Minimum Wages and Changing Wage Inequality in India

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Abstract

Using nationally representative data on employment and earnings, this paper documents a fall in wage inequality in India over the last two decades. It then examines the role played by increasing minimum wages for the lowest skilled workers in India in contributing to the observed decline. Exploiting regional variation in changes in minimum wages over time in the country, we find that an increase in minimum wages by one percent led to an increase in wages for workers in the lowest quintile by 0.17%. This effects is smaller at higher wage quintiles and becomes insignificant for the highest wage quintile. Since log of minimum wages increased by almost 1.3 times during 2004-2018, our estimates show that increase in minimum wages explains 78% percent of the differentially higher increase in the lowest vs the highest wage quintile in the country. Rising minimum wages, thus, play an important role over the last few decades in explaining the decline in wage inequality in India.

JEL Codes: J31, J38

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1 Introduction

There is increasing interest in the use of minimum wage as an important policy tool for poverty reduction and social justice. However, there is limited evidence for developing countries on whether changes in the minimum wage can affect wage inequality. In this paper, we examine whether increases in real minimum wage that occurred in India in the 2000s can explain the fall in wage inequality that was evident in the country in the same period. India provides an ideal context to study the effect of minimum wages on earnings inequality in a developing country setting. Under the Minimum Wages Act 1948, Indian states are empowered to set minimum wages for workers in scheduled employment categories, and in the period, 1999-2018, the median of log real administrative minimum wage across states increased by 53.83 percent. However, there was wide variation in the changes across states. At the same time, the Gini of log wages fell from 0.091 in 1999 to 0.064 in 2018, and the 50/10 earnings inequality fell from 0.830 to 0.668 in the same period. We exploit the across state and over time variation in minimum wages over the period 1999-2018 to examine whether increases in state-level minimum wages can explain the documented decreases in wage inequality in India.

We combine the nationally representative National Sample Surveys, Employment rounds (1999, 2004, 2007, 2009, 2011) and the Periodic Labor Force Surveys (2017, 2018) with data on state level minimum wages prevailing during these years. Using a two way fixed effects strategy, where we account for district and time level fixed effects, we examine the impact of growth in minimum wages on growth in daily wages for casual and regular wage workers by quintiles of the wage distribution.

We find that an increase in minimum wages by 1% leads to an increase in lowest wage quintiles in rural India by 0.17%, on the third and fourth quintile by 0.14% and 0.07% respectively, while there is no effect on the highest wage quintile. During 2004-2018 there was a rise in log of average nominal minimum wage in the country by 130%, leading to an increase in wages for the lowest quintile by 21% relative to the highest quintile. During this period the nominal wages for the 10th percentile grew by 65% while that for the 90th percentile grew by 38%, the gap between the two was thus, 27%. Our results show that 78%(=21/27) of the differentially higher growth in the lower vs higher wage percentiles can be explained by the rise in minimum wages in India. The magnitude of our results are larger for urban India, perhaps due to greater possibility of enforcement in these areas. We also estimate the differential effects of rise in minimum wages by worker skill and education level. We find that least skilled workers and those with lowest education levels benefit the most from a rise in minimum wages. At the same time, we do not find any negative impacts on employment of the least educated workers, showing that while minimum wages reduce wage inequality, these do not reduce employment levels contemporaneously in the country.

We test the robustness of our findings to including only including districts situated on the State border, which are more likely to be similar to adjacent districts culturally and in terms of agro-climatic conditions. All our results go through this subset of districts. We also include district specific time trends in our analyses, and find that our results continue to hold. Additionally, as a placebo check, we estimate the effects of changes in minimum wages on highest quintile, highest skilled and highest educated workers. We find these impacts to be insignificant. This allays any concern that our findings are driven by other economic factors correlated with differential rise in minimum wages across states over the years. We also use the concept of effective minimum wage proposed by Lee (1999) and Autor *et al.* (2016), to check the distributional implications of a rise in minimum wage by wage percentile. We again find that a rise in effective minimum wage increases wages at lower percentiles in India. Lastly, we rule out that other factors like NREGA during this period confound our analyses.

Our paper contributes to the emerging literature that documents impacts of minimum wages on wage inequality for developing countries (Gindling, 2018). Using a similar empirical strategy as our paper, Bosch & Manacorda (2010) use variations in minimum wages across municipalities and over time in Mexico to show that the growth in earnings inequality between 1989 and 2001 can be explained in part due to the steep decline in the real value of the minimum wage. Similarly, Sotomayor (2021) find that the regional variations in the minimum wage in Brazil along with increases in the Brazilian national wage floor over time led to decline in poverty and inequality by 2.8 per cent and 2.4 per cent respectively, within three months of the hikes in the minimum wage. Our paper provides a different regional context than Brazil and Mexico, since the share of employment in the informal sector in India is larger as compared to Latin America. This may suggest that minimum wages are less likely to play a role in wage determination for a large number of workers in India, and therefore, may not be an important contributing factor to changes in wage inequality in the country [1]

The rest of the paper is organized as follows. Section 2 discusses related literature while Section 3 discusses the trends in wage inequality in India and the minimum wage legislation in the country. Section 4 discusses the data used for the analyses and Section 5 elucidates the empirical strategy. The results and robustness tests are discussed in 6 and Section 7 concludes.

2 Related Literature

Much literature on the impact of minimum wages has focused on its employment effects, as compared to the possible effects of minimum wages changes on wage inequality. For the developed countries, the evidence on how changes in minimum wages affect wage inequality is mostly inconclusive (DiNardo *et al.* , 1996; Lee, 1999; Autor *et al.* , 2016; Dickens & Manning, 2004; Stewart, 2012; Fortin & Lemieux, 1997). A pioneering study by Lee (1999) examines the impact of effective real minimum wages (gap between the State median wage and the applicable state or federal minimum wage) on wage inequality during 1979 to 1991 at the state level in the U.S. and finds that reduced real minimum wages (on account of

[1] Around 40 per cent of employment is in the informal sector in Latin America as compared to 83 per cent in India (see ILO 2018 and NSSO 2019).

reduced real federal minimum wages) account for a 25% increase in overall wage inequality and 40-60% for the lowest percentile. Autor *et al.* (2016) extends this analyses further by twenty years and using an instrumental variable strategy, where the effective minimum wage is instrumented with the U.S. statesâ minimum wages over and above the federal minimum wage, finds that the reduction in real minimum wages explains 30-40% of the rise in wage inequality at the lower percentile level. Bossler & Schank (n.d.) exploits the introduction of minimum wages in Germany and finds a decline in wage and earnings inequality post the legislative change. Other studies in developed country contexts also find spillover effects of rising minimum wages upto the 60th percentile of the wage distribution (Neumark *et al.* , 2008; Stewart, 2012).

As noted earlier, relatively less is known about the impact of minimum wages on wage inequality in developing countries. The case of developing countries is different due to existence of segmented labor markets. Lemos (2009) using a two-sector model show that minimum wage increases the wages in the formal sector and displaces the workers from the formal to the informal sector, leading to a fall in wages in the informal sector. In developing countries, raising the minimum wage is difficult due to weak enforcement Bhorat *et al.* (2021), determine the minimum wage effectiveness when multiple minimum wages exist, and little or no penalty clauses are in place (Broecke *et al.* , 2017). Results also vary by institutional factors across developing countries. For instance, studies show a very strong wage compression and negative employment effects for Latin America (Gindling & Terrell, 2007). The same is not observed for Brazil (Lemos, 2009). For China, Lin & Yun (2016) finds that wage inequality in terms of earnings gap between the median and the bottom decile has decreased due to increasing minimum wages in the country during 2004-2009. Many recent studies such as those by Ferraro *et al.* (2018) and Lin & Yun (2016) have followed the approach developed by Lee (1999). This was extended by Autor *et al.* (2016), which uses variation in both State and centrally mandated minimum wages.

In the Indian context, inequality in wage earnings up to 2004 has been examined by

Kijima (2006) and Chamarbagwala (2006), and up to 2011 by Azam (2012) and Sarkar (2019). Most recently, Khurana & Mahajan (2020) find that while there was a rise in wage inequality in India during 1983-2004, the wage inequality showed a distinct decline during 2004-2011. This decline is attributable to the increase in wages at the lower percentiles. This pattern holds for overall earnings as well as within rural and urban areas. Further, the paper does not find that earnings polarization was a contributing factor to the observed decline post 2004 in the country. In India, evidence on effects of minimum wages on labor market outcomes is limited. It is likely the result of the complexity of the minimum wage system in the country and the fact that it has limited coverage and enforcement (Belsar & Rani, 2011). Soundararajan (2019) examines the impact of minimum wage changes on employment in the construction sector. Using variation in State mandated minimum wages for the construction sector and the number of labour inspectors as a measure of enforcement, Soundararajan (2019) finds a negative impact on employment for low enforcement levels and a positive impact for high enforcement levels. Menon & Rodgers (2017) finds that from 1983 to 2008, changes across State-occupation level minimum wages in India did not impact the employment but increased earnings and consumption in rural areas. This led to an increase in the residual gender wage gap.

To sum up, while the literature for developed and developing economies shows that the decline (rise) in minimum wages increases (decreases) the wage inequality at lower percentiles, there is almost no evidence for India. This study contributes to the existing literature by estimating these effects for India and quantifying the role played by the rising minimum wages in the country on reducing wage inequality. These results have important policy implications for the country given that institutional setting have been shown to affect the relationship between minimum wages, wage inequality and employment. Reduction in wage inequality, with little effects on employment for India shows that using minimum wages as a tool to decrease inequality can be effective.

3 Background

3.1 Wage Inequality in India

Figure 1 plots the median, 90^{th} and 10^{th} percentile of log daily wages for all India (panel A), rural (panel B) and urban areas (panel C) from 1999 to 2018 using the data on regular and casual laborers from the National Sample Surveys and the Periodic labor force Surveys in India. We find that median wages have steadily increased in both rural and urban areas, especially after 2004. Wage inequality can be observed by the distance between 90th percentile and median of daily wage distribution for the high-income earning individuals and by the distance between 10^{th} percentile and median of daily wage distribution for the low-income earning individuals. Clearly, the distance between the 10^{th} percentile and the median wage has fallen over time. This shows a reduction in wage inequality in India.

For ease of comparison, median, 90^{th} and 10^{th} percentile are indexed at 100 in the year 1999 in Figure 2. For all India, median wages are 16.27% higher in 2018 than in 1999. Notably, the growth rate of 90^{th} percentile is much lower than that of the 10^{th} percentile of the daily wage distribution. Real wages at 10^{th} percentile are 23.61% higher in 2018 than in 1999 while real wages at 90^{th} percentile are 7.56% higher in 2018 than in 1999. This implies that the wage inequality has fallen in India due to steeped growth in wages of low-income group individuals. The decline in wage inequality is more pronounced in rural areas than in urban areas. In rural areas, the growth rate of wages at 10^{th} percentile is steeper than the median of wage distribution post-2004 while growth rate of 90th percentile has always been flatter than the median of wage distribution. Thus, we find clear evidence for a decline in wage inequality in rural India. In urban areas, the decline in wage inequality is more visible at extremes (difference between 10^{th} percentile and 90^{th} percentile) after 2009.

The changes in wage inequality are also observed by interquartile ratios, variance of wages and Gini coefficients in Table 1. At all India level, we observe that wage inequality has fallen from 1999 to 2018 for all measures of wage inequality, except for a slight increase between

2007-09. There has been an almost consistent decline in wage inequality in rural areas from 1999 to 2018 when measured using the Gini coefficient. There is slight increase between 2007-11 when other measures like the distance between the 90^{th} and the 10^{th} percentile and that between the 50^{th} and the 10^{th} percentile are used, but all indicators show a decline in wage inequality over this period in rural areas too. In urban India, there is slight rise in wage inequality observed prior to 2009 due to growth in the upper percentile of the wage distribution. The Gini coefficient of urban area increased from 0.087 in 1999 to 0.088 in 2009, after that it has continuously declined and reached a level of 0.068 in 2018. Overall, the above results show that wage inequality has declined between 1999-2018 in India and that the decline in wage inequality in any sub-period is attributable to higher growth in wages at lower percentiles.

3.2 India Minimum Wage setting

The Minimum wage Act 1948 in India empowers the States to fix the minimum wages for the workers in the scheduled employment categories. Over the years the Act has been amended to increase its coverage by across scheduled employment categories. The minimum wage rates vary by age (adult vs children) and by detailed job categories ($\approx$ 1700 job categories currently) in each State.[2] These wage rates are meant to provide a floor for both formal and informal sectors for the same type of worker attributes. Given the complexity and the large number of occupations for which the minimum wages are fixed, more than 1,000 different minimum wage rates operate in a given State in the country in any given time frame.

As per the Minimum wage Act 1948, MW should be revised by the States at least once in five years. However, this recommendation was not legally binding for the period of analyses considered (ILO, 2018). This leads to substantial variation in the growth rate of minimum wages across the Indian States. However, all states have changed the legislative minimum

[2] The States set the minimum wages depending on several factors: including socioeconomic conditions, prices of essential commodities, as well as local factors influencing the wage rate (NCIB, n.d.). For instance, Kerala, a state with higher income per capita, has had historically higher minimum wages for all job types viz other low per capita income states like Bihar.

wages for agricultural sector within 5 years. Additionally, the methodology Minimum Wages are not reported for all occupations by all States leading to ambiguities in enforcement. Thus, it becomes difficult to rely on all the job categories of MW to evaluate the effect on wage distribution. Lastly, selection into occupations can itself be affected by differential changes in minimum wages across job categories. Due to the aforementioned reasons, in this paper, we examine the effects of changes in the minimum wages for the unskilled category of workers in the agriculture sector on wage inequality. We use agricultural wages for the unskilled workers since this is the lowest minimum wage, and thus less prone to ambiguities which arise otherwise in the enforcement. Though, implementing lowest minimum wages is also challenging in the informal sector due to lack of written employment contracts between workers and the employers in such jobs. Second, since India has a large agricultural workforce (almost 40%), thus to increase labour supply in non-agricultural occupation, MW are relatively higher for other sectors. Agricultural wages act as a light-house effect, which implies that MW in agricultural sector act as a signal to other MW in non-agricultural sector.

Figure 3 plots the average minimum wage for unskilled agricultural laborers across the Indian States for each year in our analyses. Clearly, there has been a rapid increase in nominal minimum wages in India post 2007 with the wages increasing almost three times between 2007 and 2018.[3] Figure 4 plots the growth in daily minimum wages for unskilled agricultural labor across the Indian States for each geographic region (North, South, east and West India) during 1999-2018. It can be seen that between 1999 and 2018 there has been a wide variation across states in minimum wages, with some states increasing it three times (Uttar Pradesh in the North) while the other increasing it by almost 11 times (Karnataka in the South).

We also examine the relation between the growth in minimum wages for unskilled labor in agriculture and the minimum wages consistently reported for some of the other job categories by the States for the years 1999, 2004, 2007 and 2011 based on the detailed industry level

[3]the inflation rate in India was around 8-10% per annum during 2008-2013 but has remained at 4=6% per annum levels between 2014-2018. Thus, there has been a rise in real minimum wages too during 2007-2018.

minimum wages compiled by Mansoor & O'Neill (2021). Table 2 reports the results from a regression of log of minimum wage in the sectors reported in each row of the table and on the log of minimum wage in the agriculture sector for unskilled laborers, at the state level, including state and year fixed effects. Column (1) reports the coefficient obtianed from this regression and column (5) reports the adjusted R-square. Clearly, out of the 10 sectoral wages, for 7 of these we have a R-Square value of more than 0.9. Even for the remaining three the value is more than 0.8. These results show a high correlation in growth between lowest minimum wages fixed by State governments and that of other job categories, thus, showing the validity of using agriculture unskilled minimum wages as the benchmark minimum wage at State level.

4 Data

We use data from the nationally representative Employment and Unemployment rounds of Indiaâs National Sample Surveys (NSS) in 1999-00, 2004-05, 2007-08, 2009-10, 2011-12 (referred to as 1999, 2004, 2007, 2009 and 2011 in this paper) and Periodic labor force surveys (PLFS) in 2017-18 and 2018-19 (referred to as 2017 and 2018 in this paper) which have replaced the National Sample Surveys since 2017. Each survey starts from July of the first year to June of the second year, thus covering an entire year.

The NSS surveys are comparable to the PLFS surveys in methodology, design, and the variables on which data are collected. Both surveys include repeated cross-sections of households who are selected through stratified random sampling. The NSS and the PLFS follow a two stage sampling design. In rural areas, the first stratum is a district and villages are the primary sampling units (PSU), picked randomly in a district. In urban areas, towns and cities are stratified on the basis of population and then within each strata, urban blocks, which form the PSU are selected using probability proportional to size with replacement. Equal number of households surveyed in each quarter within each PSU (over an entire year of July to June) to ensure equal spacing of observations across the year. The households are randomly chosen in the selected PSUs. There is a small difference difference in stratification in the PFS - households in villages and urban blocks are additionally stratified on the basis of the general education level of their members. However, this has no bearing on population estimates since all estimates are weighted by sampling weights provided in each round.

These surveys capture age, gender, educational qualifications and employment status of the sampled individuals, with details about occupation and industry of employment. We restrict data for working age adults who are 15-64 years of age at the time of survey who work either as paid employees (salaried or casual laborer) for majority of time in the last year (at least six months) and records his/her daily income in the last reference week before the survey was conducted. Over time state and district boundaries have changed in India, thus, we combine the new states with the original states from which they were created in order to maintain a consistent set of state codes across years. Similarly, districts of all states have been mapped to the districts of 2001 Census.

We use the daily employment schedule which records the earnings and days of work for each regular employee and casual worker in the last reference week.[4] We compute the daily wage for each individual by dividing the total earnings by the total number of days worked in the last week. Further, we winsorise wages at top 1 and bottom 1 percentile to reduce the noise in the estimates from the outliers.

We obtain data on administrative nominal minimum wages (MW) for agricultural workers from the Labor Bureau for each State in India. The data is reported at the end of each calendar year. In general, each State sets the MW for 8-hours of work per day. In some cases, states report the MW for less than 8 hours of work, in that case unitary method is used to keep values consistent. This data is merged with the NSS data using survey months. For instance, the 2011-12 NSS survey's first sub-round from July to December 2011 is matched to the MW with effective date of 31st December 2010 and second sub-round from January

[4]Notably, the NSS do not capture the earnings from self-employment. In fact, for our purpose, the earnings from self-employment do not matter.

to June 2012 is matched to the MW with effective date of 31st December 2011.[5]

For the empirical analyses, we do not deflate either the minimum wages or the daily wages calculated from each round of employment survey. This is in line with the existing studies for India which find nearly no relation of changes in minimum wages with changes in inflation in India (Soundararajan, 2019). Table 3 shows the average minimum wages in rural and urban areas, over during 1999-2018, for all districts as well as those located on the border of states in India. The minimum wages are higher for urban areas and also slightly higher for urban areas of border districts. The daily wages calculated from the surveys for all regular and casual workers are higher in urban than rural areas, however, there are no differences across border and all districts in rural areas while the average daily wages are slightly higher in urban areas of border districts.

Further, we look at wage distribution by skills and education levels. Skills are defined by the occupational categories (i.e. National Classification of Occupations (NCO)) where low skilled workers are defined as those employed in elementary occupations like laborers, skilled agricultural workers and construction workers; medium skilled workers as those employed in clerical, administrative support, sales, and production occupations; and high skilled as those employed in professional, technical, and managerial roles. Education is defined by the worker's educational qualification where low educated worker is a worker having upto primary education; medium educated worker is a worker upto secondary education (upto class 10); and highly educated worker is a worker with post-secondary education. Table 3 reports the wage distribution across these worker categories as well. For every type of worker, daily wages are higher in the urban India viz rural India. The daily wages increase along the skill and education distribution. Importantly, the wages of low skilled and least educated workers are almost equal to the minimum wages. Thus, these worker types are

[5] Over this time period, new states were carved out, which introduced minimum wages different from their original states. The new states formed are assigned the minimum wages declared by the new state governments. For example, Jharkhand was carved out of Bihar in 2000, and the Jharkhand government publicised a range of new minimum wages in October 2001; therefore, post-2001, districts in Jharkhand had a minimum wage decided by the Jharkhand government, and pre-2001, districts in Jharkhand had the minimum wages decided by the Bihar government.

likely to be the most affected by any rise in minimum wages.

Table 3 also reports the average wages by wage quintile. Clearly, workers in the lowest wage quintile receive daily wages which are in fact lower than the postulated minimum wages. This shows imperfect enforcement of the minimum wages legislation in the country (Belsar & Rani, 2011; Rani & Belser, 2012; Rani *et al.* , 2013; Soundararajan, 2019; Mansoor & O'Neill, 2021).

Lastly, we use the daily employment schedule to calculate the number of days of a worker was employed in the preceding week before the survey date for each type of worker. We then calculate the proportion of workdays employed for each type of worker by skills and education and report the results in Table A.1. We find that the low skilled workers constitute 70% of the work force in rural India while they constitute 22% in urban India. Medium and High skilled workers, on the other hand, are the dominant group in urban India. Similarly, low educated workers form 64% of the workforce in rural India and constitute only 31% of the workforce in urban India.

5 Empirical Strategy

Unlike the U.S., there was no statutory national minimum wage that was binding in the Indian context during 1999-2018.[6] Therefore, we use a two-way fixed effects strategy to examine the impact of differential temporal variation across the Indian States in the evolution of minimum wages on wage inequality in the country.

[6]The national Minimum Wage introduced by the Indian Central Government in 1996 (Belsar & Rani, 2011) was never legally binding. However, India recently introduced a national Minimum Wage which has been passed as an amendment in the labor code on wages by Parliament in August 2019. See: Livemint. We use data from 1999-2018, hence the period after the introduction of the national Minimum Wage is not included in our analyses.

$$\begin{aligned} log(W_{ist}) = \beta_0 + \beta_1 * log(MW_{st}) + \sum_{q=1}^{4} \beta_2^q * D_{ist}^q + \\ \sum_{q=1}^{4} \beta_3^q * D_{ist}^q * log(MW_{st}) + \beta_4 * X_{ist} + D_d + T_t + \epsilon_{ist} \end{aligned} \tag{1}$$

where, the dependent variable is the log of daily nominal wage of worker i in state s in month-year t; $log(MW_{st})$ denotes the daily nominal minimum wage for unskilled agricultural workers in state s in time period t; D_{ist}^q is an indicator variable that takes a value of one for workers in wage quintile q when $q = 1$, zero otherwise. The base group for the wage quintile is the highest quintile of 5, the coefficient for which is β_1. X_{ist} include worker characteristics like age, education, religion, social group and industry of work. We also control for district (D_d) and time fixed effects (T_t) in all our specifications, thus, controlling for unobserved district level factors which are correlated with wages as well as other changing macroeconomic factors. We estimate the specifications separately for rural and urban areas. The standard errors are clustered at state level. We also report the wild-bootstrapped p-values given the small number of clusters (19). The main coefficients of interest are β_2^q. If minimum wages lead to a reduction in wage inequality, then workers in the lowest quintile should experience the largest increase in their wage growth i.e., $\beta_2^1 > \beta_2^2 > \beta_2^3 > \beta_2^4 > 0$.

There main concern with the above identification strategy is that states could increase minimum ages due to endogenous reasons. For instance, states that experience high economic growth could raise the minimum wages more. To address this concern, we undertake two analyses. First, we conduct separate analyses for all and border districts i.e., the districts which share a border with the neighboring states. Border districts are more similar to each other in terms of geographic and cultural factors which can affect economic growth.[7] Second, we check if increases in minimum wage affect the highest wage quintile of workers i.e., the coefficient β_1 in the above specification. If increase in minimum wage is correlated with other economic growth variables in the state then we should find a significant effect on the largest

[7] As migration rates are low in India, thus the estimates of all districts should be similar to the estimates of only border districts (Menon & Rodgers, 2017).

wage quintile of workers too. However, if the differential growth in minimum wages across the Indian States is uncorrelated with other economic factors then the minimum wage increases should have a null effect on these workers who are much farther in the wage distribution to be affected by minimum wages.

6 Results

Table 4 reports the results for the specification in Equation 1 for rural India in columns (1)-(2) and for urban India in columns (3)-(4). The results show that an increase in minimum wage by one percent results in an increase in rural daily wages for the lowest quintile workers by 0.17% in comparison to the workers in the highest quintile (column 1). As we move up the quintiles, the marginal effect of increase in minimum wages falls to 0.15% and 0.068% for quintiles 3 and 4 respectively (column 1). The results remain robost for rural daily wages when we include only border districts in our analyses (column 2). For urban areas, we find that an increase in minimum wages by 1% leads to an increase in wages for the lowest wage quintile of workers by 0.22% (column 3), in comparison to the workers in the highest quintile. This effect falls to 0.16% and 0.07% for the third and the fourth quintiles of wage workers. It again remains robust in column 4 when only border districts are included. the rows below show the wild-bootsrapped p-values using states as clusters for the overall effect of minimum wages at a particular quintile on daily wages. We find that for all wage quintiles, except the highest one, the coefficients are positive and significant.

The above results show that an increase in minimum wages of agricultural unskilled workers results in a higher increase in wages for the workers at the lowest quintiles which receive daily wages which are either below or almost equivalent to minimum wage rates. These results are in the expected direction since workers closest to the minimum wages should be affected the most when the minimum wages increase, unless, some other factors were at play. In fact, we find an insignificant effect of an increase in minimum daily wages on wages of the highest quintile workers (row 1) across all specifications. This shows that our results are unlikely to be driven by other factors correlated with differential rise in daily minimum wages across states. Notably, the marginal effect of rise in minimum daily wages is higher in the urban areas than in the rural areas for the lowest quintile of workers. Since the cutoff for wage quintiles are defined for all areas taken together, these results show that better enforcement in urban areas may be leading to greater compliance with rising minimum wages.

6.1 Robustness

As additional analyses, we first check the robustness of our findings for wage quintiles to including district specific time trends, to rule out the effects of other economic variables which could be changing at the district level. The results are reported in Appendix Table A.2. We find that our previous results continue to hold in this more strict specification as well. We also use other measures at skill and education levels to examine whether wages are affected differentially across low vs high skilled and low vs high educated workers. If the wage quintiles results are robust, then we should find a larger effect of rise in minimum wages on low skilled and less educated workers.

Table 5 reports the results by skill levels. We find that an increase in minimum wage by one percent results in an increase in wages for low skilled workers by 0.19% and that of medium skilled workers by 0.13% (column 1), relative to the high skilled workers in rural areas. In urban areas, the elasticities are slightly lower by skill levels at 0.12 and 0.06 for low and medium skilled workers, respectively (column 3). In this specification, the lower effects in urban areas are due to the fact that low skilled workers on average get higher wages in urban vs rural India (Table 3). Thus, since urban wages for low skilled wages are higher than the existing minimum wage levels on average, the effects will be less pronounced for these workers, a majority of whom are already earning more than the stipulated daily minimum wages. These results remain similar when we include only border districts in our analyses.

The results in rural and urban areas continue to hold after clustering the standard errors using the wild-bootstrapped method.

Table 6 reports the results by education levels. Again, we find that the effect of minimum wages is the largest for the lowest educated workers (upto primary education) in both rural and urban areas with an elasticity of 0.17 and 0.08, respectively. The elasticity estimates fall for secondary educated workers at 0.11 in rural areas and are almost insignificant in urban areas. These findings continue to hold for specifications in columns 2 and 4 which include only border districts. The positive effect of minimum wages on wages of rural workers having education upto secondary and those of urban workers having upto primary education also hold when standard errors are clustered using the WB method. Again, the elasticities are smaller in urban areas because the workers at the same education levels are likely to earn higher wages in urban India than rural India.

6.2 Placebo Effects

Lastly, while we observe in the above results, that the regression coefficients for the impact of minimum wages on the highest skilled and workers with graduate or more education are insignificant, we further test for this using the sub-sample of highly skilled workers (Appendix Table A.4) and highly educated workers (Appendix Table A.5). We continue to find that these sub-samples of workers are not affected by a rise in minimum wages. This allays any concerns that the effects of minimum wages are being driven by other unobserved factors changing at the State level which are also correlated with rising minimum wages.

6.3 Effect of Minimum Wages on Employment

We also estimate the effect of minimum wages on employment and report the results in Table A.3. The dependent variable is the proportion of days in the last week that an individual reports to be employed and zero if the individual is not employed. We undertake the analyses by education levels in this specification since we do not observe wage quintiles or skill levels for those who are not a part of the workforce in the last week. The results show that the a rise in minimum wages has no effect on employment of less and medium educated workers. There is a slight negative effect of minimum wages on employment of highest educated workers in rural areas but the magnitude of the effect is too small and only marginally significant at 10% levels. For urban areas, the effect of minimum wages is insignificant for all workers across the education spectrum. Thus, broadly, we do not find any reduction in employment due to an increase in minimum wages across states in India.

6.4 Distributional Effect of Minimum Wages

We now examine the distributional effect of rising minimum wages using the framework provided in Lee (1999). Recently, Autor *et al.* (2016) use this method to examine the effect of changes in state level minimum wages in the US; Bosch & Manacorda (2010) examine the effects in Mexico at the municipality-level, and Lin & Yun (2016) examine for China at the provincial level on wage distribution. Following Lee (1999), the model of the latent wage distribution is specified in terms of an identifiable function, i.e., the one that would have been observed without a minimum wage. The deviation around this function is attributed to the effect of the minimum wage, except for sampling and specification errors. Thus, an "effective minimum wage" is the minimum wage relative to measurement of local income that is not impacted by the minimum wage. This wage is a binding wage for the local standard of living. In the case of US, Lee (1999), and Autor *et al.* (2016) find that earnings at or above median wage level are unaffected by the minimum wage, and this is supported by Lin & Yun (2016) for China. However Bosch & Manacorda (2010) find that deviation from median may not be the representative of "effective minimum wage" for Mexico as spillovers of the minimum wage are realised upto the 60th percentile. Hence, they use the deviation from the 70th percentile of the wage distribution.

In the Indian context, in the absence of any national floor minimum wage, and due to large variation in wage levels across states, defining an effective minimum wage as a distance from a given percentile is unlikely to be true. To overcome this issue, we use the average wages of high-skilled workers as a proxy for the binding wage. This is an ideal proxy, as we know from our previous analyses that the changes in minimum wages do not affect wages of the high-skilled workers (Table 5). To do this, for each state-year we define the effective minimum wage as the deviation of the minimum wage from the average wage of the high skilled workers for that year. We then estimate the below specification:

$$\begin{aligned}(ln(W^{p}_{st}) - ln(W^{HW}_{st})) &= \beta^{p}_{0} + \beta^{p}_{1}(ln(MW_{st}) - ln(W^{HW}_{st})) \\ &+ \beta^{p}_{2}(ln(MW_{st}) - ln(W^{HW}_{st}))^{2} + T_{t} + T_{st} + \epsilon^{p}_{st}\end{aligned} \tag{2}$$

where, the dependent variable is the distance of log of wage for percentile p, state s and year t from log of average daily wage for high skilled workers for state s and year t . T_t is year fixed effects whereas T_{st} are state-year time trends. In the above equation W^{HW} refers to the average daily wage for high skilled workers. The marginal effect of the effective minimum wage is then given by:

$$\frac{\partial ln(W^{p}_{st}) - ln(W^{HW}_{st})}{\partial ln(MW_{st}) - ln(W^{HW}_{st})} = \beta^{p}_{1} + 2 * \beta^{p}_{2} * \overline{ln(MW_{st}) - ln(W^{HW}_{st})} \tag{3}$$

We estimate the above specfication and plot the marginal effects of minimum wages at different percentiles in Figure 5. Clearly, the effect of effective minimum wages declines at higher percentiles, especially in the urban areas. There is higher spillover effect of minimum wage in rural areas as the point estimates are statistically significant upto 80th percentile in rural areas while only upto 60th percentile in urban areas. The regression estimates show that a 10 percentage point rise in effective minimum wages leads to a 5.1 percentage points (0.51*10) increase in rural India and 5.5 percentage points (0.55*10) increase in urban India at the 10th percentile. The results are robust when only border districts are included in our analyses (Figure A.3).

Since the spillover effect of effective minimum wages defined using the wages for high skilled workers is upto 80th percentile, we also estimate a specification, where average wages of high skilled workers is replaced with the wages at the 85th percentile in Equation 2. The coefficients plotted in Figure A.4 also show that effective minimum wages have a higher impact on lower percentiles, while this effect diminishes as we move up the percentiles.

6.5 Alternate Mechanisms

We now test for other mechanism that could affect wages during this time period and whether the effect of minimum wages may be confounded by these. For instance, National Rural Employment Guarantee Act (NREGA) started in 2006, could also contribute to a rise in wages at lower quintiles. Under the NREGA, workers are entitled to receive 100 days of employment in an year in public works within 15 days of demanding work; otherwise, applicants of NREGA are eligible to receive unemployment benefits from the state. However, this scheme is limited to rural areas. In Phase I of the NREGA implementation, 200 districts in India were covered. The act was extended to 130 more districts in April 2007 (referred to as Phase II). In the final phase, all the districts were under the ambit of the act by 2008.

Thus, NREGA may serve as a competitive wage to guarantee minimum statutory wages to NREGA workers, thereby encouraging the agricultural sector to pay the minimum wage. hence, we account for implementation of NREGA in our analyses in three ways. First, since the NREGA had been implemented in all districts by 2008 [8], the analysis is limited to the year 2007-08 to provide a comparison between NREGA implemented (treatment districts) and non-implemented districts (control districts). As the policy was implemented in 2006, 1999 and 2004 can serve as a baseline for comparison. In another specification, we use data from 1999-2018 and control for NREGA trends which is defined as years of NREGA implementation in a district based on the phase in which it came under NREGA. In the final specification, we utilise the NREGA intensity with which NREGA is implemented in a given district defined as the proportion of population working for NREGA public works by

[8] There is an overlap between the April to June period of the NSS survey conducted in 2007-2008 and the introduction of NREGA in Phase III districts. Existing literature suggests that little implementation was done in these districts by then (Imbert & Papp, 2015), so we can utilise those districts as non-NREGA districts.

districts.

The results are presented in Table 8 for all districts in rural India. The wages increase for lower wage quintiles due to the increase in the minimum wages, despite controlling for the NREGA in all specifications. Thus, the effect of minimum wages on wage inequality found in the above estimations is not driven by NREGA. The significant effect of minimum wage on lower wage quintiles is robust when only border districts are considered (Table A.6).

7 Conclusion

Wage inequality has declined by as much as 35% during 1999-2018 in India. However, there is little understanding about what factors have contributed to this decline. Our analyses shows that rising minimum wages in India have contributed significantly towards reducing inequality in wages. This is due to the large positive impact of rising minimum wages on the lowest wage quintile workers, even in sectors where enforcement is difficult. At the same time, there are no accompanying negative effects on employment. These results show that changing minimum wages could be an effective policy tool to reduce wage inequality without significantly reducing jobs in the country.

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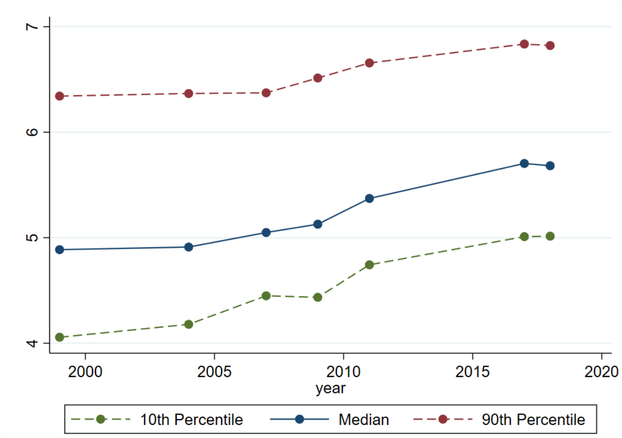
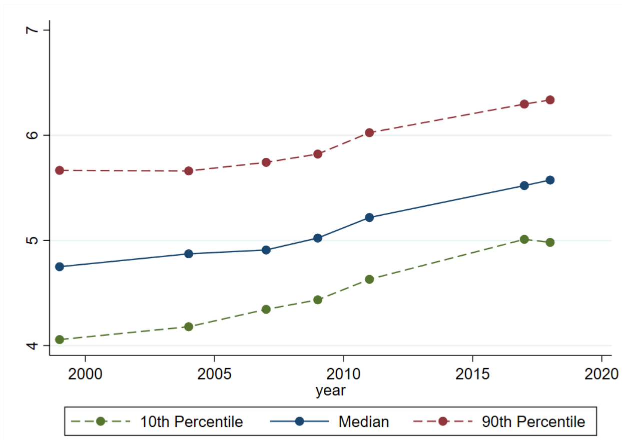
Figure 1: Log Real Wages from 1999-2018

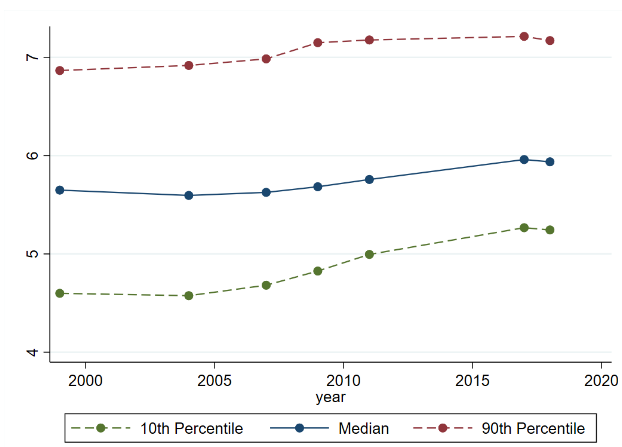
Panel A: All



Panel B: Rural Area



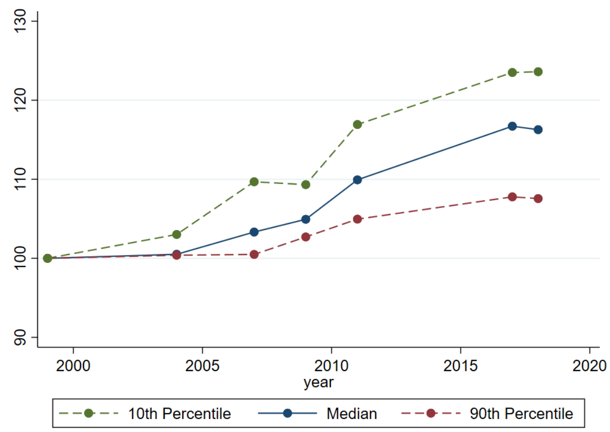
Panel C: Urban Area



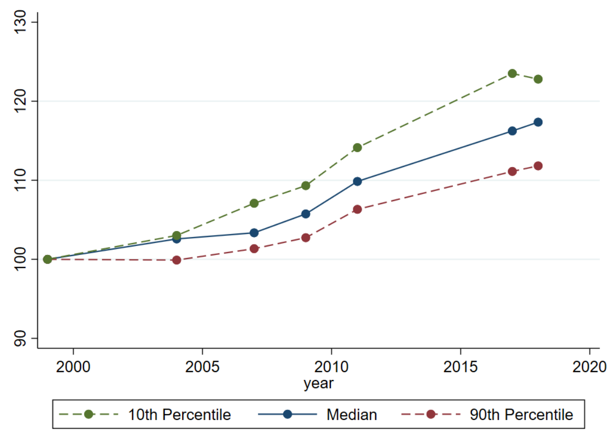
Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018.

Figure 2: Indexed log of Real Wages from 1999-2018

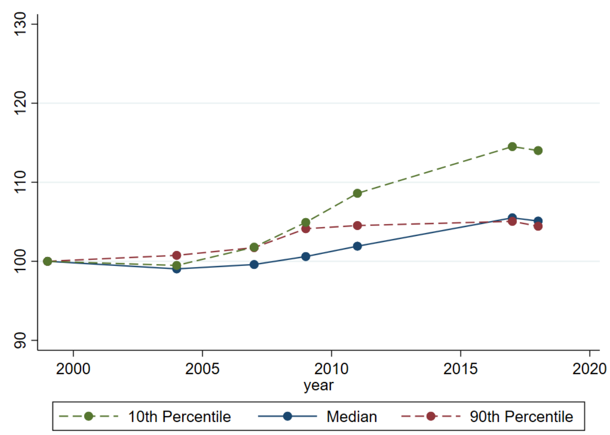
Panel A: All



Panel B: Rural Area

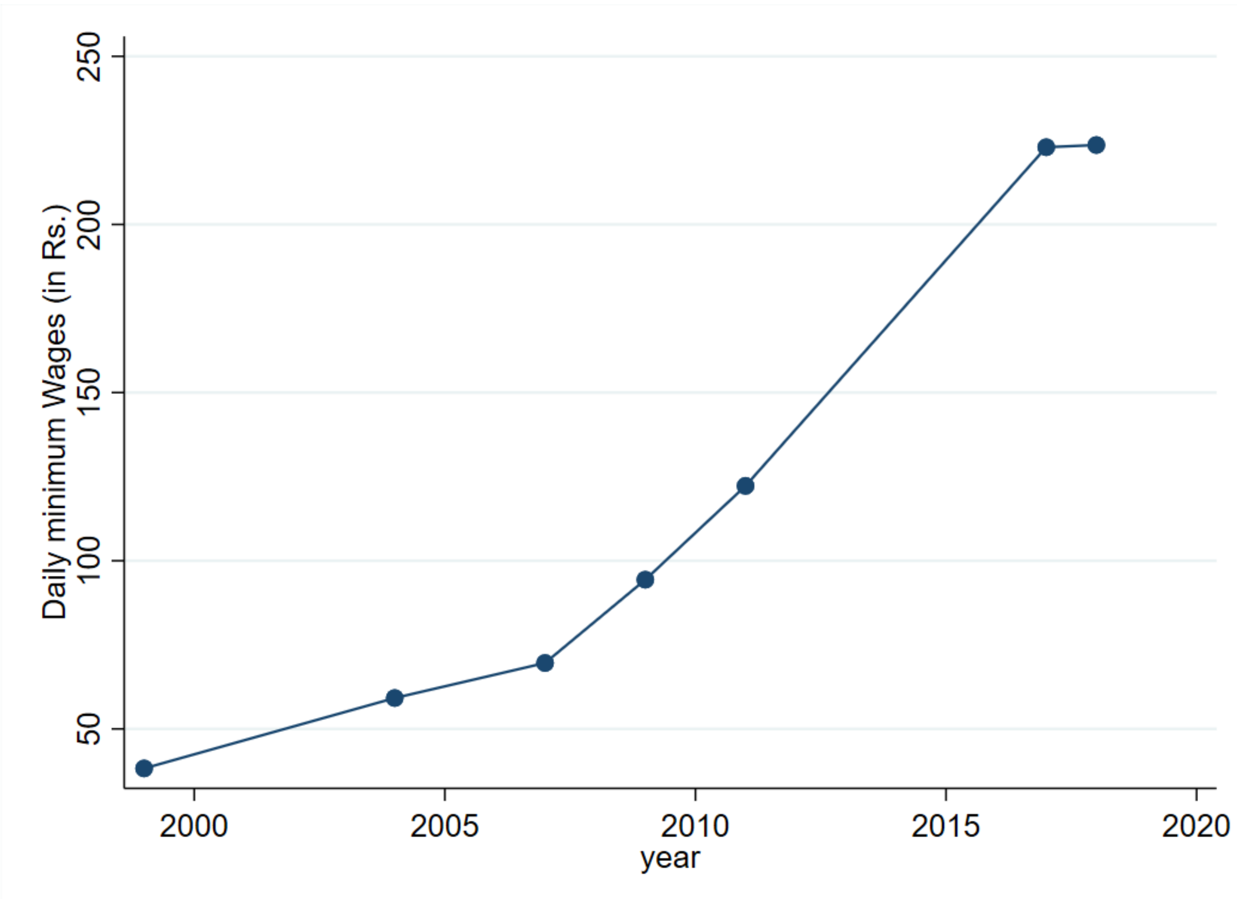


Panel C: Urban Area



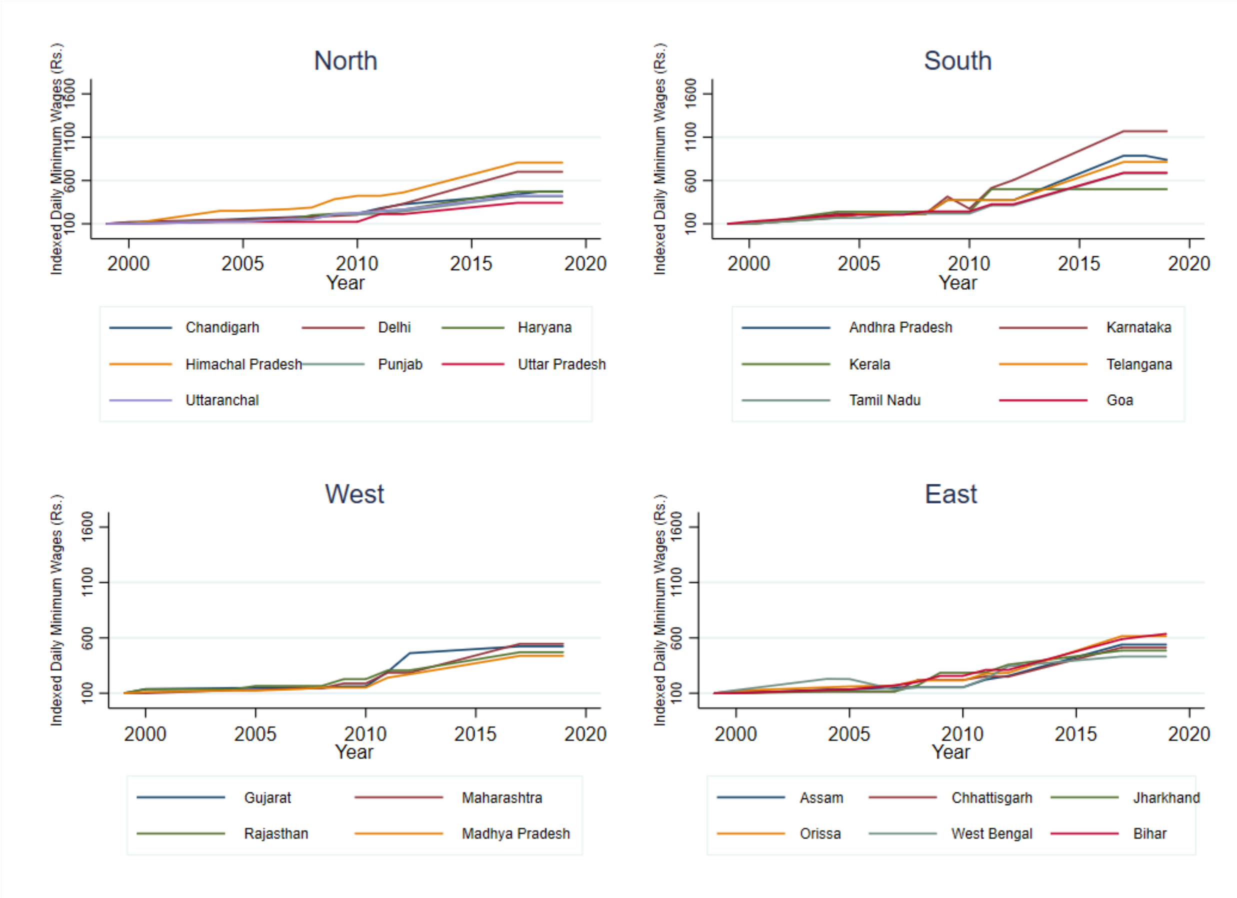
Notes: Log of average daily Wages are indexed at 100 in 1999 for each percentile group. *Source:* Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018.

Figure 3: Average Daily Administrative Nominal Minimum Wages 1999-2018 (Agriculture)



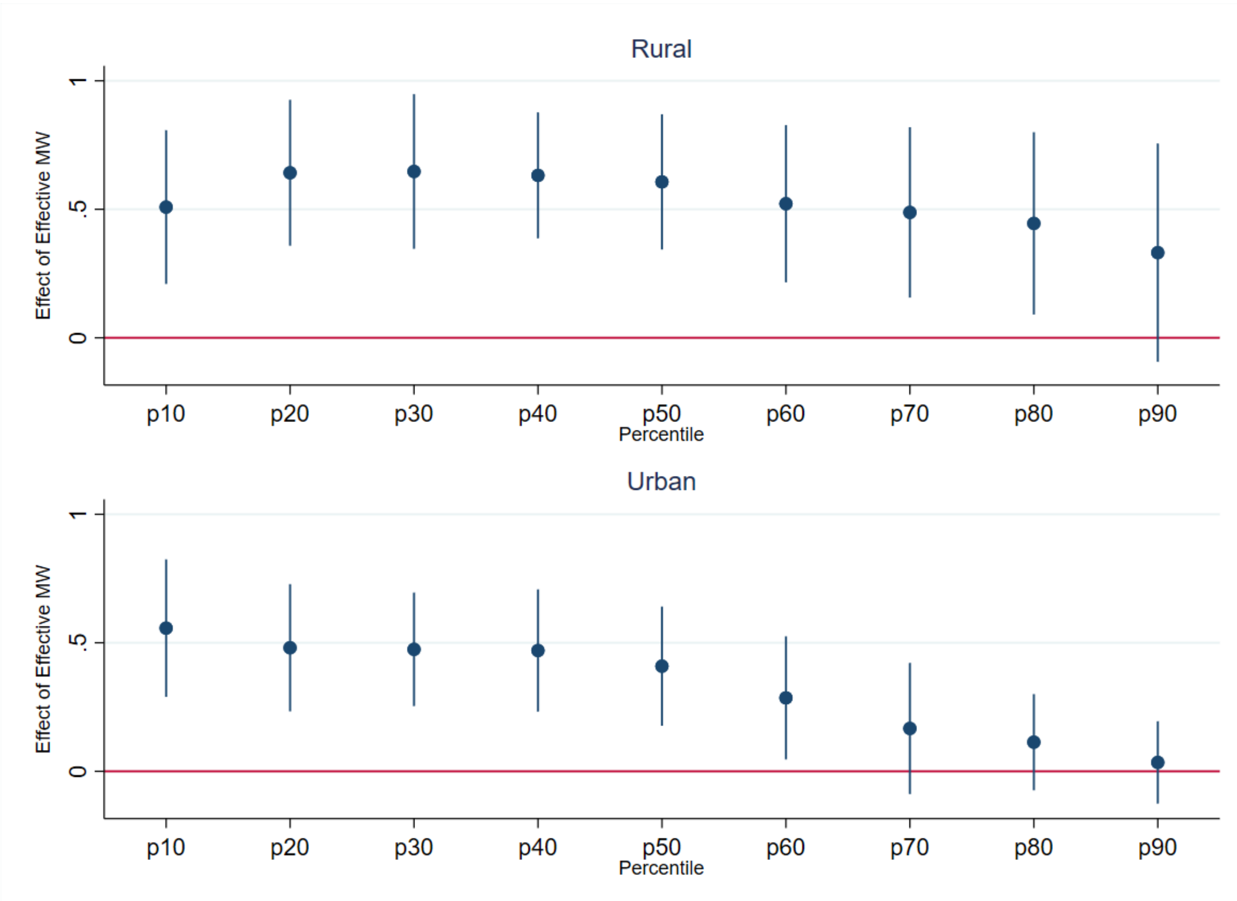
*Notes:*Average daily administrative nominal minimum wage. *Source:* Authors' calculations based on Labour Bureau data.

Figure 4: Indexed Daily Administrative Nominal Minimum Wages 1999-2018 (Agriculture)



Notes: Daily administrative nominal minimum wages are indexed at 100 in 1999 for each state.
Source: Authors' calculations based on Labour Bureau data.

Figure 5: Marginal Effects of Effective Minimum wages on Wage Percentiles by Sector



Notes: Estimates are the marginal effects of log(MW) - log(Average wages of High skilled workers) and its square on log(p) - log(Average wages of High skilled workers) across states and years. Observations are at state-year level. Regressions are controlled for year fixed effects and state-time trend. Standard errors are clustered at the state-level. 95% confidence interval is represented by the spikes.
Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018 and Labour Bureau data.

Table 1: Interquantile ratios and summary inequality indices

	1999	**2004**	**2007**	**2009**	**2011**	**2017**	**2018**
				All			
ln(q90)-ln(q10)	2.285	2.188	1.924	2.079	1.913	1.825	1.807
ln(q90)-ln(q50)	1.455	1.455	1.324	1.386	1.284	1.132	1.139
ln(q50)-ln(q10)	0.830	0.732	0.600	0.693	0.629	0.693	0.668
Var(log wage)	0.699	0.665	0.591	0.632	0.592	0.496	0.472
Gini(log wage)	0.091	0.087	0.080	0.081	0.075	0.067	0.064
				Rural			
ln(q90)-ln(q10)	1.609	1.482	1.398	1.386	1.394	1.286	1.355
ln(q90)-ln(q50)	0.916	0.788	0.833	0.799	0.806	0.775	0.762
ln(q50)-ln(q10)	0.693	0.693	0.565	0.588	0.588	0.511	0.593
Var(log wage)	0.423	0.418	0.347	0.358	0.356	0.344	0.312
Gini(log wage)	0.073	0.071	0.063	0.063	0.060	0.057	0.053
				Urban			
ln(q90)-ln(q10)	2.266	2.342	2.303	2.323	2.181	1.946	1.926
ln(q90)-ln(q50)	1.216	1.322	1.358	1.465	1.419	1.253	1.233
ln(q50)-ln(q10)	1.050	1.020	0.944	0.857	0.762	0.693	0.693
Var(log wage)	0.761	0.811	0.754	0.819	0.779	0.580	0.562
Gini(log wage)	0.087	0.090	0.085	0.088	0.084	0.070	0.068

Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018

Table 2: Effect of Agricultural Sector's Minimum Wages to other Sector's Minimum Wages

	(1)	(2)	(3)	(4)	(5)	(5)
	Coeff	SE	p-value	R-sq	Adj. R-sq	Obs
Mining, Construction, Manufacturing	0.585	0.082	0.000	0.966	0.948	75.000
Electricity, Water supply	0.504	0.134	0.001	0.955	0.925	63.000
Wholesale, retail trade	0.400	0.116	0.001	0.949	0.922	75.000
Transportation, storage	0.530	0.102	0.000	0.958	0.935	74.000
Information, communication	0.388	0.146	0.011	0.925	0.886	74.000
Financial, Professional, Technical	0.348	0.155	0.031	0.935	0.892	61.000
Administrative	0.691	0.127	0.000	0.969	0.941	41.000
Education, Health, social work	0.409	0.125	0.002	0.951	0.922	71.000
Other Activities	0.648	0.108	0.000	0.960	0.935	66.000

Notes: All regression equations include state and year fixed effects. The independent variable is administrative Minimum Wages in Agricultural Sector. Dependent variables are administrative minimum wages of the industries presented in rows of the Table.
Source: Authors' calculations based on minimum wages data provided by Mansoor & O'Neill (2021) for 1999, 2004, 2007 and 2011 collated through Labour Bureau.

Table 3: Summary Statistics- Average Wage Distribution

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
Administrative Minimum Wages	113.458	114.950	131.492	140.403
	(71.59)	(73.49)	(90.71)	(101.2)
Wages	160.232	161.768	369.186	375.567
	(189.5)	(192.2)	(424.7)	(427.1)
Wages of Low-Skilled workers	114.184	114.002	186.352	189.236
	(101.5)	(101.6)	(183.3)	(187.2)
Wages of Medium-Skilled workers	225.186	230.543	291.700	301.391
	(213.9)	(218.7)	(292.4)	(299.9)
Wages of High-Skilled workers	429.351	435.187	727.859	730.817
	(409.7)	(410.8)	(606.8)	(606.2)
Wages of Low-Educated workers	110.825	111.276	171.052	176.766
	(100.0)	(102.1)	(159.7)	(166.9)
Wages of Medium-Educated workers	201.415	203.760	291.025	297.972
	(195.8)	(198.3)	(283.1)	(290.3)
Wages of High-Educated workers	463.633	469.459	695.719	700.082
	(400.7)	(402.7)	(576.8)	(575.6)
Wages of Workers in 1st Quintile	78.261	77.857	98.711	105.206
	(59.70)	(60.29)	(73.86)	(79.08)
Wages of Workers in 2nd Quintile	121.659	118.042	160.086	164.519
	(89.44)	(87.66)	(108.0)	(112.6)
Wages of Workers in 3rd Quintile	162.687	161.514	209.802	217.897
	(116.9)	(114.0)	(139.2)	(141.6)
Wages of Workers in 4th Quintile	231.850	229.719	275.530	286.407
	(159.4)	(161.6)	(186.9)	(200.2)
Wages of Workers in 5th Quintile	596.640	584.420	757.401	755.496
	(420.0)	(415.0)	(567.9)	(569.5)

Notes: Average wages by different categories are provided in the table with their standard deviation in parentheses.
Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018.

Table 4: Effect of Minimum Wages on Wages at Different Wage Quintiles

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	0.017	-0.011	0.012	-0.023
	(0.05)	(0.05)	(0.07)	(0.06)
Wage Quintile=1 × log MW	0.167***	0.175***	0.215***	0.200***
	(0.03)	(0.03)	(0.04)	(0.04)
Wage Quintile=2 × log MW	0.168***	0.163***	0.195***	0.163***
	(0.02)	(0.03)	(0.04)	(0.04)
Wage Quintile=3 × log MW	0.137***	0.152***	0.163***	0.155***
	(0.02)	(0.03)	(0.03)	(0.04)
Wage Quintile=4 × log MW	0.068***	0.096***	0.066***	0.087***
	(0.02)	(0.03)	(0.01)	(0.01)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
WB p-value of MW × 1.Wage Quintile	0.000	0.000	0.000	0.000
WB p-value of MW × 2.Wage Quintile	0.000	0.001	0.001	0.001
WB p-value of MW × 3.Wage Quintile	0.000	0.002	0.001	0.002
WB p-value of MW × 4.Wage Quintile	0.010	0.010	0.000	0.002
R-Squared	0.95	0.95	0.92	0.92
No. of Clusters	19	19	19	19
Observations	249976	170515	203543	126073

Notes: The dependent variable is log of nominal daily wages. MW refers to log of nominal administrative Minimum Wages. Other controls include education, age-group, marital status, social group, religion and industry categories. Standard errors in parentheses are clustered at state level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018.

Table 5: Effect of Minimum Wages on Wages by Skill Level

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	0.010	0.002	0.034	0.031
	(0.05)	(0.05)	(0.05)	(0.04)
Low Skill=1	-1.219***	-1.213***	-1.054***	-1.057***
	(0.17)	(0.19)	(0.13)	(0.16)
Low Skill=1 × log MW	0.193***	0.189***	0.121***	0.118***
	(0.03)	(0.04)	(0.02)	(0.03)
Med Skill=1	-0.794***	-0.841***	-0.614***	-0.603***
	(0.12)	(0.12)	(0.10)	(0.13)
Med Skill=1 × log MW	0.127***	0.135***	0.060***	0.056**
	(0.02)	(0.02)	(0.02)	(0.03)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
WB p-value of MW × Low	0.000	0.000	0.001	0.003
WB p-value of MW × Med	0.000	0.000	0.022	0.075
R-Squared	0.78	0.79	0.71	0.72
No. of Clusters	19	19	19	19
Observations	249976	170515	203543	126073

Notes: The dependent variable is log of nominal daily wages. MW refers to log of nominal administrative Minimum Wages. Other controls include education, age-group, marital status, social group, religion and industry categories. Standard errors in parentheses are clustered at state level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018.

Table 6: Effect of Minimum Wages on Wages by Education Level

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	0.040	0.035	0.060	0.053
	(0.05)	(0.05)	(0.04)	(0.04)
Low Edu=1	-1.471***	-1.429***	-1.435***	-1.412***
	(0.18)	(0.20)	(0.09)	(0.10)
Low Edu=1 × log MW	0.173***	0.162***	0.083***	0.082***
	(0.04)	(0.04)	(0.02)	(0.02)
Med Edu=1	-1.053***	-1.014***	-0.858***	-0.866***
	(0.18)	(0.19)	(0.08)	(0.09)
Med Edu=1 × log MW	0.112***	0.103**	0.027	0.032*
	(0.03)	(0.04)	(0.02)	(0.02)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
WB p-value of MW × Low	0.001	0.003	0.002	0.006
WB p-value of MW × Med	0.009	0.021	0.185	0.140
R-Squared	0.78	0.78	0.69	0.69
No. of Clusters	19	19	19	19
Observations	250041	170556	203588	126108

Notes: The dependent variable is log of nominal daily wages. MW refers to log of nominal administrative Minimum Wages. Other controls include age-group, marital status, social group, religion and industry categories. Standard errors in parentheses are clustered at state level. ***, **, * show significance at 1%, 5% and 10%, respectively.

Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018.

Table 7: Effect of Minimum Wages on Employment (daily status) by Education Level

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	-0.035**	-0.042*	0.017	0.015
	(0.02)	(0.02)	(0.01)	(0.01)
Low Edu=1	0.043	0.036	0.013	0.003
	(0.07)	(0.08)	(0.04)	(0.03)
Low Edu=1 × log MW	-0.004	-0.001	-0.010	-0.008
	(0.02)	(0.02)	(0.01)	(0.01)
Med Edu=1	-0.094	-0.112	-0.062**	-0.068**
	(0.06)	(0.07)	(0.03)	(0.03)
Med Edu=1 × log MW	0.016	0.020	-0.004	-0.002
	(0.01)	(0.01)	(0.01)	(0.01)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
WB p-value of MW × Low	0.781	0.945	0.226	0.259
WB p-value of MW × Med	0.242	0.203	0.506	0.710
R-Squared	0.42	0.40	0.46	0.46
No. of Clusters	19	19	19	19
Observations	1130630	741754	749456	459256

Notes: The dependent variable is proportion of working days in a week. MW refers to log of nominal administrative Minimum Wages. Other controls include age-group, sex, marital status, social group and religion categories. Standard errors in parentheses are clustered at state level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018.

Table 8: Effect of Minimum Wages on Wages at Different Wage Quintiles after controlling for NREGA in all districts of rural India

	(1) NREGA dummy	(2) NREGA Trend	(3) NREGA Intensity
log MW	-0.218***	0.017	0.007
	(0.07)	(0.05)	(0.05)
Wage Quintile=1 × log MW	0.299***	0.167***	0.165***
	(0.05)	(0.03)	(0.03)
Wage Quintile=2 × log MW	0.240***	0.168***	0.168***
	(0.05)	(0.02)	(0.02)
Wage Quintile=3 × log MW	0.159***	0.137***	0.137***
	(0.05)	(0.02)	(0.02)
Wage Quintile=4 × log MW	0.074	0.068***	0.067***
	(0.04)	(0.02)	(0.02)
District FE	✓	✓	✓
Year FE	✓	✓	✓
WB p-value of MW × 1.Wage Quintile	0.000	0.000	0.000
WB p-value of MW × 2.Wage Quintile	0.000	0.000	0.000
WB p-value of MW × 3.Wage Quintile	0.005	0.000	0.000
WB p-value of MW × 4.Wage Quintile	0.066	0.010	0.010
R-Squared	0.90	0.95	0.95
No. of Clusters	19	19	19
Observations	132007	249976	249976

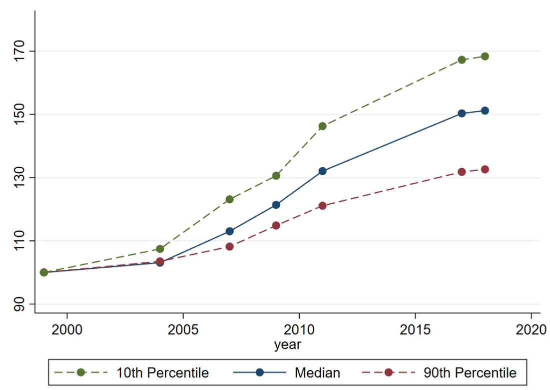
Notes: The dependent variable is log of nominal daily wages. MW refers to log of nominal administrative Minimum Wages. Other controls include education, age-group, marital status, social group, religion, industry categories and NREGA. In column 1, NREGA is controlled as a dummy varaible which takes value 1 for NREGA implemented Phase 1 and Phase 2 districts in the year 2007. Only 1999, 2004 and 2007 years have been utilised for the analysis. In column 2, NREGA is controlled as years of NREGA implementation in a district based on the phase in which it came under NREGA. In column 3, NREGA is controlled as a intensity defined as the proportion of population working in the NREGA public work by district and year. Standard errors in parentheses are clustered at state level. ***, **, * show significance at 1%, 5% and 10%, respectively.

Source: Wages and Employment data is from 55th, 61st, 64th, 66th and 68th Employment-Unemployment NSS rounds and 1st and 2nd PLFS rounds. Minimum Wages data is from Labour Bureau.

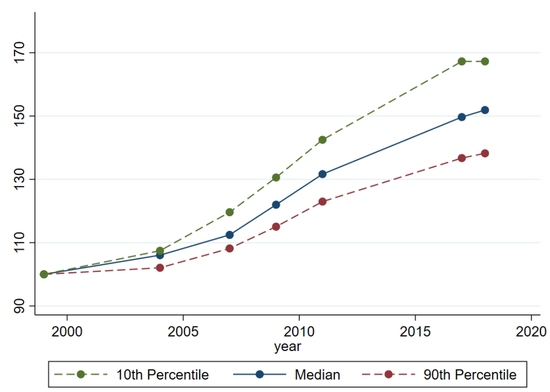
A Additional Tables and Figures

Figure A.1: Indexed log of Nominal Wages from 1999-2018

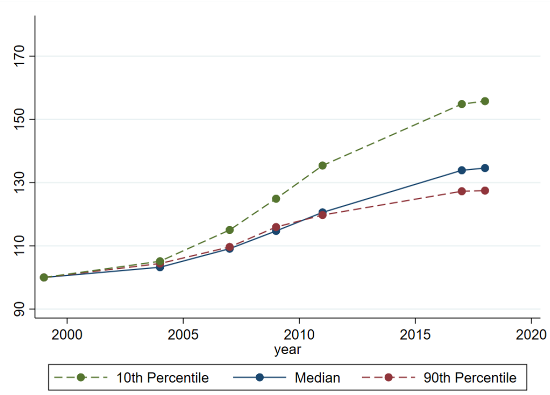
Panel A: All India



Panel B: Rural India



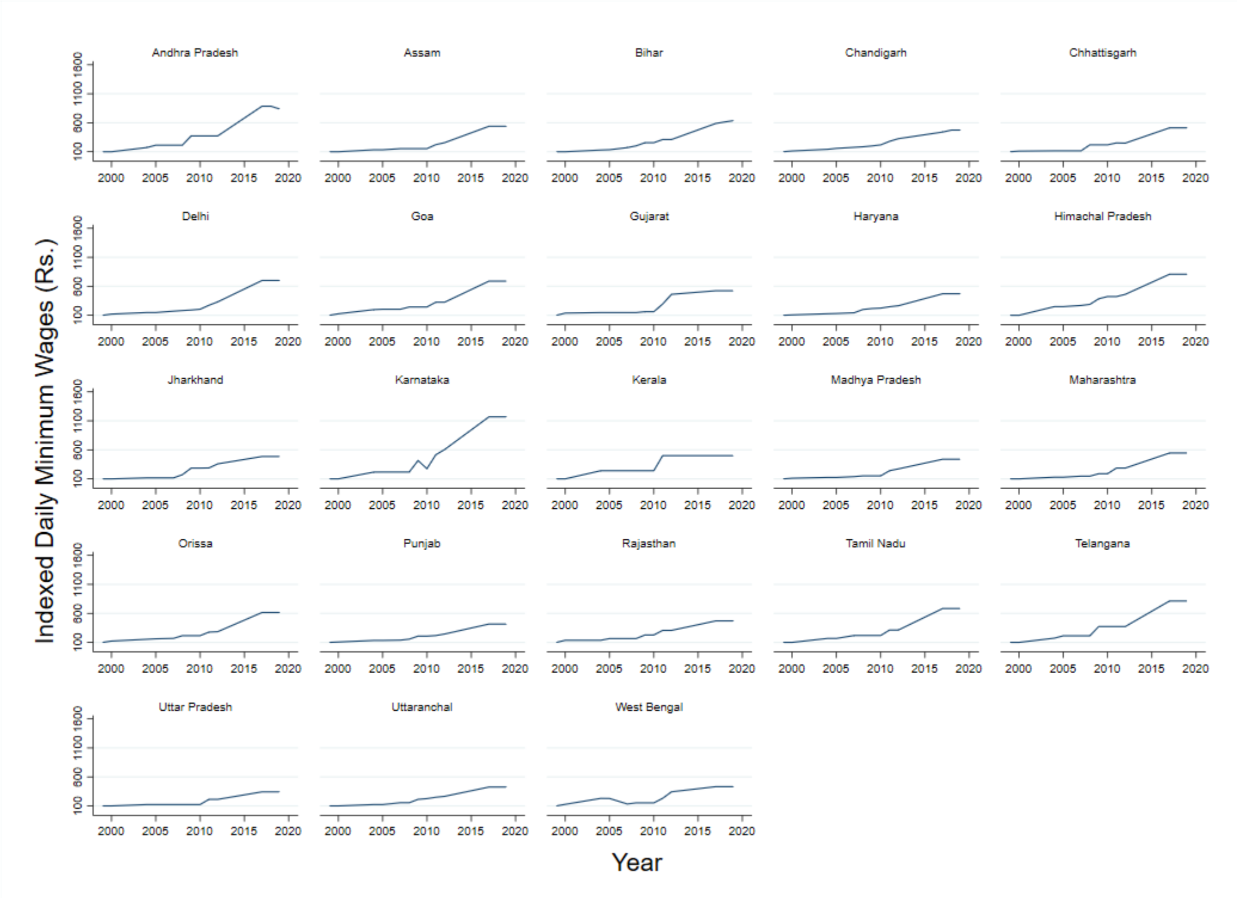
Panel C: Urban India



Notes: Average daily wages calculated using the earnings and days worked in the reference week a wage worker. The average wage for year 1999 is indexed to 100 for each wage quintile.

Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018

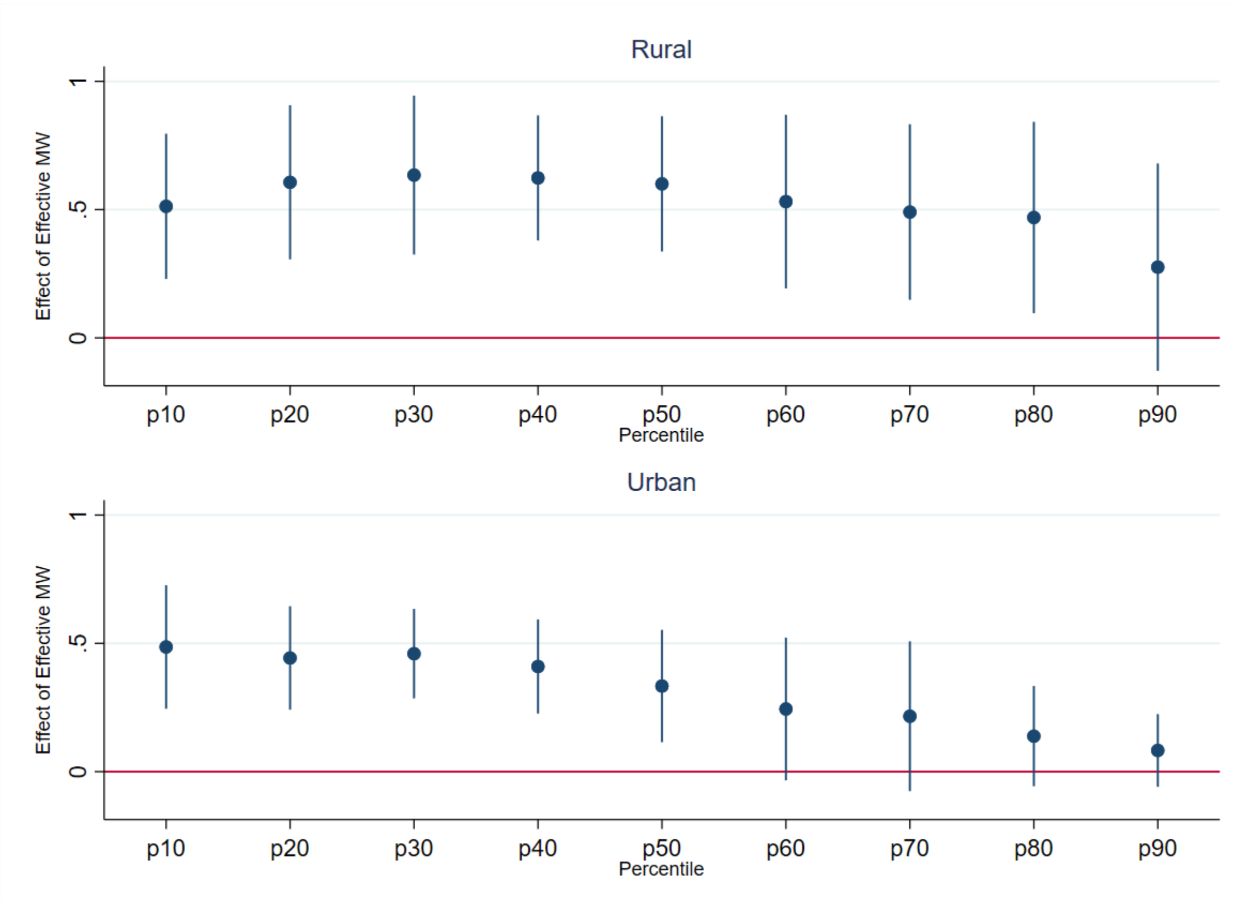
Figure A.2: Indexed Administrative Nominal Daily Minimum Wages 1999-2018 (Agriculture)



Notes: Average daily wages calculated using the earnings and days worked in the reference week a wage worker. The average wage for year 1999 is indexed to 100 for each wage quintile.

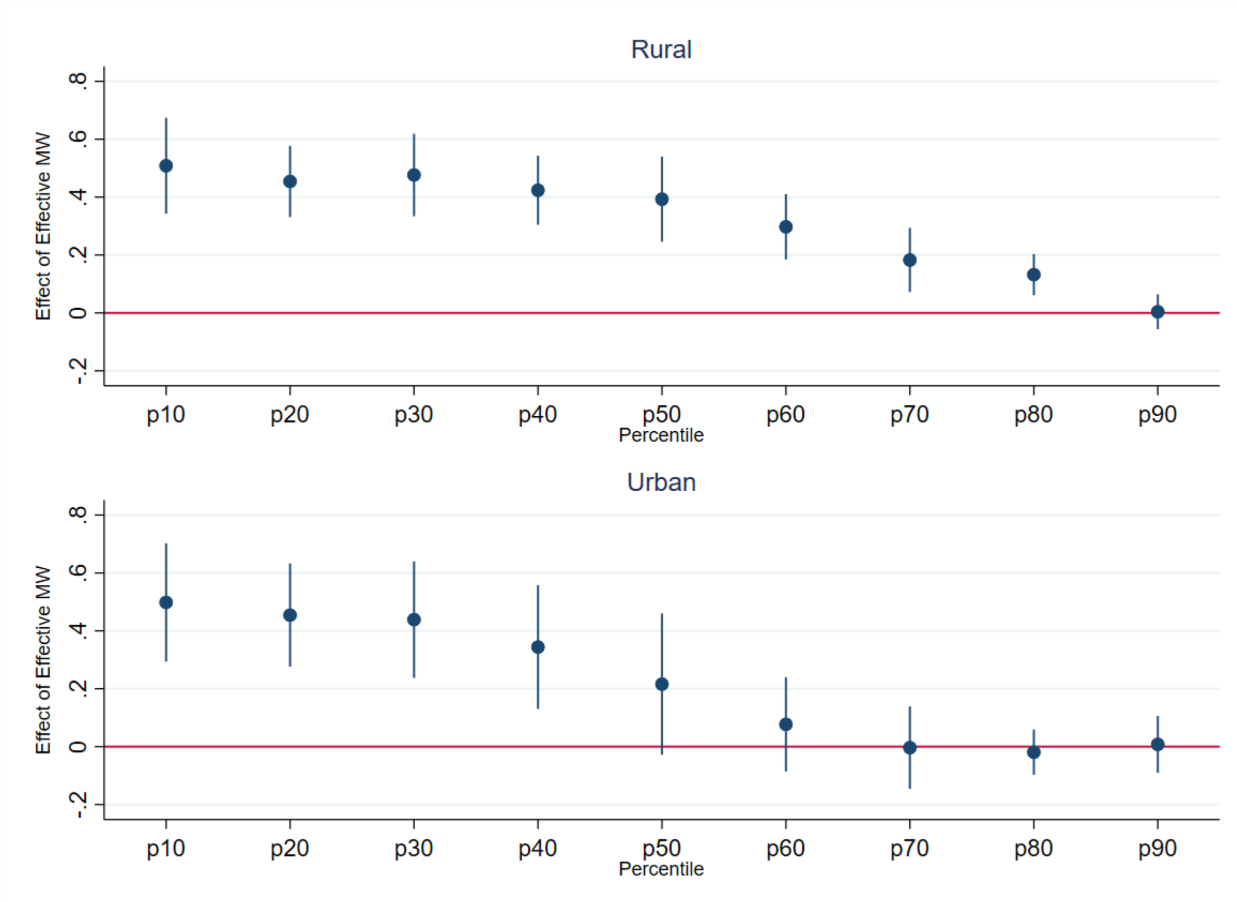
Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018

Figure A.3: Marginal Effects of Nominal Minimum wages on Wage Percentiles by Sector in Border Districts



Notes: Estimates are the marginal effects of log(MW) - log(Average wages of High skilled workers) and its square on log(p) - log(Average wages of High skilled workers) across states and years. Observations are at state-year level. Regressions are controlled for year fixed effects and state-time trend. Standard errors are clustered at the state-level. 95% confidence interval is represented by the spikes.
Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018 and Labour Bureau data.

Figure A.4: Marginal Effects of Nominal Minimum wages on Wage Percentiles by Sector relative to 85th percentile



Notes: Estimates are the marginal effects of log(MW) - log(p85) and its square on log(p) - log(p85) across states and years. Observations are at state-year level. Regressions are controlled for year fixed effects and state-time trend. Standard errors are clustered at the state-level. 95% confidence interval is represented by the spikes.

Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018 and Labour Bureau data.

Table A.1: Summary Statistics- Proportion of workers

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
Low-Skilled workers	0.703	0.704	0.226	0.230
	(0.457)	(0.457)	(0.418)	(0.421)
Medium-Skilled workers	0.231	0.231	0.541	0.536
	(0.422)	(0.421)	(0.498)	(0.499)
High-Skilled workers	0.065	0.066	0.233	0.234
	(0.247)	(0.248)	(0.423)	(0.423)
Low-Educated workers	0.639	0.637	0.312	0.311
	(0.480)	(0.481)	(0.463)	(0.463)
Medium-Educated workers	0.298	0.299	0.403	0.402
	(0.457)	(0.458)	(0.490)	(0.490)
High-Educated workers	0.064	0.064	0.286	0.287
	(0.244)	(0.244)	(0.452)	(0.452)

Notes: Proportion of workers are provided in the table with their standard deviation in parentheses.
Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018.

Table A.2: Effect of Minimum Wages on Wages at Different Wage Quintiles

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	0.015	-0.011	0.013	-0.024
	(0.05)	(0.05)	(0.07)	(0.06)
Wage Quintile=1 × log MW	0.167***	0.175***	0.215***	0.200***
	(0.03)	(0.03)	(0.04)	(0.04)
Wage Quintile=2 × log MW	0.168***	0.163***	0.195***	0.163***
	(0.02)	(0.03)	(0.04)	(0.04)
Wage Quintile=3 × log MW	0.137***	0.152***	0.163***	0.155***
	(0.02)	(0.03)	(0.03)	(0.04)
Wage Quintile=4 × log MW	0.068***	0.096***	0.066***	0.087***
	(0.02)	(0.03)	(0.01)	(0.01)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
District Trends	✓	✓	✓	✓
WB p-value of MW × 1.Wage Quintile	0.000	0.000	0.000	0.000
WB p-value of MW × 2.Wage Quintile	0.000	0.001	0.001	0.001
WB p-value of MW × 3.Wage Quintile	0.000	0.002	0.001	0.002
WB p-value of MW × 4.Wage Quintile	0.010	0.009	0.000	0.002
R-Squared	0.95	0.95	0.92	0.92
No. of Clusters	19	19	19	19
Observations	249976	170515	203543	126073

Notes: The dependent variable is log of nominal daily wages. MW refers to log of nominal administrative Minimum Wages. Other controls include education, age-group, marital status, social group, religion and industry categories. Standard errors in parentheses are clustered at state level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018.

Table A.3: Effect of Minimum Wages on Employment (weekly status) by Education Level

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	-0.042**	-0.047*	0.010	0.008
	(0.02)	(0.02)	(0.01)	(0.01)
Low Edu=1	0.145*	0.139	0.055	0.059*
	(0.07)	(0.08)	(0.04)	(0.03)
Low Edu=1 × log MW	-0.015	-0.012	-0.012	-0.013*
	(0.02)	(0.02)	(0.01)	(0.01)
Med Edu=1	-0.059	-0.075	-0.052**	-0.055**
	(0.06)	(0.07)	(0.02)	(0.03)
Med Edu=1 × log MW	0.014	0.018	-0.004	-0.003
	(0.01)	(0.01)	(0.01)	(0.01)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
WB p-value of MW × Low	0.429	0.579	0.164	0.090
WB p-value of MW × Med	0.332	0.265	0.507	0.627
R-Squared	0.40	0.38	0.45	0.45
No. of Clusters	19	19	19	19
Observations	1130630	741754	749456	459256

Notes: The dependent variable is dummy variable of person employed during a week. MW refers to log of nominal administrative Minimum Wages. Other controls include age-group, sex, marital status, social group and religion categories. Standard errors in parentheses are clustered at state level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018.

Table A.4: Placebo effect of Minimum Wages on Wages (on High Skilled workers)

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	0.032	0.009	0.015	0.058
	(0.07)	(0.08)	(0.06)	(0.08)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
WB p-value of MW	0.726	0.923	0.826	0.486
R-Squared	0.62	0.63	0.57	0.58
No. of Clusters	19	19	19	19
Observations	26925	18405	48813	30483

Notes: The dependent variable is log of nominal daily wages. MW refers to log of nominal administrative Minimum Wages. Other controls include education, age-group, marital status, social group, religion and industry categories. Standard errors in parentheses are clustered at state level. ***, **, * show significance at 1%, 5% and 10%, respectively.

Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018.

Table A.5: Placebo effect of Minimum Wages on Wages (on High Educated workers)

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	0.036	0.025	0.007	0.035
	(0.10)	(0.11)	(0.05)	(0.06)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
WB p-value of MW	0.749	0.849	0.900	0.665
R-Squared	0.55	0.56	0.50	0.50
No. of Clusters	19	19	19	19
Observations	22398	15113	56205	35131

Notes: The dependent variable is log of nominal daily wages. MW refers to log of nominal administrative Minimum Wages. Other controls include age-group, marital status, social group, religion and industry categories. Standard errors in parentheses are clustered at state level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018.

Table A.6: Effect of Minimum Wages on Wages at Different Wage Quintiles after controlling for NREGA in the border districts of rural India

	(1) NREGA dummy	(2) NREGA Trend	(3) NREGA Intensity
log MW	-0.218**	-0.010	-0.025
	(0.09)	(0.05)	(0.05)
Wage Quintile=1 × log MW	0.324***	0.175***	0.174***
	(0.08)	(0.03)	(0.03)
Wage Quintile=2 × log MW	0.272***	0.163***	0.164***
	(0.07)	(0.03)	(0.03)
Wage Quintile=3 × log MW	0.252***	0.152***	0.153***
	(0.07)	(0.03)	(0.03)
Wage Quintile=4 × log MW	0.175***	0.096***	0.095***
	(0.05)	(0.03)	(0.03)
District FE	✓	✓	✓
Year FE	✓	✓	✓
WB p-value of MW × 1.Wage Quintile	0.000	0.000	0.000
WB p-value of MW × 2.Wage Quintile	0.000	0.001	0.001
WB p-value of MW × 3.Wage Quintile	0.000	0.002	0.002
WB p-value of MW × 4.Wage Quintile	0.003	0.010	0.010
R-Squared	0.90	0.95	0.95
No. of Clusters	19	19	19
Observations	89327	170515	170515

Notes: The dependent variable is log of nominal daily wages. MW refers to log of nominal administrative Minimum Wages. Other controls include education, age-group, marital status, social group, religion, industry categories and NREGA. In column 1, NREGA is controlled as a dummy varaible which takes value 1 for NREGA implemented Phase 1 and Phase 2 districts in the year 2007. Only 1999, 2004 and 2007 years have been utilised for the analysis. In column 2, NREGA is controlled as years of NREGA implementation in a district based on the phase in which it came under NREGA. In column 3, NREGA is controlled as a intensity defined as the proportion of population working in the NREGA public work by district and year. Standard errors in parentheses are clustered at state level. ***, **, * show significance at 1%, 5% and 10%, respectively.

Source: Wages and Employment data is from 55th, 61st, 64th, 66th and 68th Employment-Unemployment NSS rounds and 1st and 2nd PLFS rounds. Minimum Wages data is from Labour Bureau.