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ABSTRACT

Minimum Wages and Changing Wage Inequality in India*

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 effect is smaller at upper wage quintiles and insignicant for the highest wage quintile. Counterfactual wage estimations show that the increase in minimum wages explains 26% of the decline in wage inequality in India during 1999-2018. These findings underscore the important role played by rising minimum wages in reducing wage disparities in India.

JEL Classification: J31, J38

Keywords: minimum wages, wage inequality, India

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1 Introduction

There is increasing interest in the use of minimum wage as a 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. India provides an ideal context to examine this question. Under the Minimum Wages Act 1948, Indian states are empowered to set minimum wages for workers in scheduled employment categories. During the period, 1999-2018, the median of real administrative minimum wage across states increased by 69.98 percent while the average nominal minimum wage increased by almost 457 percent. However, there was wide variation across states in the minimum wage changes during this period, with the variance of real minimum wages across states increasing from 2652 in 1999 to 6875 in 2018. At the same time, the Gini of log nominal wages fell from 0.113 in 1999 to 0.063 in 2018, and the gap between the 50^{th} and the 10^{th} wage percentile fell from 0.799 in 1999 to 0.693 in 2018. In this paper, we exploit the variation in minimum wage changes across the states 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 wage on the 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 1999-2018, there was a rise in average nominal minimum wage in the country by 457%, 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 10^{th} percentile grew by 65% while those 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. Using these estimates, we then examine the counterfactual log wage distribution in 2018 using the 1999 minimum wages and find that if minimum wages across all states had remained at their 1999 levels, then wage inequality would have been 16.08% and 18.49% higher in rural and urban India in 2018, respectively (17.02% for all India). Further, we find that the rise in minimum wages explains almost 26% of the decline in wage inequality (Gini of log wages) during 1999-2018. The magnitude of these effects 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 by using a border discontinuity design, since districts on state borders are more likely to be similar to adjacent districts in neighboring states 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. We also estimate a dynamic DiD regression model using the approach proposed by De Chaisemartin *et al.* (2019) for continuous treatment which is staggered over time. We continue to find a strong decline in inequality due to minimum wage increase in urban India with no signficant pre-trends. The results are weaker for rural India and only hold for inequality measured between the 50^{the} and the 10^{the} wage percentiles.

Additionally, as a placebo check, we estimate the effect of changes in minimum wages on the highest quintile, highest skilled and highest educated workers - the groups of workers which are likely to earn higher than minimum wages in the country. 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 investigate the differential impact of rising minimum wages on wage inequality for formal and informal workers and find evidence that the effect has been almost similar for both types of workers, even for the informal sector, due to the lighthouse effect of minimum wages on informal wages. Additionally, we 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 other factors like NREGA, labor unions and enforcement rate during this period which could possibly confound our analyses.

Much literature on the impact of minimum wages has focused on its employment effects[1], 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; Fortin & Lemieux, 1997; Lee, 1999; Teulings, 2003; Dickens & Manning, 2004; Stewart, 2012; Butcher *et al.* , 2012; Autor *et al.* , 2016). 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 reduced real federal minimum wages) account for a 25% increase in overall wage inequality and at least 70% of the growth in the 50-10 wage percentile differentials. 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 difference between the state level minimum wage and the federal minimum wage, finds that the reduction in real minimum wages explains 30-40% of the rise in wage inequality at the

[1]See Neumark *et al.* (2007), Card & Krueger (2015), Dube (2019) and Manning (2021) for a review of these studies. Neumark & Corella (2021) discusses existing evidence for minimum wage impacts on employment in the developing countries.

lower percentile level. Bossler & Schank (2022) 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).

However, 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 shows that an increase in 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 the developing countries, effects of minimum wage are likely to be ambiguous due to weak enforcement (Bhorat *et al.* , 2021). The compliance to minimum wage changes is also likely to be smaller when multiple minimum wages exist, and little or no penalty clauses are in place (Broecke *et al.* , 2017). The wage and employment impacts of minimum wages hence are shown to vary by institutional factors across developing countries (Neumark & Corella, 2021).[2] An examination of the effects of minimum wage changes on wage inequality, however, remains under studied. For China, Lin & Yun (2016) finds that wage inequality in terms of earnings gap between the median and the bottom decile decreased in cities where an increase in minimum wages occurred in the country during 2004-2009. Engbom & Moser (2021) and Sotomayor (2021) using spatial variation in the bindingness of the federal minimum wage across states in Brazil also find that rise in the minimum wages accounts for a large decline in earnings inequality in the country since the 1990's.[3] 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

[2]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).

[3]The effect of minimum wage on overall income inequality are also mixed. For instance, using changes in minimum wages in Brazil, Neumark *et al.* (2006) find no effects on reduction in income inequality across households.

steep decline in the real value of the minimum wage.

In the Indian context, evidence on the 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). Distinct from other country contexts like Brazil and Mexico, there is no national minimum floor for wages in India. Thus, the nature, structure and implementation of minimum wages in India is quite different from other contexts. 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 no effect on wages for low enforcement levels and a positive impact for high enforcement levels while the employment effects are largely null. 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. In fact, there is no study to our knowledge which examines the effects of minimum wage changes on wage inequality for India.

In general, many studies document changes in wage inequality over time in India. Kijima (2006) and Chamarbagwala (2006) find a rise in wage inequality in India from the 1980's to 2004, while Azam (2012) and Sarkar (2019) examine the changes till 2011 and find that during 2004-11 there was a reversal in these trends. 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 which continued during the period of 2011-2018. This decline is attributable to the increase in wages at the lower percentiles. This pattern holds for overall earnings as well as for both 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. However, there is no causal evidence regarding the role of minimum wage changes in explaining these trends.[4]

Our paper, thus, contributes to the emerging literature that documents impacts of min-

[4]Cacciamali *et al.* (2015) show the possible impact of minimum wages in India during 1998-2011 on inequality through simulations.

imum wages on wage inequality for developing countries (Gindling, 2018). It provides a different regional context than China, Brazil and Mexico, since the share of employment in the informal sector in India is larger as compared to China and 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.[5] However, we find a sharp decrease in wage inequality due to minimum wage increases. 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.

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

2 Background

2.1 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 measured by the distance between the 90th percentile and the median of daily wage distribution for the high-income earning individuals

[5] Around 40-45 per cent of employment is in the informal sector in China and Latin America as compared to 83 per cent in India (see ILO 2018 and NSSO 2019).

and by the distance between the 10^{th} percentile and the median of daily wage distribution for the low-income earning individuals. Clearly, the distance between both the 90^{th} and 10^{th} percentile and the median wage has fallen over time. The reduction in inequality is larger at the lower percentiles though, showing a reduction in wage inequality in India.

For ease of comparison, we index the median, the 90^{th} and the 10^{th} percentile at 100 in the year 1999 in Figure 2. For all India, the median wages are 16.27% higher in 2018 than in 1999. Notably, the growth rate in wages at the 90^{th} percentile is much lower than that at the 10^{th} percentile of the daily wage distribution. Real wages[6] at the 10^{th} percentile are 23.61% higher in 2018 than in 1999 while real wages at the 90^{th} percentile are 7.56% higher in 2018 than in 1999. This implies that the wage inequality has fallen in India due to steep 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 the 10^{th} percentile is steeper than the median of wage distribution post-2004 while the growth rate at the 90^{th} 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 the 10^{th} and the 90^{th} percentile) after 2009.

Similar changes in wage inequality are also observed using other measures – interquartile wage ratios, variance of wages and Gini coefficients of nominal wages in Table 1 and of real wages in Appendix Table A.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 in 2009. 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 2009-11 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

[6] Real wages are determined using the Consumer Price Index for Industrial Workers (CPIIW) in urban India and the Consumer Price Index for Agricultural Laborers (CPIAL) in rural India, representing real values in 2017.

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 has continuously declined and reaching a level of 0.067 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 the lower percentiles.

2.2 India Minimum Wage setting

The Minimum wage Act 1948 in India empowers the Indian 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.[7] 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 at any given time.

As per the Minimum wage Act 1948, minimum wages 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 changed the legislative minimum wages for agricultural sector within a span of 5 years. Notably, minimum wages are not reported for all occupations by all states leading to ambiguities in enforcement. Thus, it is difficult to rely on all the occupation level minimum wages to evaluate their effect on wage distribution in India. Lastly, selection into occupations can itself be affected by differ-

[7]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.

ential changes in minimum wages across occupational 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 the lowest minimum wage is also challenging in the informal sector due to lack of written employment contracts between the workers and the employers in such jobs. Second, because of the large number of agricultural workers in India (approximately 40%), minimum wages are relatively high in non-agricultural occupations to stimulate labor supply. Agricultural wages, thus, provide a light-house effect, which implies that minimum wages in the agricultural sector act as a signal for other minimum wages in non-agricultural sectors.

Figure 3 plots the average minimum wage for unskilled agricultural laborers across all 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.[8] 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 wage growth, 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 non-agricultural categories by the states for the years 1999, 2004, 2007 and 2011 based on the detailed industry level 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 (as the dependent variable) on the log of minimum wage in the agriculture

[8]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.

sector for unskilled laborers, at the state level, while controlling for state and year fixed effects. Column (1) reports the coefficient obtained from this regression and column (4) reports the within R-square. All the coefficients are economically large and significant. Clearly, out of the 10 sectoral wages, for 7 of these we have a within R-Square value of more than 0.9.[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.

3 Data

We use data from the nationally representative Employment and Unemployment rounds of India's 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 are 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

[9]Within R-Square shows how much of the variance within the different types of wages over time is accounted for by the agricultural wages.

are randomly chosen in the selected PSUs. There is a small difference in stratification in the PLFS - 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 use data for working age adults aged 15-59 years at the time of the survey who work as paid employees (salaried or casual laborer) for majority of time in the last year (at least six months). For these employed individuals, both the NSS and the PLFS record daily income in the last reference week before the survey was conducted. We then 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 to compute daily wages.[10] We compute the daily wage for each individual by dividing the total weekly 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. State and district boundaries have changed over time 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 parent districts of 2001 Census.

We obtain data on administrative nominal minimum wages (MW) for agricultural workers from the Labor Bureau for 19 states[11] 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.

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

[11]Andhra Pradesh, Assam, Bihar, Chandigarh, Delhi, Goa, Gujarat, Haryana, Himachal Pradesh, Karnataka, Kerala, Madhya Pradesh, Maharastra, Odisha, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh and West Bengal. The states of Jharkhand, Chhattisgarh and Uttarakhand started reported their minimum wages after a few years of creation in 2000 and Telangana in 2014, so we use their minimum wages since the year these states begin reporting these for all district lying within these.

For instance, the 2011-12 NSS survey's data from July to December 2011 is matched to the MW with effective date of 31st December 2010 and that from January to June 2012 is matched to the MW with effective date of 31st December 2011.[12]

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 for 1999-2018, for all districts as well as those located on the state borders. The minimum wages are higher for urban areas and also slightly higher for urban areas of border districts. This shows that rate of urbanization is greater in states having higher minimum wages. The daily wages (calculated from the surveys) 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 examine the 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 a low educated worker is a worker having upto primary education; a medium educated worker is a worker upto secondary education (upto class 10); and a 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 urban India viz rural India. The daily wages increase along

[12] 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.

the skill and education distribution. Importantly, the wages of the low skilled and the least educated workers are almost equal to the minimum wages. Thus, these worker types are likely to be the most affected by any rise in minimum wages.

Table 3 also reports the average wage 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 wage 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 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 Appendix Table A.2. 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.

4 Empirical Strategy

Unlike the U.S., there is no statutory national minimum wage that binds in the Indian context during 1999-2018.[13] 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.

[13] 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 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, zero otherwise. The base group for the wage quintile is the highest quintile i.e., 5th quintile of the wage distribution. X_{ist} include worker characteristics like age, education, religion, social group, marital status 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_3^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., $\beta_3^1 > \beta_3^2 > \beta_3^3 > \beta_3^4 > 0$. The effect of minimum wage on the base quintile group of 5 is given by the coefficient β_1.

The main concern with the above identification strategy is that states could increase minimum wages due to endogenous reasons. For instance, states that experience high economic growth could raise minimum wages more. To address this concern, we undertake two further sets of 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.[14] 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

[14] 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).

correlated with other economic growth variables in the state then we should find a significant effect on the largest 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.

5 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 increases 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 0.14% and 0.068% for quintiles 3 and 4 respectively (column 1). The results remain robust 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 we include only border districts in our analyses. 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 who receive daily wages which are either below or almost equivalent to minimum wage rates. These results are in the expected direction since workers earning 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. We also check differential impacts for workers in casual vs salaried work and find no differences as long as workers are in the same quintile of wage distribution (Appendix Table A.3).

Additionally, we also estimate the impact of minimum wages on wage inequality across formal and informal workers. Theoretically postulations by Harris (1970) and Mazumdar (1989) show that a rise in minimum wages increases the wages of workers in covered sectors (formal workers), while the displacement of workers in these sectors results in a rise in labor supply in uncovered sectors (informal sectors). This can exert downward pressure on the wages of informal workers and also results in no change in inequality in this sector. To check this, we classify formal workers as workers with written job contracts, given that such contracts imply a greater likelihood of companies complying with minimum wage regulations. We report the estimates for formal workers in Panel A, and those for informal workers in Panel B of Table 5. In rural India, the lowest quintile formal workers earn 0.27% more than the highest quintile workers (Column 1 of Panel A), while the lowest quintile informal workers earn 0.24% more than the highest quintile workers (Column 1 of Panel B), when minimum wages increase by 1%. We find similar effects on both formal and informal workers in urban India. Our findings demonstrate that minimum wages reduce wage inequality for both formal and informal workers to a similar extent. Our results remain consistent under alternative definitions of formal and informal workers (Appendix Table A.4). These results indicate that the minimum wage acts as a benchmark for equitable compensation in the labor market, consequently resulting in a rise in the wages of both informal and formal workers

(Gindling & Terrell, 2005; Khamis, 2013).

5.1 Robustness

We check the robustness of our findings to a number of specifications. We first check the results by 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.5. We find that our previous results continue to hold in this stricter specification as well. Second, we check the results after including quarter-year fixed effects to rule out macro economic shocks at a higher frequency like it controls for the seasonal effects on agricultural wages which are mostly in the bottom quintile of the rural wage distribution. Again, our results continue to hold (Appendix Table A.6). Additionally, we also check the robustness of our findings to using changes in real wages and real minimum wages over time across states. The results are reported in Appendix Table A.7. The results using nominal wages continue to hold with increase in real wages as well as the largest increase in real wages is observed for lower quintiles. 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 6 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 (WB) method.

Table 7 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 to 0.11 for secondary educated workers 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 level are likely to earn higher wages in urban India than rural India.

Also, we check if the positive results for wages also hold for total weekly earnings, which are calculated as daily wages multiplied by the days worked in a week. If days worked in a week are reduced due to higher wages paid by the employer then weekly earnings may not necessary increase at lower quintiles. To check this, we estimate equation 1 with log of weekly earnings as the dependent variable. The results reported in Appendix Table A.8 show that the earnings increase by 24-27% for the two lowest earnings quintiles. The effect reduces to 10% for the fourth earning quintile and is insignificant for the highest earning quintile. Thus, our findings lend support to a decline in earnings inequality due to rise in minimum wages in India during 1999-2018.

The emerging literature on the difference-in-differences estimation when using a staggered implementation has emphasized the concern about negative weights associated with TWFE (Goodman-Bacon, 2021). It recommends estimating heterogeneous treatment effects on the outcome over time taking into account staggered nature of the treatment by creating appropriate control groups (De Chaisemartin *et al.* , 2023). Some recent methods to overcome this issue when treatment is dichotomous are provided in Roth *et al.* (2022). Our case is different since not only the treatment variable is continuous but it also changes for every unit in every time period. To address this, we use the average dynamic DiD estimator for continuous treatment, proposed by De Chaisemartin *et al.* (2019) in their ongoing research. This method compares 'switchers' i.e., states that change their minimum wages over time, with 'stayers' i.e., states that do not change their wages between 1999 and 2004.[15] The effect of minimum wage treatment (T) on wage inequality (Y) with respect to switcher states (S) can be computed as follows:

$$\delta_t = E((Y_t(T_t) - Y_t(T_{t-1}))/(T_t - T_{t-1})|S_t = 1)$$

$$=> \delta_t = E((\triangle Y_t)/(\triangle T)|S_t = 1)$$

This method involves data aggregation at the district-sector-year level (i.e., creating a panel data at district-sector-year level) where sector $\in \{rural, urban\}$, taking into account population weights. The outcome variable is real wage inequality, measured by the distance between the 90^{th} and the 10^{th} percentile, the 90^{th} and the 50^{th} percentile, and the 50^{th} and the 10^{th} percentile of the wage distribution. The treatment variable is the log of real minimum administrative wages.[16]

The results are reported in Appendix Figure A.3 for rural (Panel A) and urban India (Panel B). The x-axis displays the periods (t), with t=-1 representing the period preceding the minimum wage change (baseline), and t=0 indicating the period where minimum wages changed for the first time. We refer to the districts that experienced their first minimum wage change as 'first-time switchers' (S = 321 in rural India, S = 316 in urban India). When minimum wages increase for the second time in a district, then the first-time switcher districts transition for the first time, as denoted by $t = 1$ in the figure (S = 321 in rural

[15]There are no states where minimum wage has not changed from 1999 to 2018.

[16]Since the dynamic DiD estimator does not readily support fully continuous treatments, an approximation is made by rounding the real minimum wages to the nearest INR 50.

India, $S = 314$ in urban India). Similarly, when minimum wages increase for a third time in a district, this indicates that the first-time switcher districts transition for the second time, as shown by $t = 2$ in the figure ($S = 200$ in rural India, $S = 193$ in urban India)[17].

Based on our previous analyses, we expect that a rise in minimum wages will lead to a decline in wage inequality during post-treatment periods. Appendix Figure A.3 shows a decline in wage inequality during the instant switch ($t = 0$) and when the first-time switchers transition ($t = 1$). These results are more pronounced for urban India, in accordance with the earlier reduced form estimates. However, for rural India, there is a positive effect seen when first-time switcher districts switch for the second time ($t = 2$). The average dynamic effect during the post-treatment period (combining the effects for $t = 0, 1, 2$) are reported in Appendix Table A.9. Each row in the table shows the estimates from a different regression, with the wage inequality measure displayed in the row as the dependent variable and the estimates in column (2). We find that a rise in minimum wages leads to decreased wage inequality across all inequality measures for urban India and between the 90^{th} and the 50^{th} percentile, and between the 50^{th} and the 10^{th} percentile of the wage distribution in rural India, but the effects are imprecise. The estimates in the table show a significant decline of 0.13% for wage inequality between the 50^{th} and 10^{th} percentile of wage distribution in rural India (Panel A, row 3) and a 0.28% reduction for wage inequality between the 90^{th} and 10^{th} percentiles of wage distribution in urban India (Panel B, row 2), when minimum wages increase by one percent (Panel A).

Additionally, Appendix Figure A.3 also shows the estimated pre-trends.[18] Here, $t = -2$ compares wage inequality between first-time switcher states and not-yet switcher states before the first-time switcher transition for the first time; $t = -3$ compares the change in wage inequality between first-time switcher states and not-yet switcher states before the first-time switcher states transition for the second time. Thus, these show the difference in

[17]The number of observations decreases to below 50 if periods are increased further. hence, the analysis is limited to $t = 2$.

[18]The computation of pre-trends ($t = -2, -3$) is only feasible for the corresponding number of dynamic effects observed in switcher states ($t = 1, 2$).

wage inequality between initial switchers and non-switchers prior to any treatment change (De Chaisemartin *et al.* , 2023).[19]

This pre-trends are insignificant for the wage inequality measures that show a significant and consistent decline after the treatment (panels (b) and (d) for urban India and panel (e) for rural India). However, it is important to exercise caution when interpreting these results. The estimators used in this analysis are primarily designed for evenly spaced time intervals, which does not conform to our data since the years for which data are available are spread across interval of years.[20] Also, our context lacks non-stayers, since all states undergo minimum wage changes in some time period. This implies that there are no natural control groups available to analyze the impact of the minimum wage policy using never-treated states.

5.2 Placebo Effects

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.10) and highly educated workers (Appendix Table A.11). We continue to find that these sub-samples of workers are not affected by a rise in minimum wages. This allays any concern that the effects of minimum wages are being driven by other unobserved factors changing at the state level which are also correlated with rising state minimum wages.

[19]It is computed by replacing $\triangle Y_t$ by $\triangle Y_{t-1}$ in the above equation, and restricting the sample, for each pair of consecutive time periods $(t-1, t)$, to units whose treatment did not change between $t-2$ and $t-1$.

[20]De Chaisemartin *et al.* (2019) suggests that missing years can be supplemented with data from preceding years. Using this approach, the results largely remain consistent to our current findings. We have opted not to include those results due to the substantial gap between years for all districts, which is considerably larger than what the paper anticipates.

5.3 Counterfactual Wage Distribution

We also investigate the degree to which the decline in wage inequality between 1999-2018 can be explained by the increase in minimum wages. To do this, we conduct a reduced-form counterfactual analysis to estimate the counterfactual wage inequality in 2018 had there been no change in minimum wages from 1999 levels, following the approach proposed by Lee (1999). This allows us to estimate the change in wage inequality that would have occurred if the minimum wages had remained constant at a reference point while accounting for other factors that influence wages over time. We construct a counterfactual log wage distribution for 2018, by adding the below estimated value for each individual, using 1999 minimum wages as a base.

$$\Delta log\ w_{is,2018} = \hat{\beta}_2^q * (log\ MW_{s,1999} - log\ MW_{s,2018}) + \hat{\beta}_1 * (log\ MW_{s,1999} - log\ MW_{s,2018}) \tag{2}$$

where, q represents the wage quintiles, and $\hat{\beta}_2^q$ and $\hat{\beta}_1$ indicate the estimated coefficient from the regression equation 1.

The resulting actual and counterfactual log wage distribution is depicted in Appendix Figure A.4. The differences between the actual and counterfactual wage distributions at various quintiles are displayed in Figure 5. Due to the increase in minimum wages between 1999 and 2018, the lowest quintile wage earners have experienced a 38.52% increase in rural India and a 48.39% increase in urban India. As we move up the quintiles, we observe a smaller impact on wages, with the top most quintile workers experiencing almost no change if the minimum wages had remained constant at the levels in 1999.

We also examine the percentage change in the Gini coefficient between the actual and counterfactual log wages for 2018. We find that the Gini Coefficient for the actual log wage distribution in the rural sector is 16.08% lower than its counterfactual estimate (0.0522 vs. 0.0622) while in the urban sector it is 18.49% lower that the counterfactual estimate (0.067 vs. 0.0822). The actual Gini in 1999 in rural India was 0.0949 and in urban India was 0.109.

Thus, of the total change in Gini in urban India of -0.0427, around 23.4%(=0.01/0.0427) can be explained by the rise in minimum wages. Similar calculations show that for all India, around 26% of the decline in wage inequality can be explained by the increase in minimum wages.[21]

5.4 Effect of Minimum Wages on Employment

We estimate the effect of minimum wages on employment and report the results in Table 8. The dependent variable in Equation 1 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. If we include self-employed, casual and salaried workers, 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. However, the significant impact on highly educated workers vanishes if we donot include self-employed as employed workers (Table 9). For urban areas, the effect of minimum wages is insignificant for all workers across the education spectrum. Thus, in line with earlier studies on India, we find negligible impact on employment due to an increase in minimum wages (Soundararajan, 2019; Menon & Rodgers, 2017).

5.5 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

[21]India Gini 1999: .11265, India Gini in 2018: 0.0634, Counterfactual Gini in 2018 (with 1999 Minimum wages): .0765 – refer to Table 1 for actual Gini values.

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 the median may not be representative of the "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 for the 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 hold. To overcome this issue, we use the average wages of high-skilled workers in a given state 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 6). 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:

$$\begin{aligned}(ln(W_{st}^{p}) - ln(W_{st}^{HW})) &= \beta_0^p + \beta_1^p(ln(MW_{st}) - ln(W_{st}^{HW})) \\ &+\beta_2^p(ln(MW_{st}) - ln(W_{st}^{HW}))^2 + T_t + T_{st} + \epsilon_{st}^p\end{aligned} \tag{3}$$

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:

$$\frac{\partial ln(W^p_{st}) - ln(W^{HW}_{st})}{\partial ln(MW_{st}) - ln(W^{HW}_{st})} = \beta^p_1 + 2 * \beta^p_2 * \overline{ln(MW_{st}) - ln(W^{HW}_{st})} \tag{4}$$

We estimate the above specification and plot the marginal effects of minimum wages at different percentiles in Figure 6. 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 the 80^{th} percentile in rural areas while only upto the 60^{th} percentile in urban areas. The 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 wages and 5.5 percentage points (0.55*10) increase in urban wages at the 10th percentile. The results are robust when only border districts are included in our analyses (Figure A.5).

Since the spillover effect of effective minimum wages defined using the wages for high skilled workers is upto the 80^{th} percentile, we also estimate a specification, where average wages of the high skilled workers are replaced with the wages at the 85^{th} percentile in Equation 3. The coefficients plotted in Figure A.6 also show that the effective minimum wages have a higher impact on lower percentiles, while this effect diminishes as we move up the wage distribution.

5.6 Alternate Mechanisms

We now test for other mechanisms that could affect wages during 1999-2018 and whether the effect of minimum wages may be confounded by these. For instance, National Rural Employment Guarantee Act (NREGA) implemented 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.

As NREGA guarantees minimum statutory wages to NREGA workers, the implementation of this scheme may encourage the informal sector employers to pay the minimum wage, thus generating greater compliance with minimum wage legislation during this period. We account for the implementation of NREGA in our analyses in three ways. First, since the NREGA had been implemented in all districts by 2008[22], the analysis is limited to the year 1999, 2004 and 2007-08 to provide a comparison between NREGA implemented (treatment districts) and non-implemented districts (control districts). The years 1999 and 2004 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 utilize the intensity with which NREGA is implemented in a given district defined as the proportion of population working in NREGA in a given district. This is estimated using the employment data since the data also captures days worked under public work schemes.

The results are presented in Table 10 for all districts in rural India. The wages increase for lower wage quintiles due to the increase in the minimum wages, despite controlling for various measures of NREGA across columns. Thus, the effect of minimum wages on wage inequality obtained in the main results is not driven by NREGA. The significantly positive effect of minimum wages on lower wage quintiles is robust when only border districts are considered while controlling for NREGA (Appendix Table A.12).

Another alternative mechanism that could affect wage inequality is increasing labor unionization. Union memberships globally, as well as within India, have been declining

[22]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.

over the last few decades.[23]. Thus, unions potentially are less likely to affect wage inequality in India. Finally, the impact of minimum wages on wage inequality could be affected by changing enforcement rates. The enforcement of minimum wages, as indicated by labor inspections in Appendix Figure A.7, has remained stable over the last two decades. Furthermore, our above analysis has demonstrated that both formal and informal workers have been affected by minimum wages at a similar rate (Table 5), suggesting that the observed effects on wage inequality may not be influenced significantly by variations in the enforcement rate.

6 Conclusion

Wage inequality has declined by as much as 35% during 1999-2018 in India. In the same period, the median of real minimum wage increased by 69.98%. Our paper examines the role of the rising minimum wages in reducing wage inequality in India in the last two decades. Since minimum wages in India are set at the state level and states increased minimum wages differentially over 1999-2018, we exploit the across state and over time variation in the minimum wage changes to examine the role of the minimum wage in the documented decrease in wage inequality in India.

Our analyses show that rising minimum wages in India have contributed significantly towards reducing inequality in wages, explaining almost 26% of the decline in wage inequality. 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. In addition, we find that the least skilled and those with lowest education levels benefit the most from the increase in minimum wages. 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 employment in the country.

[23] See: Business Line and Politico

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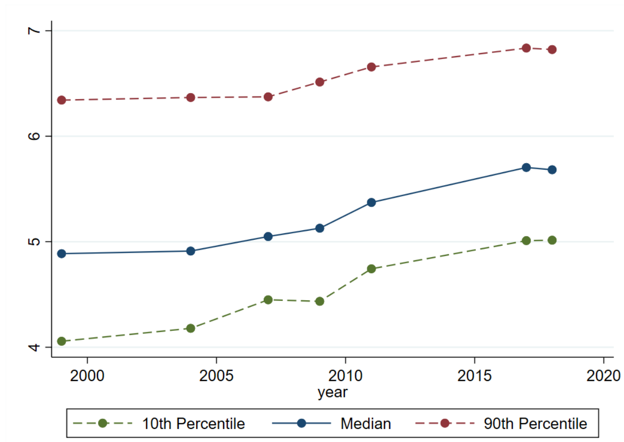
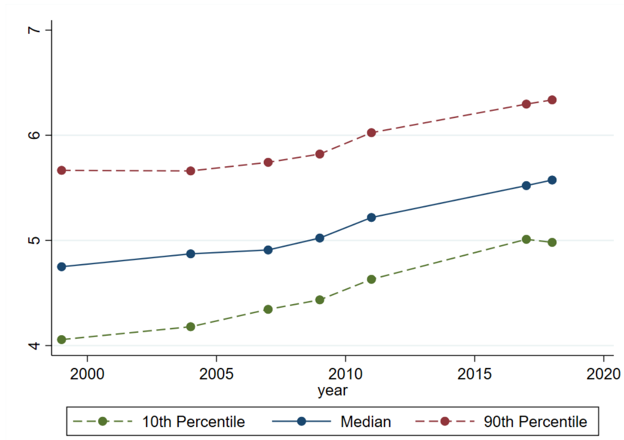
Figure 1: Distribution of Log Real Wages from 1999-2018

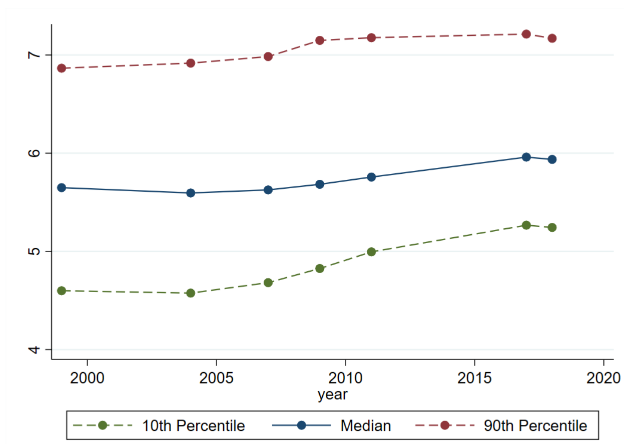
Panel A: All



Panel B: Rural Area



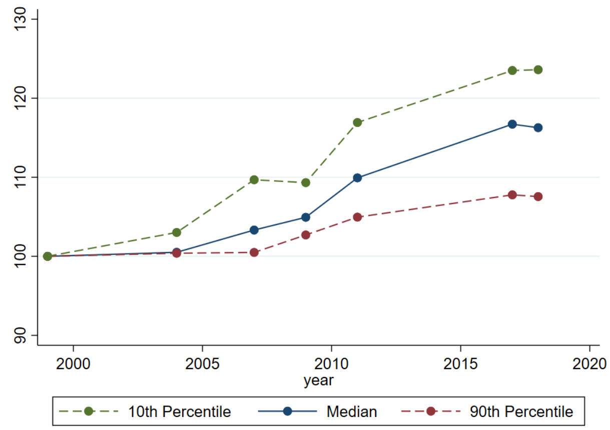
Panel C: Urban Area



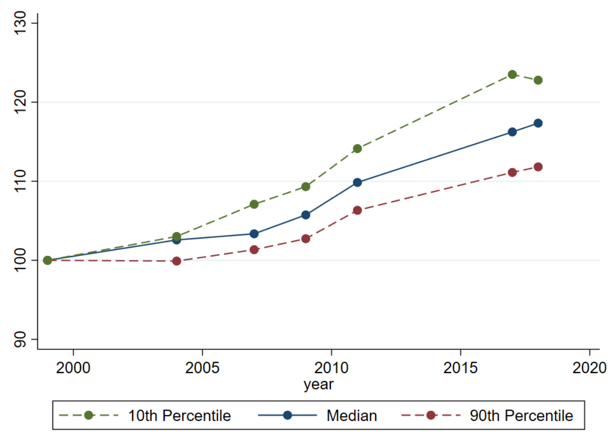
Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018.

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

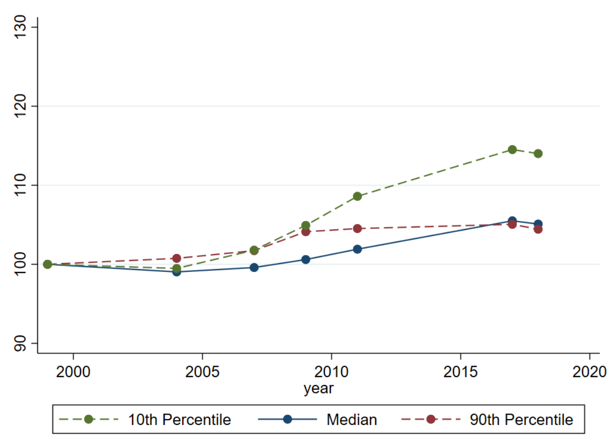
Panel A: All



Panel B: Rural Area



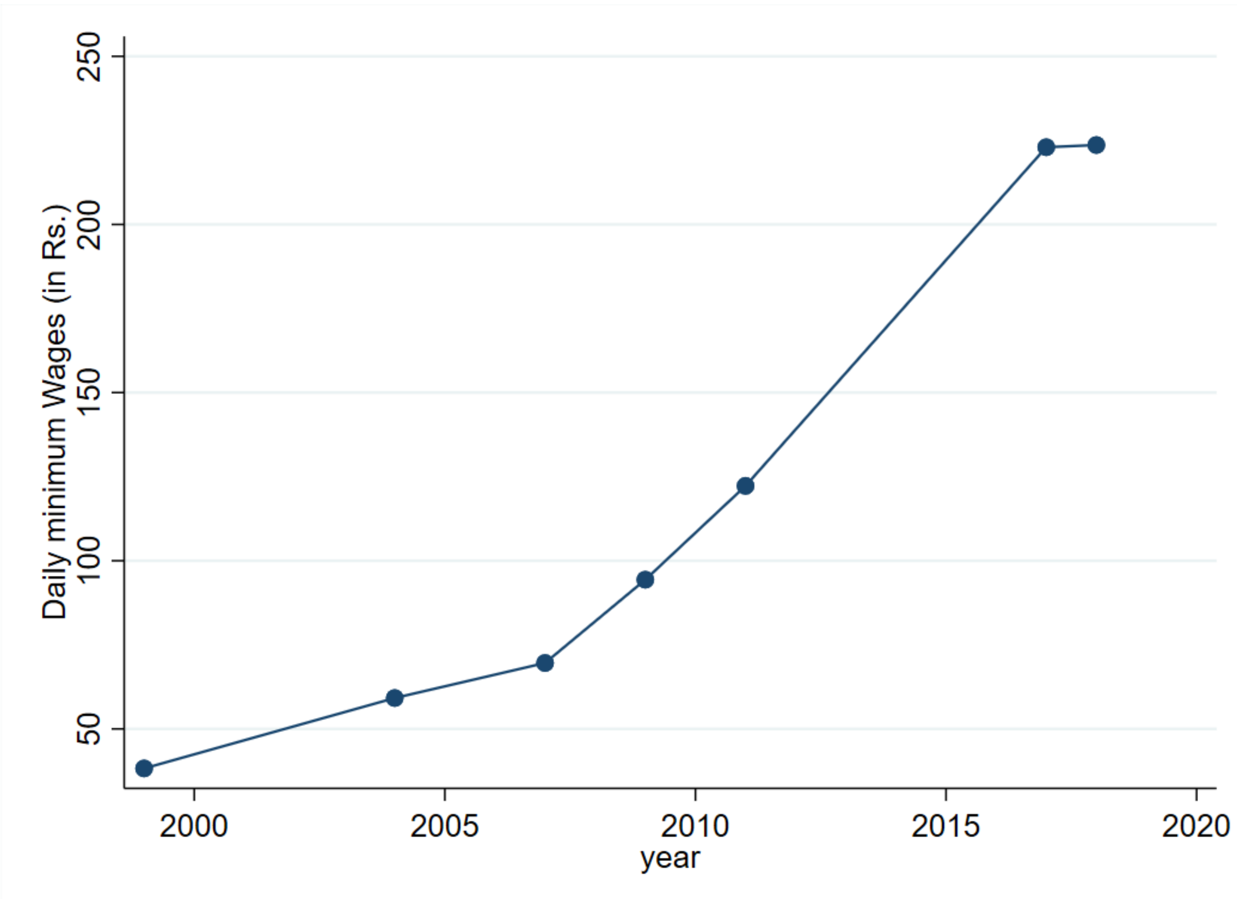
Panel C: Urban Area



Notes: Log of average daily wages for each percentile group is indexed at 100 in 1999.

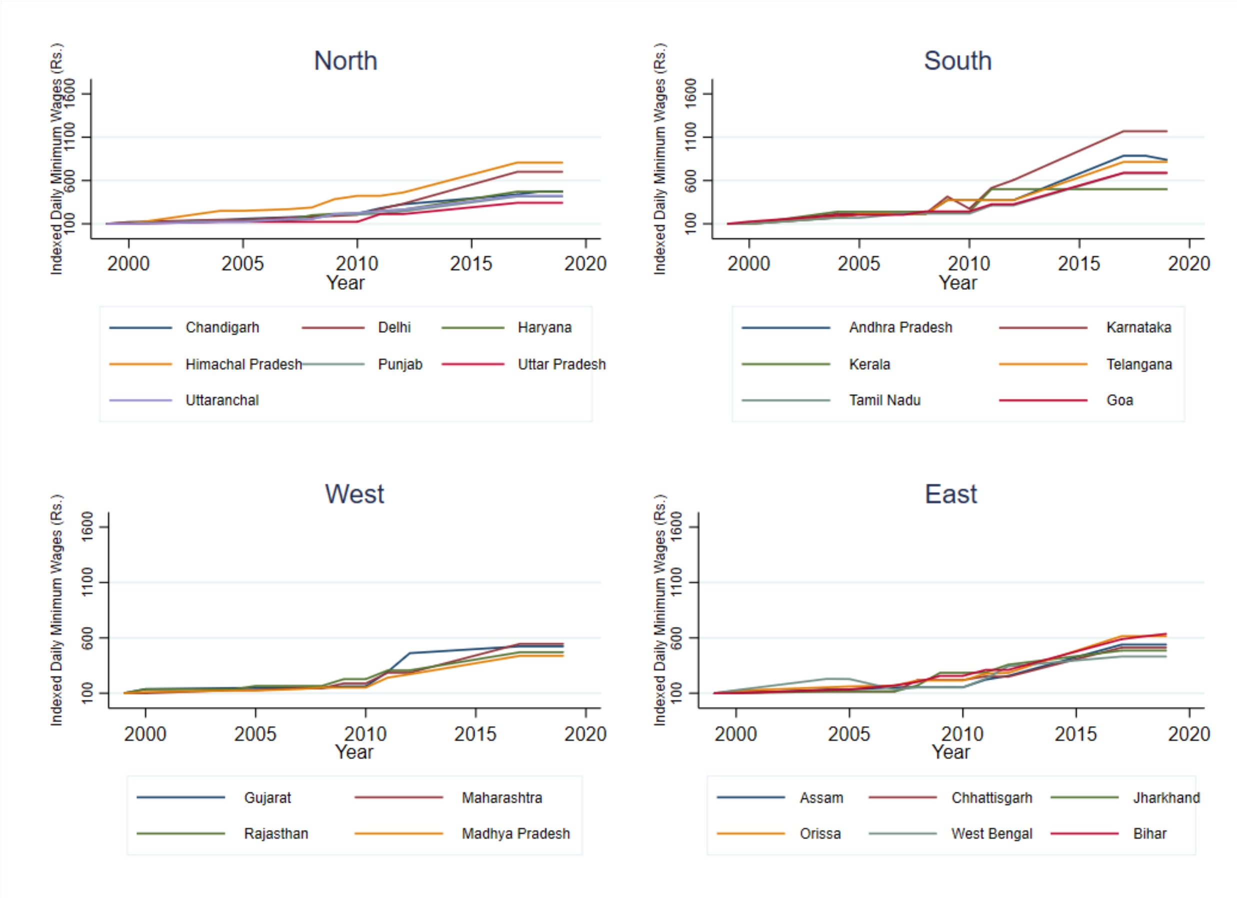
Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018.

Figure 3: Average Daily Administrative Nominal Minimum Wages from 1999-2018



*Notes:*Average daily administrative nominal minimum wage for the agricultural sector is utilized.
Source: Authors' calculations based on Labour Bureau data.

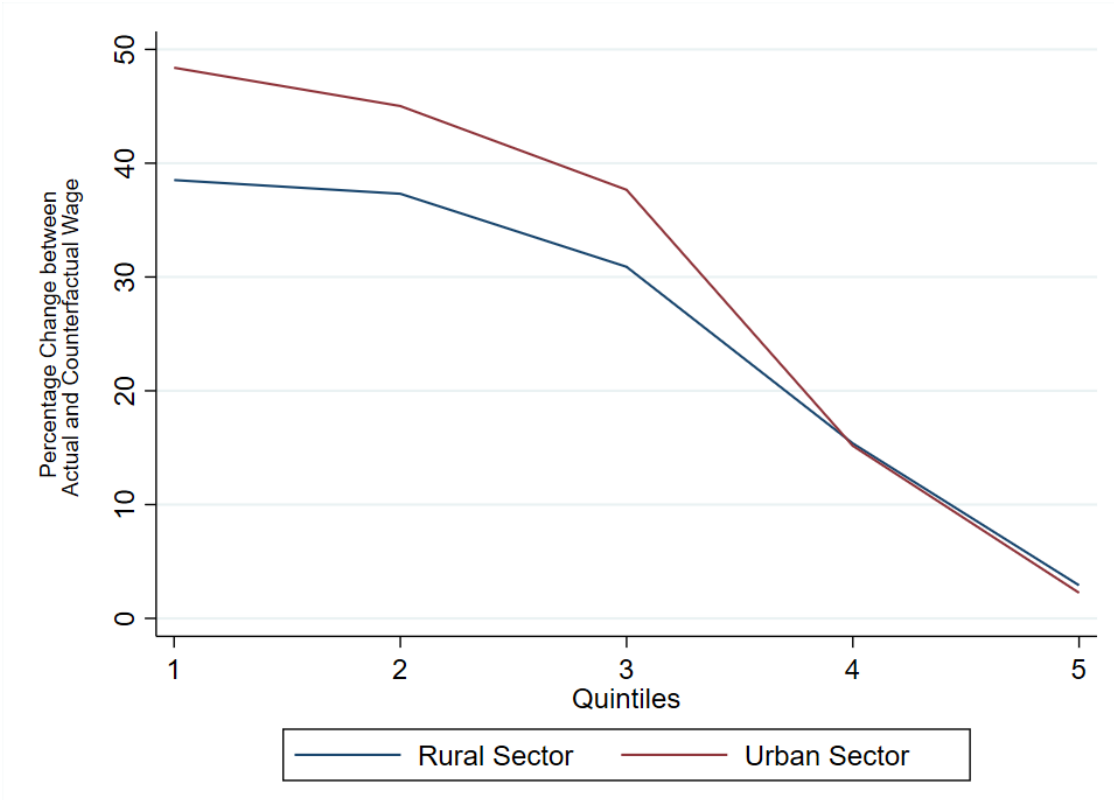
Figure 4: Indexed Daily Administrative Nominal Minimum Wages 1999-2018



Notes: Daily administrative nominal minimum wages for the agricultural sector in each state are indexed at 100 in 1999.

Source: Authors' calculations based on Labour Bureau data.

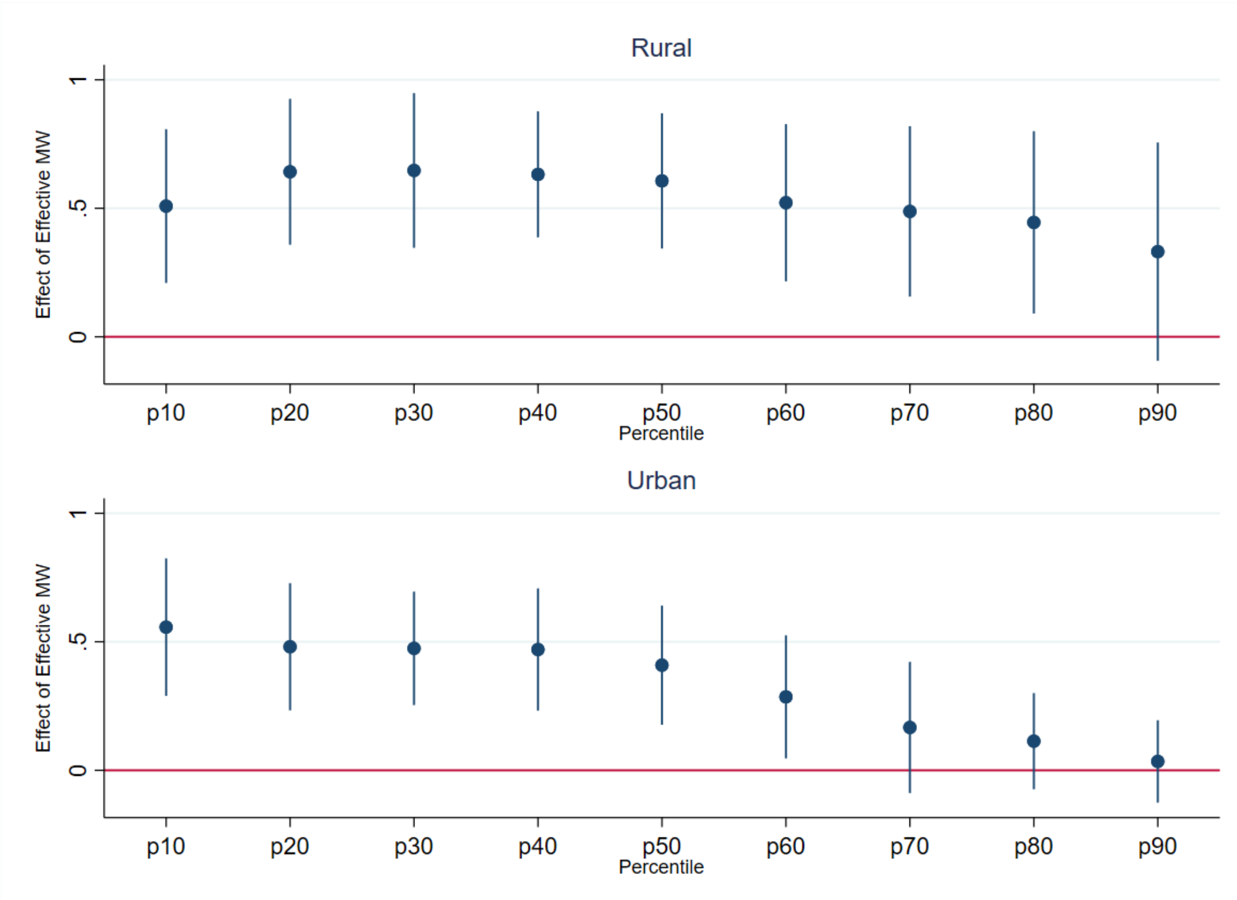
Figure 5: Percentage difference between Actual and counterfactual wages at Quintiles in 2018



Notes: The counterfactual wage distribution for the year 2018 is derived using the 1999 minimum wage levels as a basis.

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

Figure 6: 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 based on nominal wages

	1999	**2004**	**2007**	**2009**	**2011**	**2017**	**2018**
				All			
ln(q90)-ln(q10)	2.189	2.148	1.921	2.043	1.897	1.825	1.833
ln(q90)-ln(q50)	1.391	1.455	1.321	1.350	1.269	1.132	1.139
ln(q50)-ln(q10)	0.799	0.693	0.600	0.693	0.629	0.693	0.693
Var(log wage)	0.648	0.647	0.575	0.604	0.567	0.480	0.463
Gini(log wage)	0.113	0.106	0.092	0.088	0.079	0.066	0.063
				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)	0.425	0.415	0.337	0.354	0.344	0.332	0.300
Gini(log wage)	0.095	0.088	0.074	0.070	0.064	0.056	0.052
				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)	0.746	0.797	0.736	0.800	0.755	0.559	0.542
Gini(log wage)	0.109	0.109	0.098	0.096	0.089	0.069	0.067

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

	Coeff	SE	p-value	Within R-sq	Overall R-sq	Obs
Mining, Construction, Manufacturing	0.585	0.082	0.000	0.951	0.891	75
Electricity, Water supply	0.504	0.134	0.001	0.935	0.844	63
Wholesale, retail trade	0.400	0.116	0.001	0.931	0.777	75
Transportation, storage	0.530	0.102	0.000	0.940	0.849	74
Accommodation, Food service	0.846	0.340	0.048	0.892	0.808	16
Information, communication	0.388	0.146	0.011	0.880	0.658	74
Financial, Professional, Technical	0.348	0.155	0.031	0.895	0.774	61
Administrative	0.691	0.127	0.000	0.948	0.831	41
Education, Health, social work	0.409	0.125	0.002	0.921	0.766	71
Other Activities	0.648	0.108	0.000	0.938	0.838	66

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. Minimum Wages data is from Labour Bureau.

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. Minimum Wages data is from Labour Bureau.

Table 5: Effect of Minimum Wages on Wages of Formal and Informal Workers at Different Wage Quintiles

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
Panel A: Formal Workers				
log MW	0.011	-0.026	-0.046	-0.105
	(0.09)	(0.08)	(0.10)	(0.07)
Wage Quintile=1 × log MW	0.271***	0.270***	0.282***	0.252***
	(0.07)	(0.07)	(0.06)	(0.05)
Wage Quintile=2 × log MW	0.268***	0.233***	0.260***	0.233***
	(0.04)	(0.05)	(0.06)	(0.04)
Wage Quintile=3 × log MW	0.187***	0.161**	0.198***	0.195***
	(0.05)	(0.06)	(0.04)	(0.05)
Wage Quintile=4 × log MW	0.018	0.019	0.071***	0.084***
	(0.03)	(0.03)	(0.02)	(0.02)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R-Squared	0.92	0.92	0.86	0.86
No. of Clusters	19	19	19	19
Observations	23050	15949	37289	23213
Panel B: Informal Workers				
log MW	-0.040	-0.129	-0.036	-0.093
	(0.07)	(0.08)	(0.08)	(0.08)
Wage Quintile=1 × log MW	0.238***	0.268***	0.245***	0.225***
	(0.07)	(0.07)	(0.07)	(0.07)
Wage Quintile=2 × log MW	0.232***	0.256***	0.225***	0.192***
	(0.06)	(0.07)	(0.07)	(0.07)
Wage Quintile=3 × log MW	0.205***	0.227***	0.194***	0.175***
	(0.05)	(0.07)	(0.05)	(0.06)
Wage Quintile=4 × log MW	0.131**	0.151**	0.101***	0.107**
	(0.05)	(0.06)	(0.03)	(0.04)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R-Squared	0.94	0.94	0.93	0.93
No. of Clusters	19	19	19	19
Observations	135979	93227	103299	65344

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 2004, 2009, and 2011, and PLFS 2017, and 2018 and Labour Bureau data.

Table 6: 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. Minimum Wages data is from Labour Bureau.

Table 7: 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. Minimum Wages data is from Labour Bureau.

Table 8: Effect of Minimum Wages on Employment of all kinds of workers 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 the proportion of days per week self-employed, casual workers or salaried workers work. 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. Minimum Wages data is from Labour Bureau.

Table 9: Effect of Minimum Wages on Employment of Casual or Salaried worker by Education Level

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	-0.026	-0.028	0.003	-0.002
	(0.02)	(0.02)	(0.01)	(0.01)
Low Edu=1	0.070	0.046	-0.064*	-0.090**
	(0.06)	(0.06)	(0.03)	(0.04)
Low Edu=1 $\times$ log MW	-0.021	-0.016	-0.003	0.001
	(0.01)	(0.01)	(0.01)	(0.01)
Med Edu=1	-0.164***	-0.197***	-0.088**	-0.128***
	(0.04)	(0.05)	(0.03)	(0.03)
Med Edu=1 $\times$ log MW	0.013	0.019*	-0.008	-0.001
	(0.01)	(0.01)	(0.01)	(0.01)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
WB p-value of MW $\times$ Low	0.141	0.255	0.639	0.893
WB p-value of MW $\times$ Med	0.179	0.082	0.225	0.894
R-Squared	0.15	0.14	0.21	0.21
No. of Clusters	19	19	19	19
Observations	1130630	741754	749456	459256

Notes: The dependent variable is the proportion of days per week casual workers or salaried workers work. 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. Minimum Wages data is from Labour Bureau.

Table 10: 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

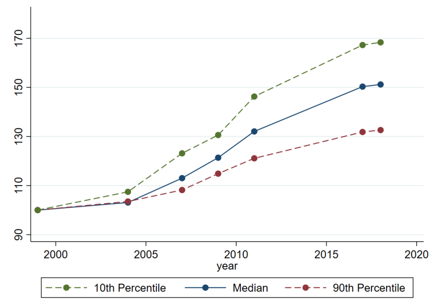
Notes: The dependent variable is log of nominal daily wages. MW refers to log of nominal administrative Minimum Wages. Other controls include education, age-group, marital status, social group, religion, industry categories and NREGA. In column 1, NREGA is controlled as a dummy varaible which takes value 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.

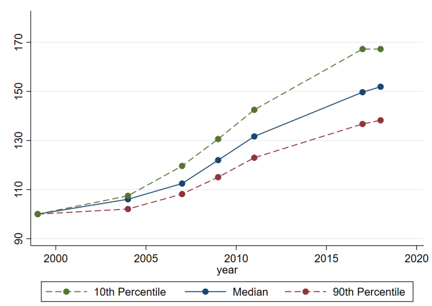
A Additional Tables and Figures

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

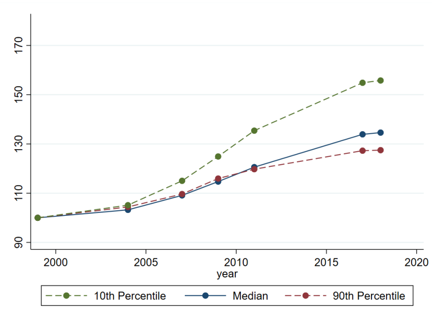
Panel A: All India



Panel B: Rural India



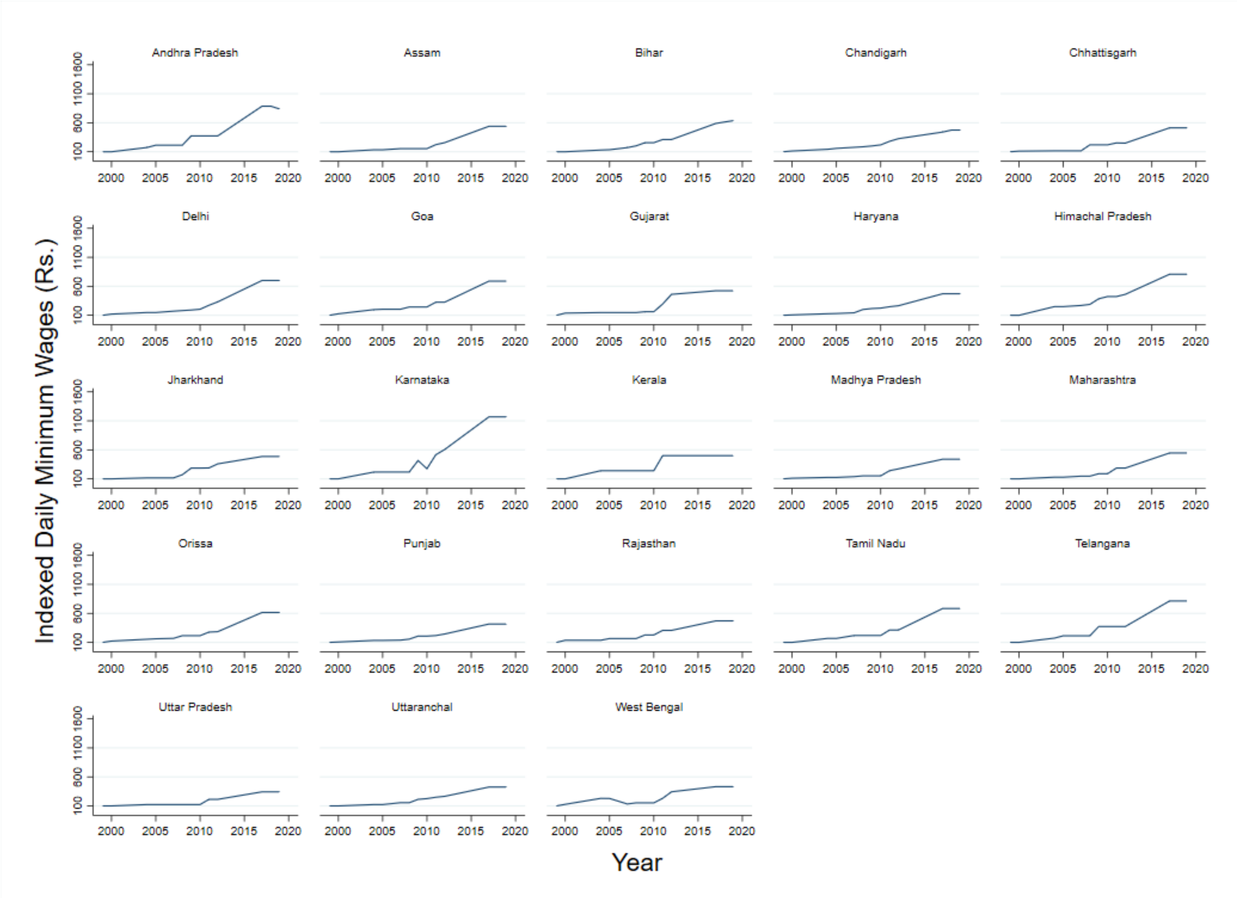
Panel C: Urban India



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.

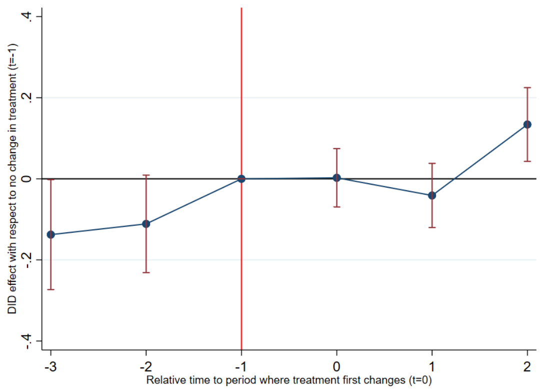
Figure A.2: Indexed Administrative Nominal Daily Minimum Wages 1999-2018 (Agriculture)



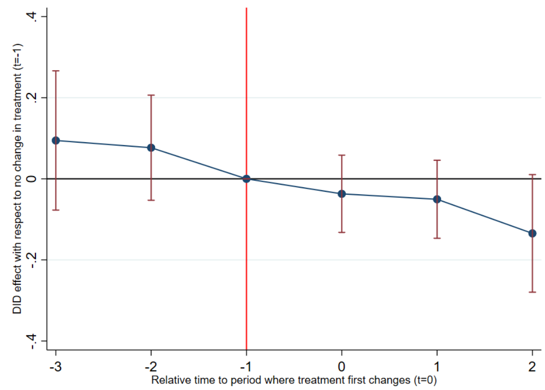
Notes: The Administrative Nominal Daily Minimum Wages for Agricultural sector for year 1999 is indexed to 100 for each state.
Source: Labour Bureau

Figure A.3: Staggered Difference in Difference estimate of the change in real minimum wages on real wage inequality at district level

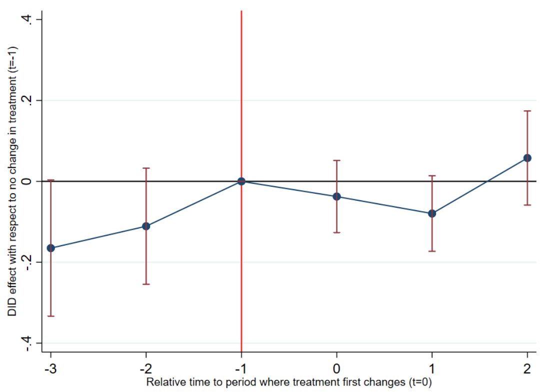
(a) Rural: ln90-ln50



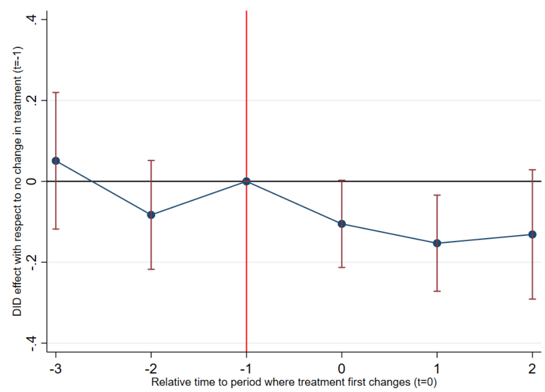
(b) Urban: ln90-ln50



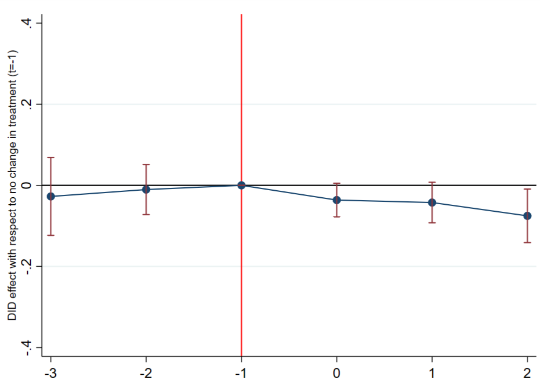
(c) Rural: ln90-ln10



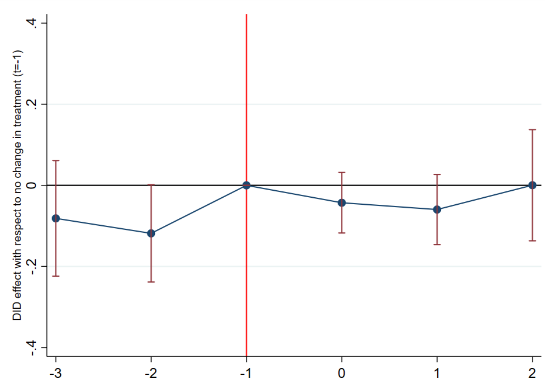
(d) Urban: ln90-ln10



(e) Rural: ln50-ln10



(f) Urban: ln50-ln10

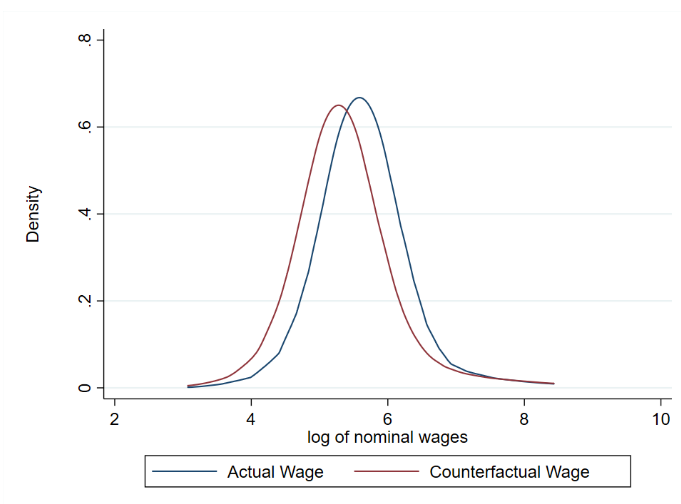


Notes: The treatment variable is the log of real minimum wage (where, real minimum wage is rounded to nearest INR 50). Spike indicates 90% confidence interval. Standard errors are clustered at the district level within each sector and bootstrapped with 200 resamples.

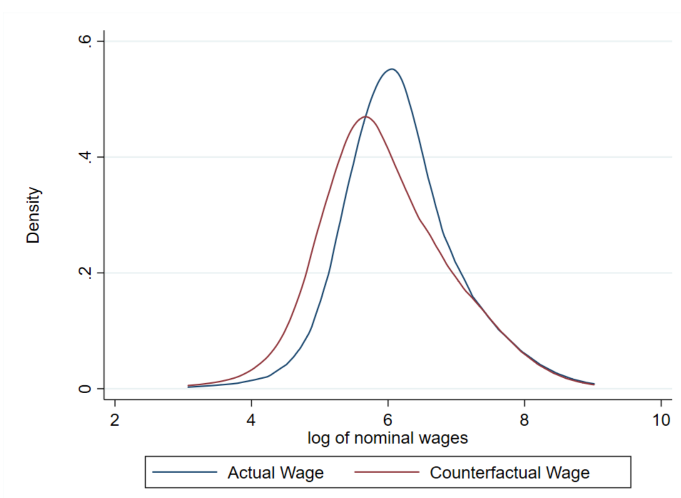
Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018.

Figure A.4: Kernel Density Plots of Actual and Counterfactual log Wage Distribution in 2018

Panel A: Rural India



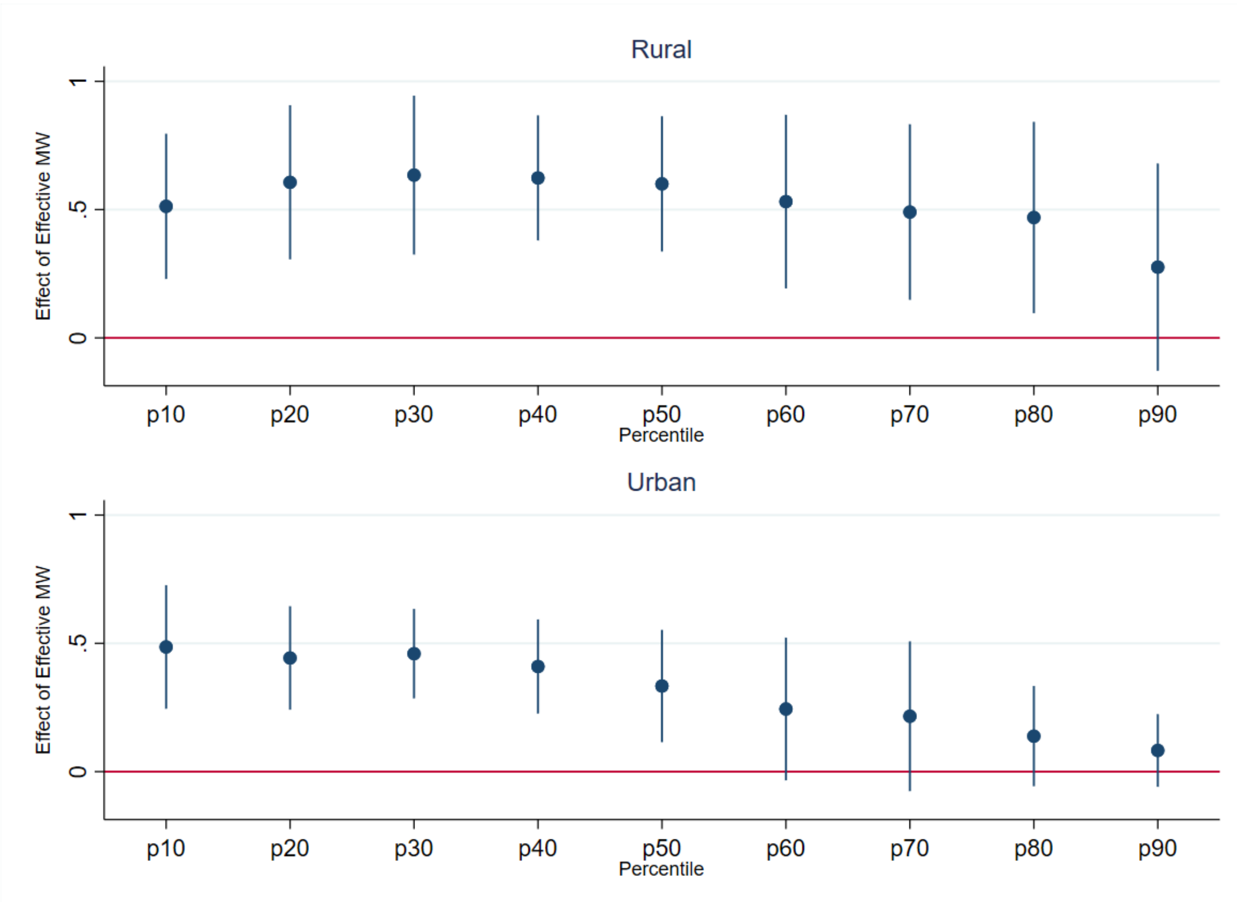
Panel B: Urban India



Notes: Counterfactual log wage distribution is based on the 1999 minimum wages.

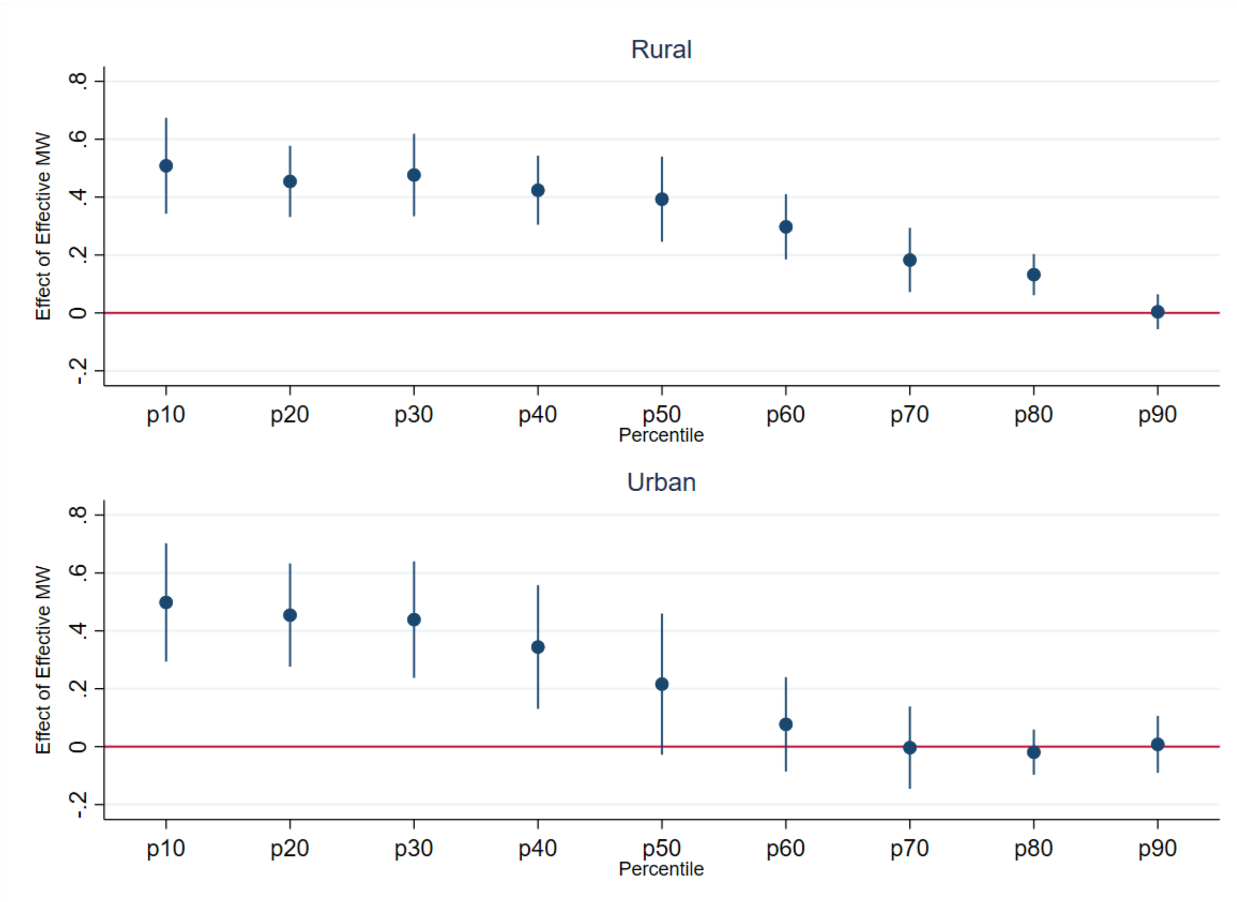
Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018.

Figure A.5: 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.

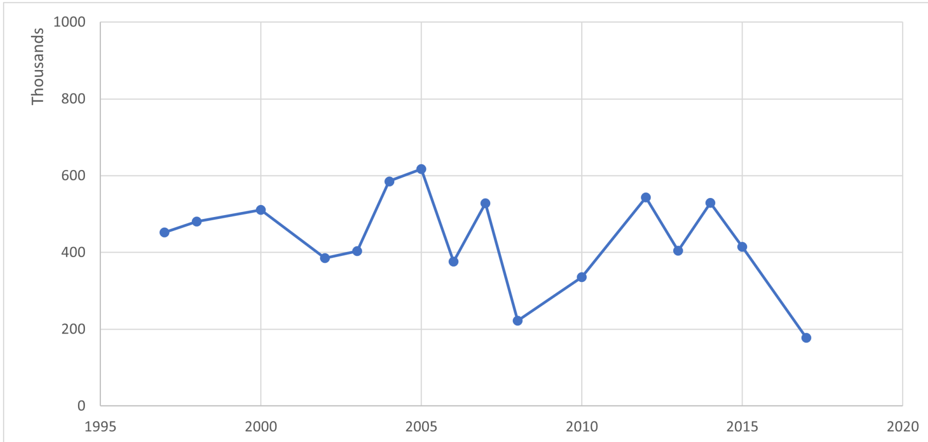
Figure A.6: Marginal Effects of Nominal Minimum wages on Wage Percentiles by Sector relative to 85th percentile



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.

Figure A.7: Labor Inspections (1996-2017)



Notes: Data has been considered from 23 states in India, including Andhra Pradesh, Assam, Bihar, Chandigarh, Chhattisgarh, Delhi, Goa, Gujarat, Haryana, Himachal Pradesh, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Telangana, Uttar Pradesh, Uttarakhand, and West Bengal.

Source: IndiaStat.

Table A.1: Interquantile ratios and summary inequality indices based on real wages

	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 A.2: 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. Minimum Wages data is from Labour Bureau.

Table A.3: Effect of Minimum Wages on Wages at Different Wage Quintiles by type of Employment

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	-0.009	-0.036	-0.001	-0.039
	(0.04)	(0.04)	(0.07)	(0.06)
Wage Quintile=1 × log MW	0.168***	0.178***	0.220***	0.206***
	(0.03)	(0.04)	(0.05)	(0.05)
Wage Quintile=2 × log MW	0.175***	0.172***	0.202***	0.166***
	(0.03)	(0.03)	(0.05)	(0.05)
Wage Quintile=3 × log MW	0.140***	0.156***	0.159***	0.145***
	(0.02)	(0.03)	(0.03)	(0.04)
Wage Quintile=4 × log MW	0.040	0.070**	0.065***	0.079***
	(0.02)	(0.03)	(0.01)	(0.01)
DCW=1 × log MW	0.027	0.008	0.022	0.019
	(0.05)	(0.04)	(0.04)	(0.04)
Wage Quintile=1 × DCW=1 × log MW	0.006	0.023	0.009	0.018
	(0.05)	(0.05)	(0.04)	(0.05)
Wage Quintile=2 × DCW=1 × log MW	-0.010	0.004	-0.010	0.006
	(0.05)	(0.05)	(0.04)	(0.05)
Wage Quintile=3 × DCW=1 × log MW	-0.006	0.010	0.018	0.038
	(0.05)	(0.04)	(0.04)	(0.05)
Wage Quintile=4 × DCW=1 × log MW	0.037	0.050	0.000	0.037
	(0.05)	(0.05)	(0.03)	(0.04)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
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. DCW refers to the dummy variable of casual workers by principal status. 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:* 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.

Table A.4: Effect of Minimum Wages on Wages of Formal and Informal Workers at Different Wage Quintiles (Based on PF Eligibility)

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
Panel A: Formal Workers				
log MW	0.065	0.032	0.055	0.041
	(0.08)	(0.07)	(0.08)	(0.06)
Wage Quintile=1 × log MW	0.171**	0.168**	0.276***	0.250***
	(0.07)	(0.06)	(0.06)	(0.06)
Wage Quintile=2 × log MW	0.179***	0.147**	0.186***	0.164***
	(0.05)	(0.06)	(0.05)	(0.04)
Wage Quintile=3 × log MW	0.099**	0.101*	0.110**	0.078
	(0.04)	(0.05)	(0.04)	(0.05)
Wage Quintile=4 × log MW	-0.032	-0.006	-0.002	0.011
	(0.03)	(0.03)	(0.02)	(0.02)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R-Squared	0.92	0.92	0.86	0.86
No. of Clusters	19	19	19	19
Observations	28036	19993	58620	36795
Panel B: Informal Workers				
log MW	0.017	-0.039	-0.010	-0.055
	(0.05)	(0.07)	(0.08)	(0.08)
Wage Quintile=1 × log MW	0.182***	0.208***	0.230***	0.210***
	(0.04)	(0.05)	(0.06)	(0.06)
Wage Quintile=2 × log MW	0.177***	0.189***	0.202***	0.170***
	(0.04)	(0.04)	(0.06)	(0.06)
Wage Quintile=3 × log MW	0.147***	0.178***	0.175***	0.170***
	(0.03)	(0.04)	(0.04)	(0.05)
Wage Quintile=4 × log MW	0.092***	0.130***	0.094***	0.112***
	(0.02)	(0.04)	(0.02)	(0.03)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R-Squared	0.95	0.95	0.93	0.93
No. of Clusters	19	19	19	19
Observations	173864	118452	115685	71171

Notes: The dependent variable is log of nominal daily wages. MW refers to log of nominal administrative Minimum Wages. Formal Worker refers to the dummy variable of workers eligible for Provident Fund (GPF, CPF, PPF). 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, 2009, and 2011, and PLFS 2017, and 2018 and Labour Bureau data.

Table A.5: Effect of Minimum Wages on Wages at Different Wage Quintiles (with district specific time trends)

	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. Minimum Wages data is from Labour Bureau.

Table A.6: Effect of Minimum Wages on Wages at Different Wage Quintiles (with Quarter-Year Fixed Effects)

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	0.024	-0.006	0.012	-0.031
	(0.05)	(0.05)	(0.07)	(0.06)
Wage Quintile=1 × log MW	0.167***	0.176***	0.215***	0.200***
	(0.03)	(0.03)	(0.04)	(0.04)
Wage Quintile=2 × log MW	0.169***	0.164***	0.196***	0.164***
	(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	0.067***	0.096***	0.066***	0.087***
	(0.02)	(0.03)	(0.01)	(0.01)
District FE	✓	✓	✓	✓
Quarter-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, sex, 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. Minimum Wages data is from Labour Bureau.

Table A.7: Effect of Real Minimum Wages on Real Wages at Different Real Wage Quintiles

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	-0.152*	-0.146	-0.090	-0.109
	(0.08)	(0.10)	(0.08)	(0.07)
Wage Quintile=1 × log MW	0.379***	0.352***	0.355**	0.290**
	(0.09)	(0.09)	(0.13)	(0.12)
Wage Quintile=2 × log MW	0.375***	0.351***	0.352**	0.271*
	(0.08)	(0.09)	(0.14)	(0.13)
Wage Quintile=3 × log MW	0.279***	0.311***	0.298***	0.267**
	(0.06)	(0.09)	(0.09)	(0.11)
Wage Quintile=4 × log MW	0.120**	0.180**	0.144***	0.185***
	(0.06)	(0.07)	(0.03)	(0.04)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
WB p-value of MW × 1.Wage Quintile	0.002	0.004	0.012	0.023
WB p-value of MW × 2.Wage Quintile	0.002	0.004	0.012	0.038
WB p-value of MW × 3.Wage Quintile	0.006	0.009	0.011	0.023
WB p-value of MW × 4.Wage Quintile	0.062	0.044	0.006	0.006
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 real daily wages. MW refers to log of real administrative Minimum Wages. Other controls include education, age-group, sex, marital status, social group, religion and industry categories. Consumer Price Index for Industrial Workers (CPI-IW) and Consumer Price Index for Agricultural Laborers (CPI-AL) are used to deflate wages in urban and rural areas, respectively. 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. Minimum Wages data is from Labour Bureau.

Table A.8: Effect of Minimum Wages on Weekly Earnings at Different Earnings Quintiles

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	-0.028	-0.026	-0.005	-0.019
	(0.05)	(0.06)	(0.07)	(0.06)
Earning Quintile=1 × log MW	0.274***	0.250***	0.270***	0.243***
	(0.02)	(0.03)	(0.04)	(0.05)
Earning Quintile=2 × log MW	0.241***	0.221***	0.249***	0.219***
	(0.02)	(0.03)	(0.04)	(0.05)
Earning Quintile=3 × log MW	0.197***	0.180***	0.199***	0.182***
	(0.02)	(0.03)	(0.02)	(0.04)
Earning Quintile=4 × log MW	0.121***	0.123***	0.092***	0.099***
	(0.02)	(0.03)	(0.01)	(0.02)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
WB p-value of MW × 1.Earning Quintile	0.000	0.000	0.000	0.001
WB p-value of MW × 2.Earning Quintile	0.000	0.000	0.000	0.001
WB p-value of MW × 3.Earning Quintile	0.000	0.000	0.000	0.001
WB p-value of MW × 4.Earning Quintile	0.002	0.004	0.000	0.001
R-Squared	0.92	0.92	0.91	0.91
No. of Clusters	19	19	19	19
Observations	249976	170515	203543	126073

Notes: The dependent variable is log of nominal weekly earnings. MW refers to log of nominal administrative Minimum Wages. Other controls include education, age-group, sex, 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. Minimum Wages data is from Labour Bureau.

Table A.9: Average dynamic effect of minimum wages on wage inequality under the staggered DID framework

	(1)	(2)	(3)	(4)	(5)	(6)
	Estimate	SE	Lower CI	Upper CI	N	Switchers
			Panel A: Rural			
ln90 – ln50	.046	.101	-.12	.212	2582	842
ln90 – ln10	-.083	.124	-.287	.121	2582	842
ln50 – ln10	-.129	.064	-.235	-.023	2582	842
			Panel B: Urban			
ln90 – ln50	-.174	.133	-.393	.044	2198	823
ln90 – ln10	-.28	.157	-.537	-.022	2198	823
ln50 – ln10	-.105	.121	-.305	.094	2198	823

Notes: Each row represents real wage inequality measured via percentile log differences. The treatment variable is the log of real minimum wage (where, real minimum wage is rounded to nearest INR 50). Table indicates 90% confidence interval. Standard errors (SE) are clustered at the district level within each sector and bootstrapped with 200 resamples. CI refers to Confidence Interval.
Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018. Minimum Wages data is from Labour Bureau.

Table A.10: 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. Minimum Wages data is from Labour Bureau.

Table A.11: 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. Minimum Wages data is from Labour Bureau.

Table A.12: 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: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018. Minimum Wages data is from Labour Bureau.