proportion of women in the upper deciles in IFE is similar to that in FE. This indicates that IFE offers women an opportunity to participate at higher wages than they would have if they were employed as IIE. Women's participation in the formal labor market is



Figure 8. Gender-Distribution Across Wage Deciles, by Employment Type, 2011–2012 *Source*: Author's computations using NSS EUS 68th (2011–12) Round



Figure 9. Educational Attainment Across Wage Deciles, by Employment Type, 2011–2012 *Source*: Author's computations using NSS EUS 68th (2011–2012) Round.

polarized between high and wage activities. Informal work in the formal enterprises has allowed for women to engage in the labor market at higher wage levels, although it is possible that it has also become one more hurdle keeping women from formal employment. This point is returned to in the later section looking at the factors contributing to differences in wage inequality between IFE and IIE.

Expectedly, educational qualifications improve as we progress along wage deciles, irrespective of employment type (Figure 9). However, this trend is most prominent among FE where almost 90 percent of individuals in the 10th decile have above higher secondary education. Interestingly, the IFE also show similar educational attainment in the upper wage deciles as the FE. For the IIE, there is a broadly similar attainment of education across most deciles, with the exception of the tenth decile. From Figure 9, it appears that the proportion of workers with high educational attainment in the top three deciles of IFE is similar or higher than in the top three deciles of FE. The IFE workers in these three deciles are employed in services sub-sector comprising of Trade, Hotels, Transport and Communication (THTC), and in Construction (Figure 10). FE workers are predominantly in public sector activity in the services subsector in the Public Administration and Community Services (PACS) as well as in THTC (Figure 10). THTC therefore employs workers with different training and in differently-paid work.

On the other hand, sector like Financial Services, Insurance and Real Estate (FIRE) sectors are predominantly high wage activities particularly in the case of informal workers. Manufacturing, as an industry, has largely failed to create formal employment, and manufacturing workers are predominant as IIE.

Higher wage earnings in FE accrue largely to individuals who are highly experienced and prior to their retirement (Figure 11). On the other hand, in IIE, it is the younger age group of 36 to 45 year olds who enjoy higher earnings, and among the IFE, the higher earnings accrue largely to a younger working age group.

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Figure 10. Sectoral Distribution Across Wage Deciles, by Employment Type, 2011–2012 *Notes:* THTC-trade, hotels, transport and communication; FIRE-financial services, insurance and real estate; PACS-public administration and community services. *Source:* Author's computations using NSS EUS 68th (2011–2012) Round.



Figure 11. Age Distribution Across Wage Deciles, by Employment Type, 2011–2012 *Source*: Author's computations using NSS EUS Rounds.

4.2. What Factors Explain Wage Inequality in Each Employment Type?

The above analysis showed the variation in demographic characteristics across the wage distribution within employment groups and across employment groups. To what extent do these factors influence the wage disparity in each employment group? This is analyzed using the method of Fields (2003) and

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		OVERALL	
Dependent Var—Log (weekly wages)	FE	IIE	IFE
Male	0.03***	0.61***	0.43***
Has Primary Education	0.03***	0.02*	0.01
Has Secondary Education	0.03***	0.04***	0.03
Has Higher Secondary Education	0.03***	0.04**	0.19***
Has Graduate education	0.03***	0.28***	0.53***
Age	0.004***	0.04***	0.03***
Age Squared	0.000***	0.00	0.00***
Has Vocational Training	0.00**	-0.02^{***}	-0.02^{***}
Is in Professional/Technical/Managerial	0.01***	0.07***	0.29***
Occupation			
Is in Professional/Technical/Managerial	0.03	0.08**	-0.14^{***}
Occupation & Woman			
SC household	0.02***	0.02	-0.11***
ST household	0.03***	-0.12^{***}	-0.16***
OBC household	0.01***	0.00	-0.11***
Hindu household	0.02***	-0.06***	-0.05*
Muslim household	0.03	-0.05^{**}	-0.03
Days worked	0.01***	0.22***	0.27***
Enterprise size	0.01***	0.00	0.18***
Has written job contract	0.01***	0.13***	0.15***
Is member of union	0.01***	0.15***	0.15***
Is in Manufacturing/Construction sector	0.02***	0.20***	0.29***
THTC	0.02***	0.05***	0.35***
FIRE	0.02***	0.12***	0.28***
PACS	0.02***	-0.07***	0.10***
Selection	0.02***	-0.31^{***}	0.12***
Constant	0.14***	3.55***	3.89***
MODEL STATISTICS			
$\operatorname{Adj} \mathbb{R}^2$	0.51	0.40	0.49
P > f	0.00	0.00	0.00

 TABLE 3

 Estimates of Semi Log Wage Model, 2011–2012

Note: *, **, *** Indicates significance at 10%, 5% and 1% level of significance. THTC – Trade Hotels Transport and Communication, FIRE- Financial Services, Insurance and Real Estate. PACS – Public Administration and Community Services.

Source: Author's computations using NSS EUS 68th (2011-12) Round unit level data.

Shorrocks (1982) For the decomposition, a selectivity-corrected semi-log wage equation is estimated for each of the subgroups. Selectivity bias is corrected using the Lee (1983) technique which models the labor market outcome as a polychoto-mous choice model and then estimates wages after correcting for the selection bias². The estimates of the semi-log wage equation are presented in Table 3 for overall India, and Table 4 for rural and urban.

Being a male worker had significant positive effects on wage outcomes, irrespective of the nature and sector of employment. Further, age seemed to have a linear monotonic relation with wages, as seen by the positive and significance of the age-squared term. Higher age meant more experience earning higher wages.

²Results of the polychotomous employment choice model are available on request. The exclusion variables (variables that appear in the polychotomous model but not in the wage model are household income and status of individual in the household (head of household or not). It is tenable that an individual's household income and his/her status in the household can impact the nature of his/her participation in the labour market, but not the wage returns for participation.

		RURAL			URBAN	
	FE	IIE	IFE	FE	IIE	IFE
Male	0.40^{**}	0.58***	0.49***	0.27***	0.59***	0.44***
Has Frimary Education Has Secondary Education	0.06	0.01	-0.04	-0.15^{***}	-0.07***	0.02***
Has Higher Secondary Education	0.03	0.06^{**}	0.16^{***}	-0.28***	-0.18^{***}	0.25***
Has Graduate education	0.02	0.12^{***}	0.40^{***}	-0.32^{***}	-0.05	0.59***
Age	0.02***	0.04***	0.02***	0.03***	0.04***	0.04***
Age Squared Has vocational traininσ	0.00***	-0.01	-0.01	0.00	-0.00	-0.00***
Is in Professional/Technical/Managerial	0.11***	0.05	0.09***	0.40^{***}	0.08***	0.31***
Occupation Is in Professional/Technical/Managerial	0.03	0.12*	0.00	0.04	0.05	-0.04
Occupation & Woman						
SC household	-0.05*	0.04	0.01	-0.30^{***}	0.11^{***}	-0.18^{***}
ST household	0.00	-0.04	-0.09	-0.43^{***}	0.01	-0.18^{***}
UBC household	*0.0 *0.00-	-0.03	-0.01	-0.13	0.03^{**}	-0.20***
Mustim household	0.03	000	0.05	0.00	-0.00	-0.04
Days_worked	0.32***	0.20^{***}	0.26^{***}	0.29***	0.23***	0.28***
Enterprise_size	0.10^{***}	0.00	0.11^{***}	0.05***	0.00	0.14^{***}
Has written job contract	0.01	0.02	0.10^{**}	0.13***	0.17***	0.20***
is union memoer Employed in Manufacturing/Construction sector	-0.24	0.74***	0.11	0.20	0.16***	0.23
THTC	-0.04	0.08***	0.16^{***}	0.31^{***}	0.01	0.27^{***}
FIRE	-0.01	-0.18^{***}	0.11^{**}	0.28^{***}	0.13^{***}	0.22^{***}
PACS	0.01	-0.11^{**}	-0.03	0.15^{***}	-0.05^{**}	0.10^{***}
Selection	0.51***	-0.20***	-0.13**	0.84***	-0.76***	-0.24***
CONSTANT MODEL STATISTICS	. .02***	4.02***	<i>5.</i> 40***	0.14^{***}	3.30***	5.21 ***
Adi R ²	0.46	0.398	0.43	0.5411	0.4532	0.52
$P \check{>} f$	0.00	0.00	0.00	0.00	0.00	0.00
<i>Note:</i> *, **, *** Indicates significance at 10%, 5% and Services, Insurance and Real Estate. PACS – Public Admin. <i>Source</i> : Author's computations using NSS EUS 68 th (20	 1% level of significant si si significant significant significant significant significant	nificance. THT mmunity Servic nit level data.	C – Trade Hotels es.	s Transport and C	ommunication, F	'IRE-Financial

TABLE 4 ESTIMATES OF SEMI LOG WAGE MODEL, 2011–2012

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Education, as would be expected, increased wage returns in the case of FE. In the case of IIE, higher levels of education had insignificant impact on earnings. The marginal returns to higher education was positive and significant only for a certain level of education and above among the IFE, suggesting the premia on education among this labor force. Interestingly, the marginal return from increasing educational attainment was higher in the case of IFE, than FE for all levels of education. Notably vocational training positively influences wages of formal workers, but has an insignificant impact on informal worker earnings.

Being in a large enterprise, having a written job contract as well as union membership had positive influences on wage earnings. Finally, in terms of the industry of occupation, while PACS in rural areas earned the highest in FE, in the case of urban, it was the Trade, Hotels and Transportation sector that was lucrative. Similarly, for the IIE, being employed in manufacturing/construction had a larger positive impact on wages compared to other sectors. Finally, for the IFE, the marketed services sector (THTC and FIRE) proved to be the most lucrative in terms of marginal returns on employment. There were no major deviations from the overall trends when analyzed separately across rural and urban areas (Table 4).

Based on the regression estimates of wages, the wage inequality shares are derived using the Fields method (Table 5). In order to estimate the inequality shares of specific attributes, say age, education etc. the relative inequality shares of each corresponding dummy variables are summed together. For instance, the relative inequality shares of age given in Table 5 include the sum of inequality shares of age and age squared. Similarly, for education, the inequality shares attributed to education is essentially the sum of the inequality share of primary, secondary and other related variables.

Rural			Urban	
E FE IIE	IFE	FE	IIE	IFE
2 6.1 20.8	26.9	2.1	24.7	7.1
9 -0.9 0.8	10.7	-9.8	-2.8	25.9
0 8.9 4.6	0.5	4.8	3.3	2.4
7 0.1 0.1	0.3	0.0	1.3	0.7
8 3.6 -0.2	0.7	17.9	0.8	11.6
8 -0.2 0.6	1.0	5.2	-0.1	4.1
9 7.1 1.9	4.1	7.3	2.9	9.9
2 5.1 5.0	2.2	2.0	2.6	1.0
1 8.8 31.0	6.7	4.5	11.7	6.0
3 44.0 -1.0	-0.8	48.5	25.6	-0.1
100 100	100	100	100	100
	$\begin{array}{c cccc} & & & & & & \\ \hline \textbf{E} & & & \\ \textbf{E} & & & \\ \hline \textbf{E} & & & \\ \hline \textbf{E} & & & \\ \textbf{E} & & & \\ \hline \textbf{E} & & & \\ \textbf{E} & & \\$	$\begin{tabular}{ c c c c c c c c c c c } \hline Rural \\ \hline FE & IIE & IFE \\ \hline \hline 2 & 6.1 & 20.8 & 26.9 \\ 9 & -0.9 & 0.8 & 10.7 \\ 0 & 8.9 & 4.6 & 0.5 \\ 7 & 0.1 & 0.1 & 0.3 \\ 8 & 3.6 & -0.2 & 0.7 \\ 8 & -0.2 & 0.6 & 1.0 \\ 9 & 7.1 & 1.9 & 4.1 \\ 2 & 5.1 & 5.0 & 2.2 \\ 1 & 8.8 & 31.0 & 6.7 \\ 3 & 44.0 & -1.0 & -0.8 \\ 100 & 100 & 100 \\ \hline \end{tabular}$	$\begin{tabular}{ c c c c c c c c c c c c c c c c c c c$	$ \begin{array}{c c c c c c c c c c c c c c c c c c c $

 TABLE 5

 Sources of Wage Inequality for each Employment Type

Note: The relative inequality shares of different groups of categorical variables, say education (primary, secondary, middle etc.) or religion (Hindu or Muslim) is aggregated for ease of interpretation. Enterprise Attributes includes dummy for having written contract, number of days worked, being union member, and being part of a large enterprise (more than 6 workers). Education captures primary to graduate and above dummies. Age include age and age-squared terms. Occupation captures dummy for being a professional/technical/managerial role. Industry includes manufacturing, construction, and services.

Source: Author's computations using NSS EUS 68th (2011-2012) Round.

While the wage regression models for each of these employment types indicate that most of these variables contributed significantly to wages, as pointed out by Dutta (2005), their contribution to wage inequality varied considerably. Moreover, there are notable differences in the structure of wage inequality between the rural and urban. Among FE, selection was an important factor explaining inequality indicating the significant segmentation of the labor market. In the case of rural FE, industry affiliations played an important role in explaining wage inequality. By 2011–2012, state-level distinctions as well as age were important contributors to wage inequality. In urban FE, occupation was a significant factor. In rural areas, among the IIE, the structure of inequality was almost similar with that in urban areas. Gender was also an important factor for IIE.

Among the IFEs education was an important explanatory factor. Variations in returns to education within this sector accounted for a large share in variations in wages. This was seen in urban and rural areas, with the share increasing over time. This is not surprising since the IFE is comprised of a substantial number of highly educated individuals as well as under educated individuals. These large disparities in human capital attainments within this workforce may explain the large within group inequality accruing from education here. Additionally, variations across the IFE workforce in having a written contract as well being a union member also explained a moderate share of the wage inequality in this employment group.

4.3. *What Explains the Difference in Wage Inequality Between Employment Types?*

Based on Yun (2006), the relative influence of coefficient (price) and characteristics (quantity) effects of factors on the differences in wage inequality between two employment categories is examined (Table 6). The price/coefficient effect is

	Characteristic Effect	Coefficient Effect	Residual
			79.7
Gender	132.8	-84.9	
Education	10.2	20.0	
Age	5.2	-17.7	
Vocational Training	0.1	0.2	
Occupation	-0.5	2.3	
Caste	4.9	-4.1	
Religion	0.1	1.1	
Enterprise Attributes	16.6	-11.2	
Industry	19.8	-26.7	
State	68.4	-116.5	

TABLE 6			
Sources of Differences in Wage Inequality between IFE and	IIE,	2011-	-2012

Note: The relative inequality shares of different groups of categorical variables, say education (primary, secondary, middle etc.) or religion (Hindu or Muslim) is aggregated for ease of interpretation. Enterprise Attributes includes dummy for having written contract, number of days worked, being union member, and being part of a large enterprise (more than 6 workers). Education captures primary to graduate and above dummies. Age include age and age-squared terms. Occupation captures dummy for being a professional/technical/managerial role. Industry includes manufacturing, construction, and services.

Source: Author's computations using NSS EUS 68th (2011–2012) Round.

due to the change in the returns/coefficients of two variables. The characteristic effect, on the other hand, is due to the difference in the distribution of the particular variable between the two groups.

In 2011–2012, the variance in log wages of IFE was 0.41. The variance in log wages of IIE, on the other hand, was 0.34. What explains the higher wage inequality among IFE, compared to the IIE?

Comparing the differences in wage inequality between the IFE and IIE in 2011–2012, gender accounts for almost half of the difference in wage inequality between the two groups. In the case of gender, the characteristics effect had a positive impact on wage inequality, i.e. the average distribution of men and women in the sample changed between the IFE and IIE in such a way that it led to an increase in wage inequality. The gender distribution across wage deciles in Figure 8 shows there were relatively more women in the higher deciles in IFE than IIE. The participation of women at relatively higher wages had an inequality-exacerbating impact. The price effect of gender, on the other hand was negative, i.e. the differences in returns to male and female workers had a wage inequality dampening effect. So, the fact that women were paid relatively lower than men, contributed to a reduction in wage inequality. Therefore, while informal employment in formal enterprises allowed women to participate in the labor market at higher wage deciles, we find that since wage returns for women were relatively lower than for men, this mitigated the higher wages, leading a lower dispersion of wages. The quantity/characteristics effect of gender dominated leading to an overall increase in wage inequality.

Education also had a positive effect on the wage inequality differences between the workers. Price effect contributed largely to this implying that the difference in returns to education between the IIE and IFE exacerbated wage inequality across the two employment groups. Moreover, the distribution of educational categories across the employment type was inequality increasing. The predominance of higher educated workers in higher wage deciles in IFE as seen in Figure 9 reflects this. This resonates with similar findings by Mazumdar *et al.* (2017) on the prominent contribution of education to increase in wage inequality.

5. Conclusions

The implications for wage inequality in the presence of a growing informal workforce remains relatively unexplored. While wage inequality in India, on the whole, has declined in the first decade of the 21st century, the analysis in this paper reveals that this trend is not borne out across all employment groups. Wage inequality has declined among the IIE, increased among the FE, while increasingly among the IFE. While inequality in the IIE and FE was one of large deviation between either ends of the distribution, inequality amongst IFE is a result of large deviation between the middle, i.e. median earners and the top earners. The top quantile groups in the IFE held a disproportionate share of wages.

So while firms resort to contractualization of work to save costs and have greater flexibility, we see that this process of hiring and the nature of workers it engages has resulted in greater dispersion of wages and rising inequality.

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The comparative analysis of sources of wage inequality within each employment group reveals the differing contributions of various factors by employment types. Education does not have a significant role to play in explaining wage inequality within FE and IIE. This is because of the relatively homogenous distribution of educational attainment within this group of workers. For the IIE, the greater participation of women in this form of employment, alongside their relatively lower wages meant that the contribution of gender to wage inequality is high. For the IFE, on the other hand, education accounts for a significant share of wage inequality and this can be attributed to the large dispersion in educational attainment within these workers.

Finally, examining the sources of differences in the observed wage inequality between the IIE and IFE highlights the influence of gender as well as education. The characteristic effect has a wage inequality enhancing effect implying that the greater participation of women in the IFE workforce at lower wages compared to men has increased wage inequality. On the other hand, the price effect, i.e. the differences in returns to women and men between IFE and IIE, has reduced wage inequality. The return to wages among women being higher in IFE has meant that women workers in IFE earn relatively more than their counterparts in IIE. This has reduced the overall wage inequality. But, overall the positive characteristic effect has dominated, contributing to the higher wage inequality seen among the IFE compared to the IIE.

Therefore, while informal work in formal enterprises has enabled workers to participate at higher wages in the labor market than they would have in informal enterprises, the wage distribution points to disparities among these groups of workers. Given the increase in this form of employment, this has implications for job polarization in the future. It is likely that greater informalization, while affording firms more flexibility and cost-saving, will contribute to rising wage inequality. Offering progressive social security benefits that are not explicitly tied to the enterprise of employment but are contributed to by the employers offer one means to counter the rising trend of inequality.

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