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Abstract

Using nationally representative data on employment and earnings, this paper documents a fall in wage inequality in India over the last two decades. It then examines the role played by increasing minimum wages for the lowest skilled workers in India in contributing to the observed decline. Exploiting regional variation in changes in minimum wages over time in the country, we find that a 1% increase in minimum wages led to a 0.17% increase in wages for workers in the lowest quintile. This effect is smaller at upper wage quintiles and insignificant 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 Codes: J31, J38

Keywords: MW, wage inequality, India

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1 Introduction

There is increasing interest in the use of minimum wages as a policy tool for poverty reduction and social justice. However, there is limited evidence on whether changes in the legislative minimum wages can affect wage inequality in developing countries. In general, developing countries suffer from low enforcement of minimum wages (Bhorat & Ravi Stanwix, 2019). Under this scenario, it is not certain whether a rise in minimum wages will necessary increase wages of workers in the lowest quintiles, who are also more likely to be employed in the informal sector, where compliance is low. However, informal workers can gain from a rise in MW due to capital reallocation to the informal sector, linkages between the labor and goods market and the benchmarking effects of minimum wages as a 'fair wage' in the labor market (Khamis, 2013). Thus, whether a rise in minimum wages leads to reduction in wage inequality in such a setting, is an open question.

India provides an ideal context to examine the effect of minimum wages on wage inequality for two reasons. Firstly, India has a large informal sector employing 83% of the non-farm workforce, along with low enforcement of minimum wage laws (NCEUS, 2007) footnoteThe rate of informality in India is much higher even when compared to the Latin American countries where the number stands at 53% (WIEGO, 2018) or China between 40-50% (Liang *et al.* , 2016). In general, Latin America and China in Asia have higher compliance to minimum wages than other countries in South Asia like India (ILO, 2018) Secondly, one can exploit the variation arising from changes in minimum wages by smaller administrative units within the country. Under the Minimum Wage Act 1948, Indian states are empowered to set minimum wages for workers in scheduled employment categories. During the period 1999–2018, the median real minimum wage across states increased by 70%, while the average nominal minimum wage increased by 457%. However, there was wide variation across states in the minimum wages changes during this period, with the variance of daily real minimum wages in Rs. across states increasing from 2,652 in 1999 to 6,875 in 2018. At the same time, the Gini of the nominal logarithmic wages fell from 0.113 in 1999 to 0.063 in 2018, and the gap between the 50th and the 10th wage percentile fell from 0.799 in 1999 to 0.693 in 2018. In this paper, we exploit the variation in minimum wages 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.[1]

We combine the nationally representative National Sample Surveys (NSS) – Employment and Unemployment rounds (1999, 2004, 2007, 2009, 2011) and the Periodic Labor Force Surveys (PLFS) (2017, 2018) with data on state-level agricultural Minimum Wages (MW). There are three notable points about the MW setting in India. First, unlike economies with a national/state minimum wage, such as the US and UK, where wage floors primarily affect low wage workers, India's industry- and occupation-specific wage-setting influences wages beyond lowest paid workers. Second, changes in state-level agricultural MW are highly correlated with changes in non-farm occupation MW, which are generally set at a higher level. Third, changes in state-level agricultural MW are uncorrelated with changes in state-level macroeconomic characteristics. The latter alleviates concerns that changes in state-level agricultural MW are endogenous to economic conditions in a state. Using a two-way fixed effects strategy that controls for district and time fixed effects, we examine the impact of growth in MW on growth in daily wages for paid workers by quintiles of the wage distribution.

We find that a 1% increase in MW leads to a 0.17% increase in wages in the lowest wage quintiles in rural India, 0.14% and 0.07% in the third and fourth quintiles, respectively, with no effect on the highest wage quintile. Given that a substantial proportion of workers (around 14%) even in the fourth quintile earn lower than the stipulated MW in India this results is not surprising.[2] Using these estimates, we examine the counterfactual log wage

[1] We confine our analysis to wage inequality, and not earnings inequality (which includes self-employment income), as the MW Act in India covers wage workers but not the self-employed (NCEUS, 2007). Additionally, while self-employed form a substantial proportion of India's workforce (24%), their earnings are not captured in the surveys from 1999-2011. However, we do examine the effect of minimum wages on earnings of paid workers in our analyses and show that our findings continue to hold for them since employment in paid work is not affected by minimum wage increases.

[2] Moreover, existing evidence for developing countries shows that spillovers can be larger in these contexts. For instance, in Mexico, earnings up to the sixth decile are significantly affected by the MW (Bosch &

distribution in 2018 at the level of MW in 1999 and find that if MW 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 of India). Further, we find that the rise in MW explains almost 26% of the decline in wage inequality (Gini of log wages) during 1999–2018. The magnitude of these effects is greater for urban India, perhaps due to greater possibility of enforcement in these areas. Additionally, we find that the least skilled workers and those with the lowest education levels benefit the most from a rise in MW. At the same time, we do not find any negative impacts on employment of the least educated workers, showing that while MW reduced wage inequality, they did not reduce employment levels contemporaneously in the country.

We test the robustness of our findings 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 agro-climatic conditions. All our results go through this subset of districts. Importantly, we use a specification that exploits the differential change in MW within contiguous district pairs across state borders. Our results remain robust to this alternative estimation as well. We also estimate a dynamic difference in differences (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 the MW increase in urban India, with no significant pre-trends. The results in this specification are weaker for rural India and only hold for inequality measured between the 50th and the 10th wage percentiles.

Additionally, we find the impacts to be insignificant for the highest quintile, the highest skilled, and the highest educated workers - the ones which are likely to get higher than the MW for the non-agricultural occupations. This is suggestive of our findings are driven by other economic factors correlated with a differential rise in MW across states over the years. However, it is plausible that even the wages for these workers could be affected solely

Manacorda, 2010).

due to MW if employers prefer to maintain the same wage spread across workers. We also investigate the differential impact of rising MW on wage inequality for formal and informal workers and find evidence that the effect is similar for both types of workers. Additionally, we use the concept of effective MW proposed by Lee (1999) and Autor *et al.* (2016) to check the distributional implications of a rise in MW by wage percentiles relative to local wage conditions. We again find that a rise in effective MW[3] increases wages at lower percentiles in India. Lastly, we rule out other factors such as the NREGA (National Rural Employment Guarantee Act), labor unions, and changes in MW enforcement rate during this period, which could possibly confound our analyses.

Much of the literature on the impact of MW has focused on its employment effects,[4] as compared to the possible effects of MW changes on wage inequality. For developed countries, the evidence on how changes in MW 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)[5]. The case of developing countries is different due to the existence of segmented labor markets - formal and informal. Lemos (2009), using a two-sector model, shows that an increase in the MW increases the wages in the formal sector and displaces the workers from the formal to the informal sector, leading to a fall in wages in the informal sector. In developing countries, effects of MW are also

[3]The effective minimum wage is defined as the gap between the MW and the average wage of high-skilled workers within a given state and sector.

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

[5]A pioneering study by Lee (1999) examines the impact of effective real MW (the gap between the state median wage and the applicable state or federal MW) on wage inequality between 1979 and 1991 at the state level in the United States, and finds that reduced real MW (on account of reduced real federal MW) 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) extend this analysis by 20 years using an instrumental variable strategy, where the effective MW is instrumented with the difference between the state-level MW and the federal MW. They find that the reduction in real MW explains 30–40% of the rise in wage inequality at the lower percentile level. Bossler & Schank (2022) exploit the introduction of MW in Germany and find a decline in wage and earnings inequality following the legislative change. Other studies in developed-country contexts also find spillover effects of rising MW up to the 60th percentile of the wage distribution (Neumark *et al.* , 2008; Stewart, 2012).However, relatively less is known about the impact of MW on wage inequality in developing countries.

likely to be ambiguous due to weak enforcement (Bhorat *et al.* , 2021). Compliance with MW changes is also likely to be smaller when multiple MW exist, and little or no penalty clauses are in place (Broecke *et al.* , 2017).

The emerging literature that has studied the wage and employment impacts of MW find that they vary by institutional factors across developing countries (Neumark & Corella, 2021).[6] A few empirical studies that exist on the effects of MW changes on earnings inequality find that MW increases lead to decreases in earnings inequality[7]. For China, Lin & Yun (2016) find that earnings inequality in terms of the earnings gap between the median and the bottom decile decreased in cities where an increase in MW occurred in the country between 2004 and 2009. Engbom & Moser (2021) and Sotomayor (2021), using spatial variation in the bindingness of the federal MW across states in Brazil, also find that a rise in MW accounts for a large decline in earnings inequality in the country since the 1990s.[8] Bosch & Manacorda (2010) use variations in MW across municipalities and over time in Mexico to show that the growth in earnings inequality between 1989 and 2001 can be explained in part due to the steep decline in the real value of the MW.

In the Indian context, general evidence on the effects of MW on labor market outcomes is limited. This is likely the result of the complexity of the MW system in the country and the fact that it has limited coverage and enforcement (Belsar & Rani, 2011). Distinct from other country contexts such as Brazil and Mexico, there is no national minimum floor for wages in India. Thus, the nature, structure, and implementation of MW in India is quite different from other contexts. Using variation in state-mandated MW for the construction sector and

[6]For instance, studies show very strong wage compression and negative employment effects for Latin America (Gindling & Terrell, 2007). The same is not observed for Brazil (Lemos, 2009).

[7]Studies on wages and earnings inequality in relation to minimum wage policies differ based on whether the minimum wage is defined at an hourly, daily, or monthly level and whether income data correspond to this classification. Lee (1999) and Autor *et al.* (2016) use hourly wage data from the Current Population Survey to analyze the effects of an hourly minimum wage in the US, where wage floors are typically set at the hourly level. Lin & Yun (2016) examine an hourly minimum wage in China but rely on monthly earnings data from the Urban Household Survey due to the absence of information needed to convert monthly wages into hourly rates. Neumark *et al.* (2006) study Brazil using monthly earnings data, as the minimum wage is legislated on a monthly basis, making this measure the most relevant.

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

the number of labor 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) find that from 1983 to 2008, changes in MW at the state level of occupation in India did not affect employment, but increased earnings and consumption in rural areas. In fact, there is no study to our knowledge that examines the effects of MW changes on wage inequality in India.[9]

Our paper contributes to the emerging literature that documents the impacts of MW on wage inequality for developing countries (Gindling, 2018). First, it provides a different regional context than China, Brazil, and Mexico, since the share of employment in the informal sector in India is larger than in China and Latin America, and also level of enforcement is lower in India relative to these countries, as discussed earlier. Second, it provides insights into how occupation- and industry-specific minimum wages in a labor-surplus economy prevent wages from falling too low, even for skilled workers, by serving as broader benchmarks beyond low-wage floors. Such a structure mitigates downward pressure on earnings, counteracting the effects of excess labor supply. Low enforcement and high informality may suggest that MW 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. However, we find a sharp decrease in wage inequality due to MW increases, possibly due to the general anchoring and lighthouse effects of MW changes on the informal sector. These results have important policy implications for the country. Reduction in wage inequality, with small effects on employment for India, shows that using MW as a tool to decrease inequality can be effective in contexts of large informal sector as well.

The rest of the paper is organized as follows. Section 2 discusses the trends in wage

[9] 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 1980s to 2004, while Azam (2012) and Sarkar (2019) examine the changes up to 2011 and find that during 2004–2011 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, it showed a distinct decline during 2004–2011, which continued in 2011–2018. This decline is attributable to increased 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.

inequality in India and the MW 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, followed by a Discussion of alternative mechanisms in Section 6. Section 7 concludes.

2 Background

2.1 Wage Inequality in India

Figure 1 plots the median, 90th and 10th percentile of log real daily wages[10] for all of India (panel A), rural (panel B), and urban areas (panel C) from 1999 to 2018 using the data on regular paid workers (salaried and daily wage workers) from the NSS and the PLFS 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 the daily wage distribution for high-income individuals and by the distance between the 10th percentile and the median of real daily wage distribution for low-income individuals. Clearly, the distance between both the 90th and 10th percentiles and the median wage has fallen over time. The reduction in inequality is larger at the lower percentiles.

For ease of comparison, we index the median, the 90th, and the 10th percentile of real wages at 100 in the year 1999 in Figure 2. For all-India, the median real wages are 16.27% higher in 2018 than in 1999. Notably, the growth rate in wages at the 90th percentile is much lower than that at the 10th percentile of the daily wage distribution. Real wages at the 10th percentile are 23.61% higher in 2018 than in 1999, while real wages at the 90th percentile are 7.56% higher in 2018 than in 1999. This implies that wage inequality has fallen in India due to steep growth in the wages of low-income individuals. The decline in

[10] Real wages are determined using the Consumer Price Index for Industrial Workers (CPI-IW) in urban India and the Consumer Price Index for Agricultural Laborers (CPI-AL) in rural India, representing real values in 2017.

wage inequality is more pronounced in rural areas than in urban areas. In rural areas, the growth rate of real wages at the 10th percentile is steeper than the median of the wage distribution post-2004, while the growth rate at the 90th percentile has always been flatter than the median of the wage distribution. Thus, we find clear evidence of a decline in wage inequality in rural India. In urban areas the decline in wage inequality is more visible at extremes (the difference between the 10th and the 90th percentile) after 2009. We also plot the growth in nominal wages (Appendix Figure A.1) and find similar patterns.

Similar changes in wage inequality are also observed using other measures – interquartile wage ratios, variance of wages, and Gini coefficients of real wages in Table 1, and of nominal wages in Appendix Table A.1. At the all-India level, we observe that wage inequality has fallen between 1999 and 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 between 1999 and 2018 when measured using the Gini coefficient. There is a slight increase between 2009 and 2011 when other measures, such as the distance between the 90th and the 10th percentile and that between the 50th and the 10th percentile, are used, but all indicators show a decline in wage inequality during 1999–2018 in rural areas. In urban India there is a slight rise in wage inequality observed prior to 2009 due to growth in the upper percentile of the wage distribution. However, the Gini coefficient of urban areas has continuously declined, and stood at 0.068 in 2018. Overall, these results show that wage inequality has declined between 1999 and 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's Minimum Wage Setting

The MW Act 1948 in India empowers the Indian states to fix MW for workers in the scheduled employment categories. Enterprises employing one worker or more are covered by the Act, regardless of formality status of the worker. Over the years the Act has been amended to increase its coverage of scheduled employment categories. The MW rates vary by age (adult vs children) and by detailed job categories (≈1,700 job categories currently) in each state.[11] 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 MW are fixed, more than 1,000 different MW rates operate in a given state in the country at any given time.

As per the MW Act 1948, MW should be revised by the states at least once every five years. However, this recommendation was not legally binding for the period of analysis (ILO, 2018). This leads to substantial variation in the growth rate of MW across the Indian states. However, all states changed the legislative MW for the agricultural sector within a span of five years. Notably, MW 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 MW to evaluate their effect on wage distribution in India. Lastly, selection into occupations can itself be affected by differential changes in MW across occupational categories. In this paper, we examine the effects on wage inequality of changes in the MW for the unskilled category of workers in the agriculture sector. We use agricultural wages for unskilled workers as the benchmark MW for two reasons. First, it is the lowest MW, and thus less prone to ambiguities that arise in the enforcement (although implementing the lowest MW is also challenging in the informal sector due to lack of written employment contracts between workers and employers in such jobs). Second, because of the large number of agricultural workers in India (approximately 40% of workers), MW are relatively high in non-agricultural occupations to stimulate labor supply.

Figure 3 plots the average real administrative MW for unskilled agricultural laborers across all the Indian states for each year in our analyses. Clearly, there has been a rapid increase in real MW in India by almost 50% between 2007 to 2017. Figure 4 plots the growth in daily real MW for unskilled agricultural labor across the Indian states for each geographic

[11]The states set the MW depending on several factors, including socioeconomic conditions, prices of essential commodities, and local factors influencing the wage rate (NCIB, n.d.). For instance, Kerala, a state with higher income per capita, has historically had higher MW for all job types vs other low per capita income states such as Bihar.

region (North, South, East, and West India) during 1999–2018.[12] It shows wide variation in real MW growth across states between 1999 and 2018, with some states witnessing an increase of 6% (Uttar Pradesh in the North) and others undergoing an almost 262% increase (Karnataka in the South).

We also examine the relation between the growth in MW for unskilled labor in agriculture and MW consistently reported for some of the other non-agricultural categories by the states for the years 1999, 2004, 2007, and 2011, based on the industry-level MW compiled by Mansoor & O'Neill (2021) for about 30 industries per state. In reality, almost 60-70 industry specific MW exist for every state, hence, this data only has limited coverage. Nonetheless, it is useful to examine broad correlations. Appendix Table A.2 reports the results from a regression of the log of MW in the sectors reported in each row of the table (as the dependent variable) on the log of MW in the agriculture 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 ten sectoral wages, seven have a within R-square value of more than 0.9.[13] Even for the remaining three, the value is more than 0.8. These results show a high correlation in growth between the lowest MW fixed by state governments and that of other job categories, thus showing the validity of using unskilled agricultural MW as the benchmark MW at the state level.

3 Data

We use data from the nationally representative Employment and Unemployment rounds of India's NSS in 1999–2000, 2004–2005, 2007–2008, 2009–2010, 2011–2012 (referred to as 1999,

[12]Rate of growth in daily nominal MW for unskilled agricultural labor across the Indian states for each geographic region is plotted in Appendix Figure A.2. Clearly, the growth in nominal wages is much higher, by almost six times across many states. The inflation rate in India was around 8–10% per annum during 2008–2013, but has remained at 4–6% per annum between 2014 and 2018. Thus, there has been a rise in real MW during 2007–2018.

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

2004, 2007, 2009, and 2011 in this paper) and PLFS in 2017–2018 and 2018–2019 (referred to as 2017 and 2018 in this paper), which has replaced the NSS since 2017. Each survey starts from July of the first year to June of the second year, thus covering an entire year.

The NSS is comparable to the PLFS in methodology, design, and the variables on which data are collected. Both surveys include repeated cross-sections of households 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 (PSUs), picked randomly within 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 PSUs, are selected using probability proportional to size with replacement. An 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 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 daily wage workers) for the majority of the 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 paid worker in the last reference week, to compute daily wages.[14] 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 winsorize wages at the top and bottom 1 percentiles to reduce the

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

noise in the estimates from 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 the 2001 Census.

We obtain data on administrative nominal MW for agricultural workers from the Labor Bureau for 19 states in India.[15] The data are reported at the end of each calendar year. In general, each state sets the MW for eight hours of work per day. In some cases, states report the MW for less than eight hours of work. In that case, the unitary method is used to keep values consistent. These data are merged with the NSS data using survey months. For instance, the 2011–2012 NSS data from July to December 2011 are matched to the MW with an effective date of 31 December 2010, and data from January to June 2012 are matched to the MW with an effective date of 31 December 2011.[16]

For the empirical analyses we do not deflate either the MW or the daily wages calculated from each round of the employment survey. This is in line with the existing studies for India that find nearly no relation between changes in MW and changes in inflation in India (Soundararajan, 2019). Table 2 shows the average real wages for different category of workers in rural and urban areas for 1999–2018 for all districts, as well as those located on the state borders.[17] We examine the wage distribution by skills and education levels. Skills are defined by the occupational categories in the National Classification of Occupations (NCO), where low-skilled workers are defined as those employed in elementary occupations, such as laborers, skilled agricultural workers, and construction workers; medium-skilled workers

[15] 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 reporting their MW a few years after introduction in 2000 and Telangana in 2014, so we use their MW since the year these states began reporting these for all districts lying within them.

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

[17] Appendix Table A.3 shows the average nominal wages by worker type.

are those employed in clerical, administrative support, sales, and production occupations; and high-skilled workers are those employed in professional, technical, and managerial roles. Education is defined by the worker's educational qualification, where a less-educated worker is a worker having up to primary education; a medium-educated worker is a worker with up to secondary education (up to class 10); and a highly educated worker is a worker with post-secondary education. For every type of worker, daily wages are higher in urban India vs rural India. Daily wages increase along the skill and education distribution. Importantly, the wages of the low-skilled and the least educated workers are almost equal to the MW. Thus, these worker types are likely to be the most affected by any rise in MW.

Table 2 also reports the average real wage by wage quintile. Workers in the lowest two wage quintiles in rural India and the lowest quintile in urban India receive average daily wages that are lower than the postulated agricultural MW. This shows imperfect enforcement of the MW legislation (even for the lowest value of MW) in the country (Belsar & Rani, 2011; Rani & Belser, 2012; Rani *et al.* , 2013; Soundararajan, 2019; Mansoor & O'Neill, 2021). However, as we discussed in Section 2.2, non-agricultural MW also increase in tandem with agricultural MW. As discussed later, even with limited availability of MW information for the non-farm sector around, 14% workers earn less than the stipulated MW for their sector in the fourth quintile. This number is likely to be higher in reality.

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 work days for each type of worker by skills and education and report the results in Appendix Table A.4. We find that low-skilled workers constitute 70% of the workforce in rural India and 22% in urban India. Medium- and high-skilled workers are the dominant group in urban India. Similarly, less-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 United States, there is no binding statutory national MW in the Indian context for the period 1999–2018.[18] 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 MW on wage inequality in the country:

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

where the dependent variable is the log of the daily nominal wage of worker i in state s in year t; $\log(MW_{st})$ denotes the log of the daily nominal MW for unskilled agricultural workers in state s in time period t; and D_{ist}^q is an indicator variable that takes a value of 1 for workers in wage quintile q in state s, and 0 otherwise. The base group for the wage quintile is the highest quintile (i.e. the fifth quintile of the wage distribution in each state). X_{ist} includes worker characteristics such as age, education, religion, social group, marital status, and industry. We also control for district (D_d) and time fixed effects (T_t) in all our specifications, thus controlling for unobserved district-level factors that are correlated with wages, as well as other changing macroeconomic factors. We estimate the specifications separately for rural and urban areas. We also examine our results by constructing quintiles for each state across rural/urban areas separately to check the sensitivity of our results. However, our preferred specification includes constructing quintiles within a state for rural and urban areas together since the MW are fixed at state level and also because over time the characterization of rural-urban divide in the country has been a subject of much discussion (Chatterjee *et al.* , 2015). Standard errors are clustered at the state level. Additionally, we

[18] The national MW introduced by the Indian Central Government in 1996 (Belsar & Rani, 2011) was never legally binding. However, India recently introduced a national MW that 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 MW is not included in our analysis.

report the wild-bootstrapped p-values given the small number of clusters (19). The main coefficients of interest are β_3^q. If MW lead to a reduction in wage inequality, then workers in the lowest quintile should experience the largest increase in their wage growth – that is, $\beta_3^1 > \beta_3^2 > \beta_3^3 > \beta_3^4 > 0$. The effect of MW on the base quintile group of five is given by the coefficient β_1.

The main concern with the above identification strategy is that states could differentially increase MW due to endogenous reasons. For instance, states that experience high economic growth may witness a higher increase in MW. To examine whether state-level macroeconomic variables influence changes in MW by states, we regress log of MW in a given state and year on state-level macroeconomic indicators – these include state income (GSDP), the agricultural and service sectors' contributions to GSDP, demographics (population), inflation, socioeconomic characteristics (fertility rate, poverty rate, literacy rate), and infrastructure (invested capital by factories, length of roads). We control for state and year fixed effects in this specification, analogous to controlling for location (district) and year fixed effects in equation 1. The estimates in Appendix Table A.5 show that none of the macroeconomic variables are significantly correlated with the growth in MW within a state. Small values of the F test for the joint significance of the coefficients also confirm that state-level macroeconomic indicators do not influence the evolution of MW. These results rule out the possibility that other simultaneous state-level macroeconomic factors, coinciding with the change in MW, drive our results.

We undertake three further sets of analyses to address this concern. First, we conduct separate analyses for all and border districts (i.e. the districts that share a border with the neighboring states, 284 out of the total 444 districts in the overall analyses). Border districts across states are more similar to each other in terms of geographic and cultural factors that can affect economic growth.[19] Second, we check if increases in MW affect the highest wage quintile of workers (i.e. the coefficient β_1 in the above specification). If an increase in MW is

[19] As migration rates are low in India, 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 MW across the Indian states is uncorrelated with other economic factors, then the MW increases should have a null effect on these workers who are much higher in the wage distribution to be affected by them. However, it must be noted that this test will be violated if the MW changes have a lighthouse effect on wages of workers earning above the MW. Lastly, we control for state-year level fixed effects – while we cannot estimate β_1 in this case, we are able to examine whether coefficients for other quintiles remain stable.

Another concern could be inter-state migration rates. If individuals can freely migrate across states then we would obtain no differential effect on wages due to MW increases across states. The internal migration rate in India (as a percentage of population) increased from 30% in 2001 to 37% in 2011 (Census 2011). Notably, the major stream of migration is within the same district contributing 62% towards the internal migration rate. Inter-district migration within the same state accounts for 26% of total migration while inter-state migration is the least at 12%. Furthermore, work-related migration accounts for only 9% of total internal migration, suggesting that most internal migrants migrate for reasons other than work/employment (estimates based on the 2011 Census of India). Therefore, inter-state migration would not play a very important role in our estimates, and if any, only lead to a downward bias on the wage effects of MW changes.

5 Results

Table 3 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 a 1% increase in MW increases rural daily wages for the lowest wage 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 an increase in MW 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 a 1% increase in MW leads to a 0.22% increase in wages for the lowest wage quintile of workers (column 3), in comparison to the workers in the highest quintile. This effect falls to 0.16% and 0.07% for the third and fourth quintiles of wage workers, respectively. 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 MW of agricultural unskilled workers results in a higher increase in wages for workers in the lowest two wage quintiles, followed by the third and the fourth, with no impact seen on the fifth quintile. Notably, 88%, 45%, 12% workers in the first, second and third wage quintiles earn below the agriculture unskilled MW across all years. As discussed earlier, when agricultural MW increase, other non-agricultural occupation related MW also increase in India (Appendix Table A.2). Based on the limited availability of industry specific MW in Mansoor & O'Neill (2021), we find that 96%, 75%, 46%, 15%, 0% workers in the first-fifth wage quintiles, respectively, earn below the stipulated MW (for the missing industries we take the closest industrial match, hence, the proportions can actually be slightly larger for upper deciles where the data is more patchy). Thus, its not surprising that we see a large positive effect of MW increase on worker wages in the first two quintiles, which gradually falls in magnitude and is insignificant for the highest wage quintile (row 1) across all specifications. In fact, undertaking similar analyses by deciles (Appendix Figure A.3) shows similar results, with wage deciles up to seven showing a significantly positive increase in wages when MW increase. These results are in the expected direction since workers earning closest to the MW should be affected the most when the MW increase. Notably, the marginal effect of the rise in minimum daily wages is higher in urban areas than in rural areas for the lowest quintile of workers. Since the cutoff for wage quintiles is defined for all areas taken together, these results show that better enforcement in urban areas may be leading to greater compliance with rising MW.

We also estimate the impact of MW on wage inequality across formal and informal workers. Theoretically, postulations by Harris (1970) and Mazumdar (1989) show that a rise in MW increases the wages of workers in the 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 along with lower enforcement can exert downward pressure on the wages of informal workers. However, to the extent that informal workers are more likely to earn lower than MW, they could also witness a higher increase in wages. Alternatively, increase in wages in the formal sector due to a rise in MW can have a lighthouse effect – informal workers may bargain with their employers due to increased wages elsewhere or the MW can serve as a fair wage reference. To check whether there is a differential effect, we classify formal workers as workers with written job contracts, given that such contracts imply a greater likelihood of being employed in a firm that is subject to inspections.[20] We report the estimates for formal workers in panel A, and those for informal workers in panel B of Table 4. In rural India, the wages of the lowest quintile formal workers increase by 0.27% more than the highest quintile formal workers (column 1 of panel A) for every 1% increase in MW, while those of the lowest quintile informal workers increase by 0.24% more than the highest quintile informal workers (column 1 of panel B) when MW increase by 1%. Our findings demonstrate that MW reduce wage inequality for both formal and informal workers. The positive effects of MW changes are slightly higher for the lowest quintile formal workers. Our results remain consistent under alternative definitions of formal and informal workers (Appendix Table A.6). These results indicate that the MW acts as a benchmark for equitable compensation in the labor market, resulting in a rise in the wages of both informal and formal workers (Gindling & Terrell, 2005; Khamis, 2013).

[20]As shown in Appendix Figure A.4, informal workers consistently exhibit a higher proportion of individuals earning below the agricultural MW compared to formal workers (almost double in rural and triple in urban India). This pattern persists even when controlling for educational attainment. However, the proportion is likely to be higher for the formal workers once non-agriculture occupation specific MW are taken as a benchmark, since most formal sector workers work in the non-agriculture sector.

5.1 Robustness

We check the robustness of our findings to a number of specifications. First, we include district-specific and state-specific time trends and report the results in Appendix Table A.7 and A.8 respectively. We find that our previous results continue to hold in these stricter specifications as well. This rules out the possibility that effects of other economic factors that change at the district and state levels, and could also be correlated with changes in MW, drive our findings.[21] Second and more importantly, we include state-year fixed effects in our main specification to account for all time-varying changes at the state level, allowing us to isolate the influence of change in MW at the state-level on wage inequality.[22] The results, presented in Appendix Table A.10, show that the MW effects remain consistent on wages, unaffected by other policy changes at the state level. In fact, the magnitudes are similar for rural India, however, for urban areas the reduction in inequality is starker as the effect of increase in MW for quintiles 3 and 4 is now insignificant in column (4).[23]

Third, we exploit variation in MW changes over time across two districts that border each other but lie in different states.[24] This is akin to using differential change in MW within contiguous district pairs across state borders over time to estimate their effect on prevailing wages. There are 608 cross-state border district pairs in our data. Using these and incorporating fixed effects for each pair and year, the results reported in Appendix Table A.12 are almost similar in magnitude for urban areas. For rural areas, we find that the effects

[21]We also control for state-level macroeconomic factors in Appendix Table A.9 and find similar results.

[22]In this context, 'States' refer to the administrative boundaries as defined in each year (not parent states), accounting for any boundary changes over time. 'Year' corresponds to the calendar year (January-December) rather than the NSS year (July-June). The base category of the log of MW is omitted because state-year fixed effects absorb all variations across states and years, leaving no independent variation for a distinct reference category.

[23]We also check the results after including quarter-year fixed effects to rule out macroeconomic shocks at a higher frequency. This also controls for the seasonal effects on agricultural wages, predominant in the bottom quintile of the rural wage distribution. Again, our results continue to hold (Appendix Table A.11).

[24]Data has been restricted to border district pairs for neighboring states. Given that a district may share borders with more than one district in a neighboring state, border district data is accordingly augmented for each border pair by duplicating the individual data for each adjacent border district. This approach aligns with the methodology described in Dube (2019). Consequently, each observation incorporates numerous pair-time dummies, necessitating the inclusion of a vector for such pair-time fixed effects. Standard errors are clustered at the cross-state border segment.

are lower for all quintiles by a similar magnitude - this effects on wage inequality remain similar - but the absolute effect of change in MW on average wages is smaller.

Additionally, we check the robustness of our findings to alternative definitions of wages and wage quintiles. We use real wages and real MW, instead of nominal values for both and continue to find the largest increase in real wages due to a rise in real MW for the lower wage quintiles (Appendix Table A.13). We define the wage quintiles at state-year levels for rural and urban India separately. The findings in Appendix Table A.14 confirm that the effects of MW remain consistent, with urban workers experiencing larger impacts than rural workers. Specifically, a 1% increase in MW raises wages in the lowest quintile by 13% and 22% relative to the highest quintile workers in rural and urban sectors, respectively. This effect diminishes progressively across higher quintiles, consistent with the main specification. We prefer our baseline specification since MW at the state-level do not differentiate rural and urban areas.

We also use other measures, such as skill and education levels, to examine whether wages are affected differentially across low- vs high-skilled and less- vs more-educated workers. If the wage quintile results are robust, then we should find a larger effect of the rise in MW on low-skilled and less-educated workers. Table 5 reports the results by skill level. We find that an increase of 1% in MW results in an increase in wages for low-skilled workers of 0.19% and for medium-skilled workers of 0.13% (column 1), relative to high-skilled workers in rural areas. In this specification, the lower effects in urban vs. rural areas are due to low-skilled workers on average getting higher wages in urban vs. rural India (Table A.3). Since urban wages for low-skilled workers are higher than the existing agriculture MW levels on average, the effects are likely to be less pronounced for these workers. Our baseline specification that takes similar wage quintile cutoffs for rural and urban areas, does not suffer from this problem. Table 6 reports the results by education levels. Again, we find that the effect of MW is the largest for the least educated workers (up to primary education) in both rural and urban areas, with an elasticity of 0.17 and 0.08, respectively. The elasticity estimate falls to

0.11 for secondary educated workers in rural areas and is almost insignificant in urban areas. These findings continue to hold for specifications in columns (2) and (4), which include only border districts. Again, the elasticities are smaller in urban areas because workers having the same education level are likely to earn higher wages in urban India than in rural India.

Lastly, we check whether 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 higher wages lead employers to reduce days worked, especially for low-wage workers in flexible jobs[25], weekly earnings may not increase at lower quintiles. To check this, we estimate Equation 1 with the log of weekly earnings as the dependent variable. The results reported in Appendix Table A.15 show that the earnings increase by 24–27% for the two lowest earnings quintiles. The effect reduces to 10% for the fourth earnings quintile and is insignificant for the highest earnings quintile. Thus, our findings also lend support to a decline in earnings inequality due to a rise in MW in India during 1999–2018.

5.1.1 Alternative estimation: Staggered DID

The emerging literature on the DiD estimation when using a staggered implementation has emphasized the concern about negative weights associated with two-way fixed effects (Goodman-Bacon, 2021). It recommends estimating heterogeneous treatment effects on the outcome over time, taking into account the 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 by Roth *et al.* (2022). Our case is different since not only is the treatment variable 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 MW over time) with "stayers" (i.e. states that do not change their wages between two time periods.). Since

[25] Neumark *et al.* (2006) discuss how MW increases can lead to employment losses or reduced working hours, particularly affecting low-wage workers.

there are no states where the MW remained the same across two consecutive periods in our data, we create a quasi "stayer" state (as suggested in De Chaisemartin *et al.* (2019)) by assuming that a state is treated only when the MW increases by at least INR 50. The effect of MW treatment (T) on wage inequality (Y) with respect to switcher states (S) can then 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 panel data at the 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 90th and the 10th percentile, the 90th and the 50th percentile, and the 50th and the 10th percentile of the wage distribution. The treatment variable is the log of real minimum administrative wages.

The results are reported in Appendix Figure A.5 for rural (panel A) and urban India (panel B). The x-axis displays the periods (t), with $t = -1$ representing the period preceding the MW change (baseline), and $t = 0$ indicating the period where MW changed for the first time. We refer to the districts that experienced their first MW change as "first-time switchers" ($S = 321$ out of 438 districts in rural India, $S = 316$ out of 439 districts in urban India). When MW 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 India, $S = 314$ in urban India). Similarly, when MW 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).[26]

Based on our previous analyses, we expect that a rise in MW will lead to a decline

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

in wage inequality during post-treatment periods. Appendix Figure A.5 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 effects during the post-treatment period (combining the effects for $t = 0, 1, 2$) are reported in Appendix Table A.16. 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 MW leads to a decrease in wage inequality across all inequality measures for urban India and between the 90th and the 50th percentile, and between the 50th and the 10th percentile of the wage distribution in rural India, but the effects are imprecise.

The estimates in the table show a significant decline in wage inequality by 0.13% between the 50th and 10th percentiles of the wage distribution in rural India (panel A, row 3) and by 0.28% between the 90th and 10th percentiles of the wage distribution in urban India (panel B, row 2) when MW increase by 1% (panel A).

Appendix Figure A.5 also shows the estimated pre-trends.[27] Here, $t = -2$ compares wage inequality between first-time switcher states and not-yet switcher states before the first-time switcher transitions 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 transitions for the second time. Thus, these show the difference in wage inequality between initial switchers and non-switchers prior to any treatment change (De Chaisemartin *et al.* , 2023).[28]

These 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)

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

[28]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 $t-1$.

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 intervals of years.[29] Also, our context lacks natural stayers, since all states undergo MW changes in some time period. This implies that there are no natural control groups available to analyze the impact of the MW policy using never-treated states.

5.1.2 Alternative estimation: Using effective MW

MW in India are set at the state level, leading to heterogeneity in wage floors across regions. In contrast, studies in other countries often analyze a national minimum wage, where its binding effect varies depending on the state's wage distribution. Lee (1999) introduce the concept of effective minimum wage to account for cross-state variations in the federal minimum wage's bindingness, some states experience stronger or weaker effects of minimum wages depending on their local wage distribution. Although India's minimum wages already exhibit state-level heterogeneity, we still define an effective minimum wage to assess how binding the wage floor is relative to living standards in each state. The effective minimum wage is the difference between the legislative minimum wage and a wage level that remains unaffected by changes in the minimum wage, that is, a level where minimum wages are non-binding. In the U.S., Lee (1999) and Autor *et al.* (2016) find that median and higher earnings remain unaffected by minimum wage policies, a similar pattern is observed in China by Lin & Yun (2016). However, in Mexico, Bosch & Manacorda (2010) find that wage spillovers extend beyond the median, reaching up to the 60th percentile, making the 70th percentile of the wage distribution a more appropriate reference point.

For India, we use the average wage of high-skilled workers in each state and sector as the non-binding wage reference. This is an ideal proxy as we know from our previous analyses

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

that the changes in MW do not affect the wages of high-skilled workers (Table 5). To do this, for each state–year we define the effective MW as the deviation of the MW from the average wage of the high-skilled workers for that year.[30] We then estimate the below specification:

$$\begin{aligned}(\ln(W^p_{st}) - \ln(W^{HW}_{st})) &= \beta^p_0 + \beta^p_1(\ln(MW_{st}) - \ln(W^{HW}_{st})) \\ &+\beta^p_2(\ln(MW_{st}) - \ln(W^{HW}_{st}))^2 + T_t + S_s + S_s * t + \epsilon^p_{st}\end{aligned} \tag{2}$$

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

$$\frac{\partial \ln(W^p_{st}) - \ln(W^{HW}_{st})}{\partial \ln(MW_{st}) - \ln(W^{HW}_{st})} = \beta^p_1 + 2 \times \beta^p_2 \times \overline{\ln(MW_{st}) - \ln(W^{HW}_{st})} \tag{3}$$

We estimate the above specification using 2SLS, since Autor *et al.* (2016) observed that the OLS estimates of the above equation could lead to upward bias due to any measurement error or transitory shock in the selected non-binding wage (that is average wages of high skilled workers in our case), which correlates with the dependent variable that is wage gap between different percentiles of the wage distribution and the average wage for high-skilled workers. To address this, Autor *et al.* (2016) suggested instrumenting the effective minimum wage and its square using the log MW, its square, and their interaction with the average log wage of high-skilled workers at the state and sector levels.

We plot the marginal effects of MW at different percentiles using 2SLS in Figure 5. Clearly, the effect of effective MW declines at higher percentiles, especially in urban areas. There is a high spillover effect of MW in rural areas as the point estimates are statistically significant up to the 80th percentile in rural areas and only up to the 60th percentile in urban areas. The estimates show that a 10 percentage point rise in effective MW leads to a 3.3

[30] For robustness, we also use the 85th percentile as an alternative reference point.

percentage point (0.33×10) increase in rural wages and a 5.8 percentage point (0.58×10) increase in urban wages at the 10th percentile. The results are robust when only border districts are included in our analyses (Appendix Figure A.6).

Since the spillover effect of effective MW defined using the wages for high-skilled workers is up to the 80th percentile, we also estimate a specification in which average wages of the high-skilled workers are replaced by the wages at the 85th percentile in Equation 2. The coefficients plotted in Appendix Figure A.7 also show that the effective MW have a higher impact on lower percentiles, and this effect diminishes as we move up the wage distribution.

6 Discussion

6.1 Alternative Mechanisms

The results in Section 5.1 show that the impacts of MW on wages of high-skilled workers or those with graduate or higher education is insignificant. We further test for this using the sub-sample of highly skilled workers (panel A, Appendix Table A.17) and highly educated workers (panel B, Appendix Table A.17). We continue to find that these sub-samples of workers are not affected by a rise in MW. This allays any concern that the effects of MW are being driven by other unobserved factors changing at the overall state level that are also correlated with rising state MW. However, to the extent that states which increase MW also implement other pro-poor programs well, enforce MW better or have increased unionization which demand higher wages, this test would be violated. We examine these alternative mechanisms below.

6.1.1 NREGA

For instance, one such major scheme was NREGA, implemented in 2006 and show to have increased wages of low-skilled workers, could also contribute to a rise in wages at lower quintiles. Under NREGA, workers are entitled to receive 100 days of employment in a 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 in rural areas 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 informal sector employers to pay the MW, thus generating greater compliance with MW legislation during this period. We account for the implementation of NREGA in our analyses in three ways. First, since NREGA had been implemented in all districts by 2008,[31] the analysis is limited to the years 1999, 2004, and 2007–2008 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 the population working in NREGA in a given district. This is estimated using employment data since the data also captures days worked under public work schemes.

The results are presented in Table 7 for all districts in rural India. The wages increase for lower wage quintiles due to the increase in MW, despite controlling for various measures of NREGA across columns. Thus, the effect of MW on wage inequality obtained in the main results is not driven by NREGA. The significantly positive effect of MW on lower wage quintiles is robust when only border districts are considered while controlling for NREGA (Appendix Table A.18). We also control for other programs that include roads, health, and electricity; results remain unchanged[32]. In a next section we also consider the role of

[31] There is an overlap between the April–June period of the NSS 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 utilize those districts as non-NREGA districts.

[32] Results omitted for brevity

changing enforcement over time.

6.1.2 Enforcement

Stronger enforcement may enhance compliance by ensuring that enterprises adhere to MW laws. This could affect wages for low-wage workers who are likely to be farther from MW thresholds but it can also affect wages in the upper distribution if the formal sector workers (whose enterprises are more likely to be inspected) are more likely to gain in terms of wage increase. If this varies systematically with states that increase MW also increase enforcement, then our results could be driven by the latter. However, the estimated correlation is -0.26 and statistically insignificant.[33]

To check this, we use the enforcement intensity measured as the number of labor inspections per worker at the state level from the Labour Bureau.[34] In general, enforcement in India tends to be relatively weak due to structural factors. States exhibit heterogeneous inspection practices, with inspections administered by different government departments (NCEUS, 2007). Moreover, we observe a decline in the number of labor inspections per million workers in recent years (Appendix Figure A.8).

We first control for enforcement in Appendix Table A.19 and find that our baseline results remain very similar. Thus, changing enforcement over time across states cannot explain our main findings. Further, in Appendix Table A.20 we report whether there is any differential impact of MW on individual wages as enforcement increases. As expected, the interaction between enforcement and MW shows a positive coefficient. Notably, the effect of overall MW become noisy now indicating that with no enforcement the effect of MW on workers wages is not significantly different from zero. Thus, some enforcement combined with MW increase contributes to an overall increase in wages. Lastly, Appendix Table A.21 reports the differential effects of enforcement across wage quintiles. We continue to find a stronger

[33]We regress log of MW on log inspections, controlling for state and year fixed effects.

[34]This measure is the most frequently used in the literature (Soundararajan, 2019; Mansoor & O'Neill, 2021).

effect of MW on individual wages when enforcement is higher (coefficient of log MW $\times$ log Enforcement is positive). In rural areas, the effect of enforcement is the strongest in upper wage quintiles four and five (columns 1 and 2). In urban India, the enforcement of MW regulations has a similar impact across the wage distribution.

6.1.3 Unionization

Another alternative mechanism that could affect wage inequality is increasing labor unionization. Unfortunately, we do not have a measure of union membership in the employment data to test this directly, but evidence shows that union memberships globally, as well as within India, have been declining over the last few decades.[35] Thus, while being a part of a union is likely to increase the effect of MW, our results will only be affected if union membership is more prevalent in the lowest wage quintiles or if states that increase MW more intensely are also likely to see an increase in union membership. Given the high level of informality in India, dominating in the lower wage quintiles, the former is unlikely to hold. Further, given our results hold even after controlling for state-year fixed effects, the latter is unlikely to drive our results.

6.2 Counterfactual Wage Distribution

We also investigate the degree to which the decline in wage inequality between 1999 and 2018 can be explained by the increase in MW. To do this, we conduct a reduced-form counterfactual analysis to estimate the counterfactual wage inequality in 2018 had there been no change in MW 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 MW 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

[35] See: Business Line and Politico.

below estimated value for each individual, using 1999 MW as a base:

$$\Delta \log w_{is,2018} = \hat{\beta}_2^q \times (\log MW_{s,1999} - \log MW_{s,2018}) + \hat{\beta}_1 \times (\log MW_{s,1999} - \log MW_{s,2018}) \tag{4}$$

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

The resulting actual and counterfactual log wage distributions are depicted in Appendix Figure A.9. The differences between the actual and counterfactual wage distributions at various quintiles are displayed in Figure 6. Due to the increase in MW between 1999 and 2018, the lowest quintile wage earners have experienced a 38.52% increase in wages in rural India and a 48.39% increase in wages in urban India. As we move up the quintiles, we observe a smaller impact on wages, with the top quintile workers experiencing almost no change if the MW had remained constant at 1999 levels.

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 MW. Similar calculations for all of India show that around 26% of the decline in wage inequality during 1999–2018 can be explained by the increase in MW.[36]

6.3 Effect of MW on Employment

To complete our analyses, we finally estimate the effect of MW on employment during our analyses period – a question of interest in most studies in this literature. The dependent

[36] All-India Gini in 1999: 0.11265; all-India Gini in 2018: 0.0634; all-India counterfactual Gini in 2018 (with 1999 MW): 0.0765 – refer to Appendix Table A.1 for actual Gini values.

variable in Equation 1 is the proportion of days in the last week that an individual reports to be employed (zero if the individual is not employed). We undertake the analysis 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 and report the results in Table 8. For daily wage, and salaried workers, the results show that a rise in MW has no effect on all workers across the education spectrum in both rural and urban India. There is a slight positive effect of MW on employment of the medium educated workers in rural areas, but the magnitude of the effect is too small and only marginally significant at 10% levels. Thus, in line with earlier studies on India, we find negligible impact on employment due to an increase in MW (Soundararajan, 2019; Menon & Rodgers, 2017).

The null employment effects can potentially be explained by three factors – monopsony power in Indian labor markets, employers passing MW increases to prices, and lastly when MW changes are not large enough to have employment effects (or the own wage elasticity is relatively small). Muralidharan *et al.* (2023) find that employers exhibit monopsony power in rural India. While we do not have estimates for demand elasticity for overall rural and urban labor markets, Mahajan & Ramaswami (2017) find a substantive own wage elasticity between -0.5 to -0.3 in agricultural labor markets of India. We were unable to find any study evaluating the effect of MW changes on product prices though. Thus, monopsony power could explain small employment effects of MW increases in the Indian labor market.

7 Conclusion

Wage inequality has declined by as much as 35% during 1999–2018 in India. In the same period, the median real MW increased by 70%. Our paper examines the role of rising MW in reducing wage inequality in India in the last two decades. Since MW in India are set at the state level, we exploit the across-state and over-time variation in the MW changes to examine the role of MW in explaining the documented decrease in wage inequality in India.

We find that rising MW in India have contributed significantly toward reducing inequality in wages, explaining almost 26% of the decline in wage inequality. This is due to the large positive impact of rising MW on the lowest wage quintile workers, even in sectors where enforcement is difficult. In addition, we find that the least skilled and those with the lowest education levels benefit the most from the increase in MW. At the same time, there are no accompanying negative effects on employment. These results show that changing MW could be an effective policy tool to reduce wage inequality without significantly reducing employment in developing-country contexts where there is a large informal labor market.

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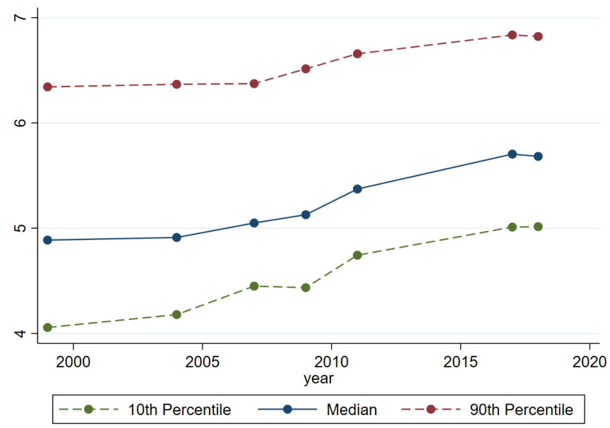
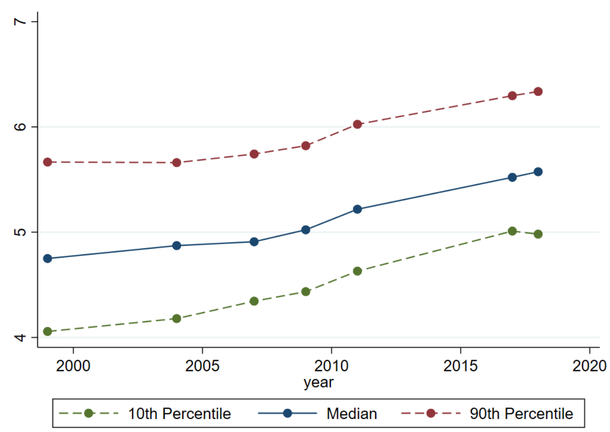
Figure 1: Distribution of Log Real Daily Wages, 1999–2018

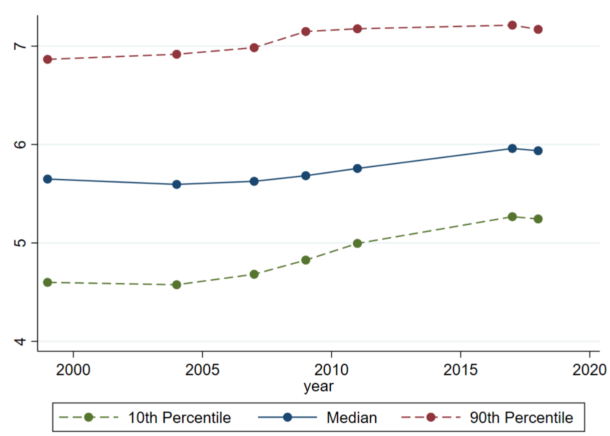
Panel A: All



Panel B: Rural Area



Panel C: Urban Area

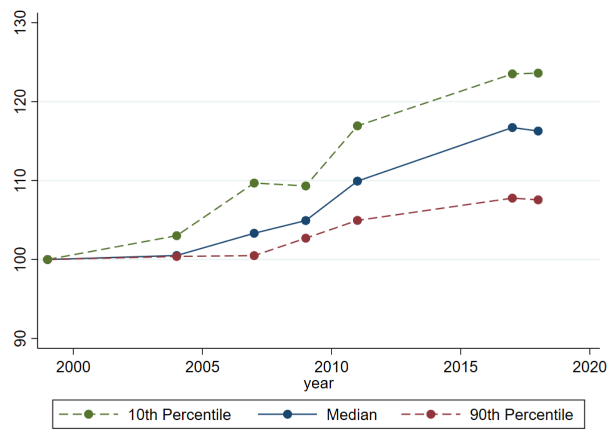


Notes: Real wages are obtained by deflating nominal wages using the CPI-IW and the CPI-AL in urban and rural areas, respectively.

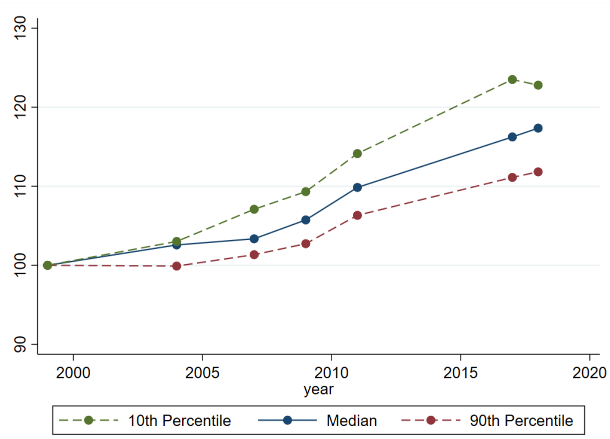
Source: Authors' wage calculations based on Employment–Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017 and 2018.

Figure 2: Log of Real Daily Wages, 1999–2018 (Indexed 1999 = 100)

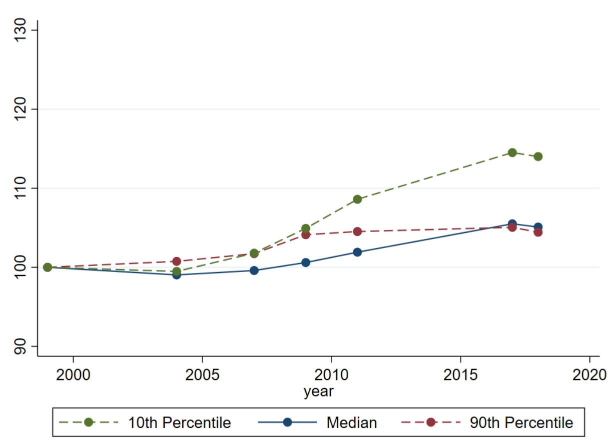
Panel A: All



Panel B: Rural Area



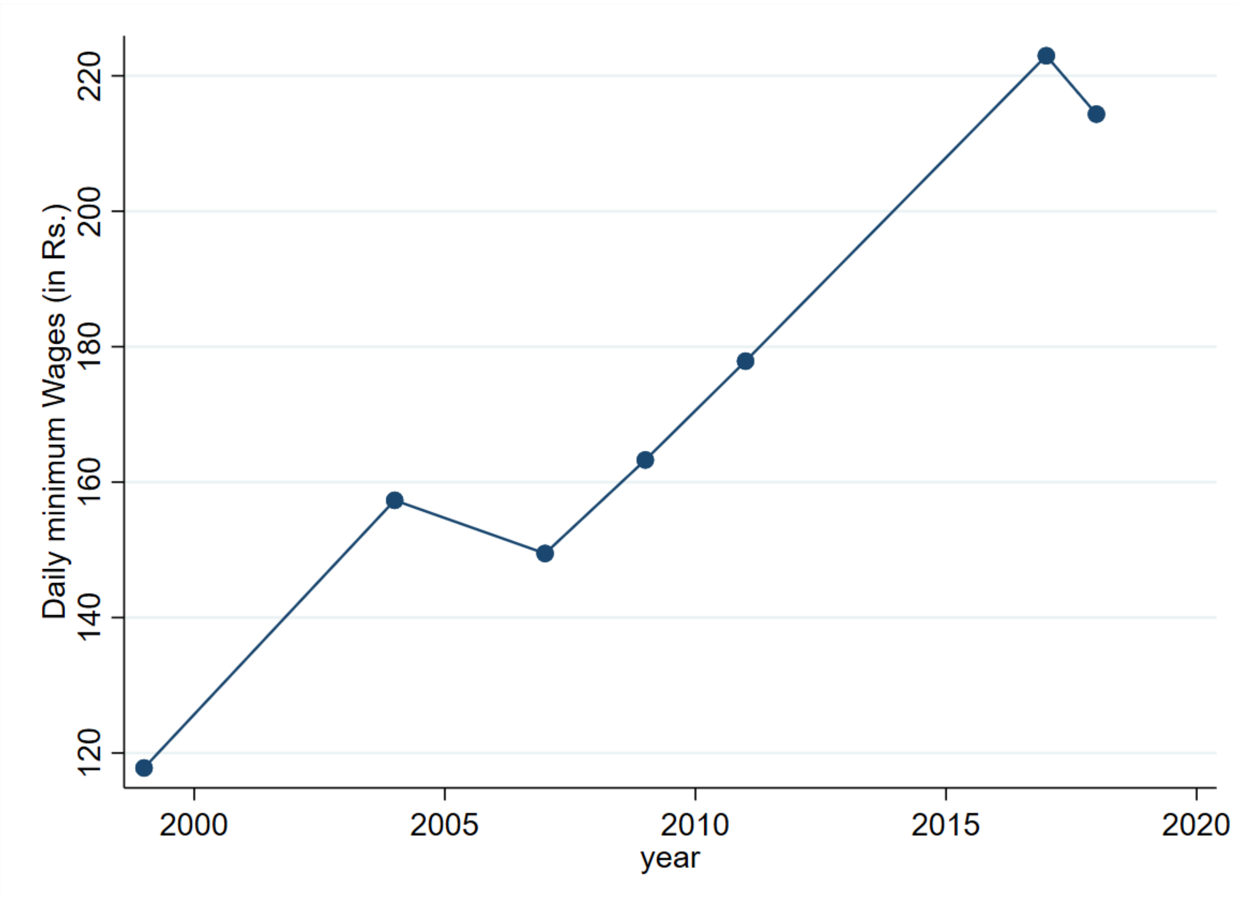
Panel C: Urban Area



Notes: Log of average real daily wages for each percentile group is indexed at 100 in 1999. Real wages are obtained by deflating nominal wages using the CPI-IW and the CPI-AL in urban and rural areas, respectively.

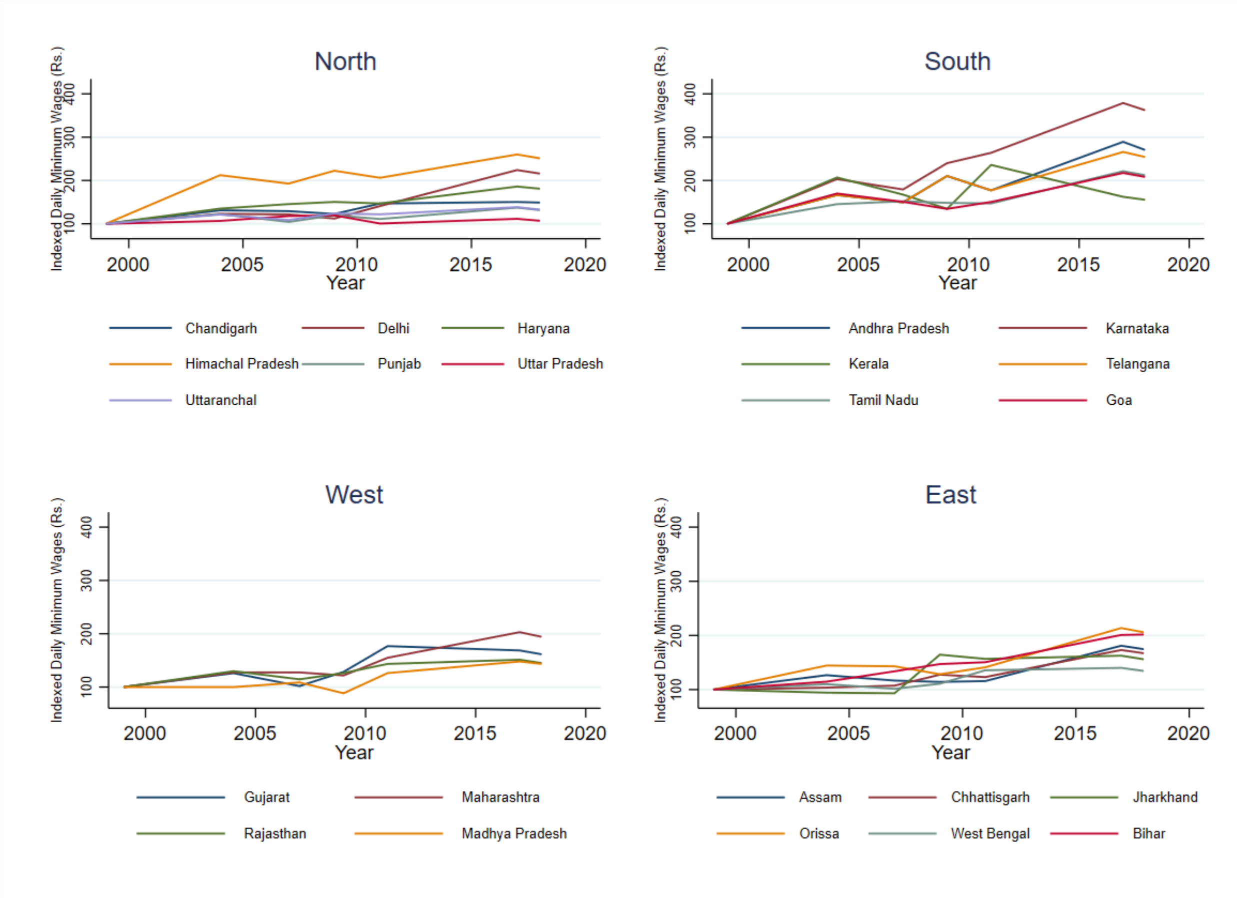
Source: Authors' wage calculations based on Employment–Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017 and 2018.

Figure 3: Average Daily Administrative Real Minimum Wages, 1999–2018



Notes: Average daily administrative real MW for the agricultural sector is utilized. These are obtained by deflating the nominal minimum agricultural wages using the average of the CPI-IW and CPI-AL.
Source: Authors' calculations based on Labour Bureau data.

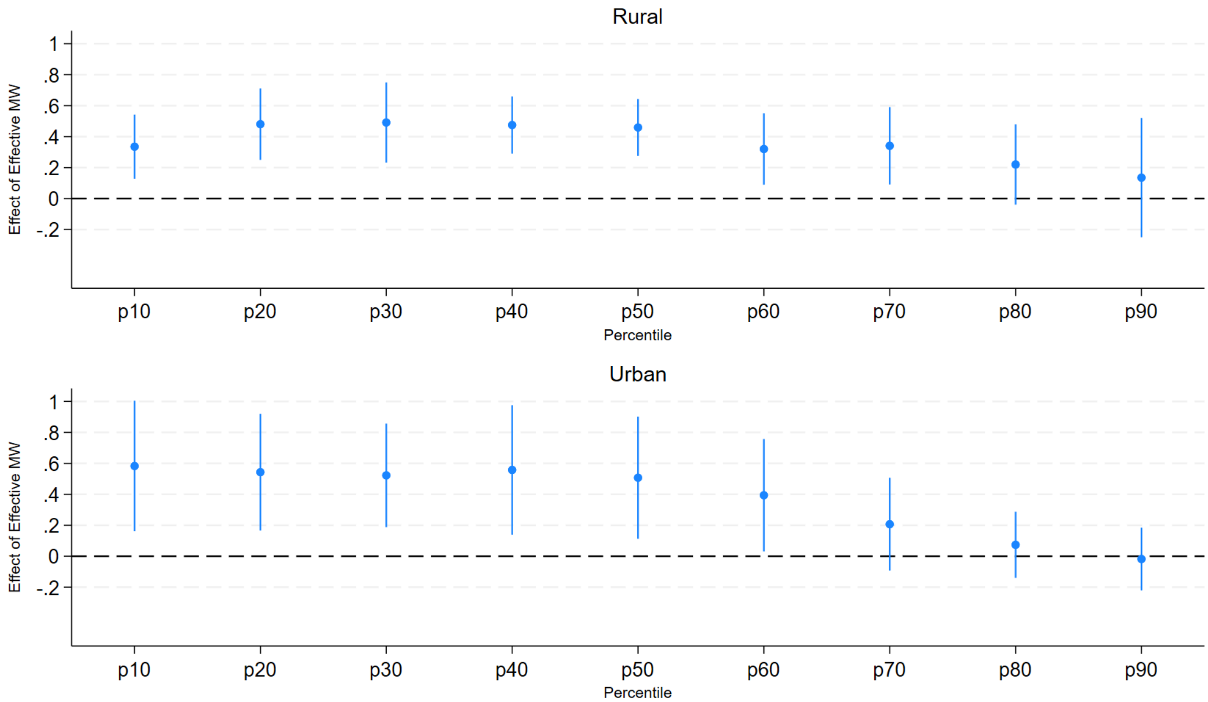
Figure 4: Indexed Daily Administrative Real Minimum Wages (1999–2018)



Notes: Daily administrative real MW for the agricultural sector in each state are indexed at 100 in 1999. These are obtained by deflating the nominal minimum agricultural wages using the average of the CPI-IW and CPI-AL.

Source: Authors' calculations based on Labour Bureau data for agricultural MW.

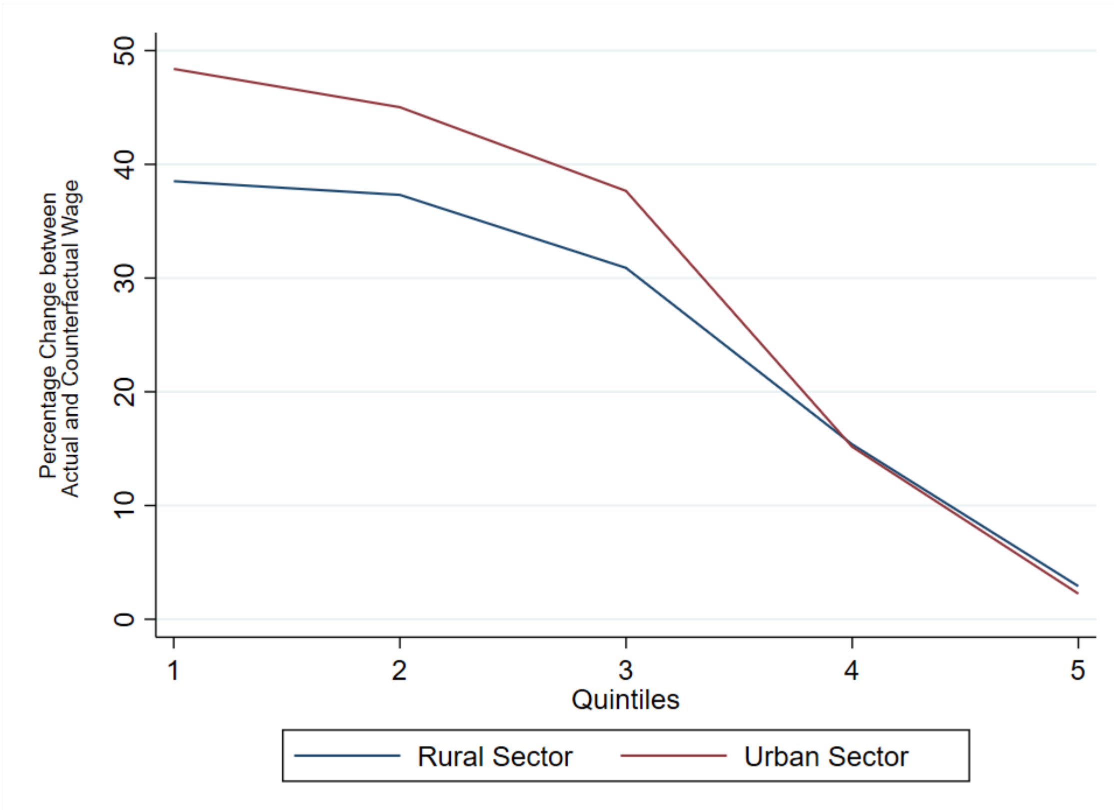
Figure 5: Marginal Effects of Effective Minimum Wages on Wage Percentiles by Sector



Notes: MW refers to administrative MW. The estimation method is 2SLS, where the effective minimum wage (log(MW) − log(Average wages of high-skilled workers)) and its square are instrumented using the log(MW), the square of the log(MW), and the log(MW) interacted with the log(Average wages of high-skilled workers) at the state and sector levels. The x-axis shows the distance of a specific percentile (p) of wage distribution from the average wages of high-skilled workers. The y-axis represents the marginal effects of effective minimum wage and its square on log(p) − log(Average wages of high-skilled workers) across states and years. Observations are at the state–year level. Regressions are controlled for year fixed effects, state fixed effects and state trends. Standard errors are clustered at the state level. 95% confidence interval is represented by spikes.

Source: Authors' calculations based on Employment–Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017 and 2018. MW data are from the Labour Bureau.

Figure 6: 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 MW levels as a basis.

Source: Authors' calculations based on Employment–Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017 and 2018. MW data are from the Labour Bureau.

Table 1: Trends in 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

Notes: Each row represents measures of real wage inequality measured via percentile log differences, Variance, and Gini of the log of real wage distribution. Real wages are obtained by deflating nominal wages using the Consumer Price Index for Industrial Workers (CPI-IW) and the Consumer Price Index for Agricultural Laborers (CPI-AL) in urban and rural areas, respectively.
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018.

Table 2: Summary Statistics: Average Real Wage Distribution

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
Administrative Minimum Wages	166.719	168.256	180.276	190.328
	(46.92)	(48.89)	(68.52)	(79.23)
Wages of All workers	228.532	230.806	538.359	541.198
	(233.4)	(239.4)	(760.0)	(608.3)
Wages of Low-Skilled workers	166.779	166.628	264.172	267.483
	(102.5)	(105.4)	(286.4)	(330.9)
Wages of Medium-Skilled workers	307.468	314.405	425.572	433.469
	(244.3)	(248.9)	(358.5)	(359.7)
Wages of High-Skilled workers	615.405	626.804	1066.570	1058.448
	(544.8)	(558.7)	(1311.6)	(900.6)
Wages of Low-Educated workers	166.867	167.363	255.150	260.801
	(106.1)	(111.5)	(181.1)	(186.9)
Wages of Medium-Educated workers	273.490	277.016	422.400	428.944
	(235.8)	(240.4)	(389.8)	(421.1)
Wages of High-Educated workers	637.357	648.212	1011.010	1002.782
	(517.8)	(528.8)	(1201.2)	(829.3)
Wage of Workers in 1st Quintile	109.003	107.600	129.057	137.097
	(46.66)	(46.62)	(63.43)	(68.29)
Wage of Workers in 2nd Quintile	168.057	167.922	207.842	216.889
	(63.59)	(65.21)	(81.74)	(87.65)
Wage of Workers in 3rd Quintile	226.720	224.880	268.839	278.567
	(83.81)	(88.12)	(104.5)	(113.6)
Wage of Workers in 4th Quintile	335.345	328.613	386.090	392.488
	(131.7)	(137.4)	(157.7)	(176.9)
Wage of Workers in 5th Quintile	889.914	867.982	1133.444	1111.254
	(480.0)	(492.7)	(1148.0)	(805.4)
Observations	250111	170601	203648	126154

Notes: Average real wages by different worker categories are provided in the table with their standard deviation in parentheses. Real wages are obtained by deflating nominal wages using the Consumer Price Index for Industrial Workers (CPI-IW) and the Consumer Price Index for Agricultural Laborers (CPI-AL) in urban and rural areas, respectively. Administrative real minimum wages are obtained by deflating the nominal minimum agricultural wages using the average of CPI-IW and CPI-AL. 'Low-skilled workers' include workers in elementary occupations such as laborers, skilled agricultural, and construction workers. 'Medium-skilled workers' refer to those in clerical, administrative support, sales, and production roles. 'High-skilled workers' are those in professional, technical, and managerial positions. 'Low educated' denote workers with at most primary education, 'medium educated' indicate workers have more than primary but at most secondary education (class 10), and 'high educated' refers to those with more than secondary education. The wage distribution is segmented into quintiles, where the 'first quintile' represents the lowest 20% of wage earners and the 'fifth quintile' represents the top 20% of earners, all within each state and year.
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

Table 3: 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 (Wage Quintile=1 × log MW)	0.000	0.000	0.000	0.000
WB (Wage Quintile=2 × log MW)	0.000	0.001	0.001	0.001
WB (Wage Quintile=3 × log MW)	0.000	0.002	0.001	0.002
WB (Wage Quintile=4 × log MW)	0.010	0.010	0.000	0.002
R-Squared	0.95	0.95	0.92	0.92
Observations	249976	170515	203543	126073

Notes: The dependent variable is log of nominal daily wages. MW refers to nominal administrative minimum wages. Wage Quintiles, ranging from 1 to 5, sequentially represent 20% segments of wage earners, with the first being the lowest and the fifth, the base category, including the top 20%, all within each state and year. Controls include education, age-group, marital status, social group, religion, industry categories, district fixed effects, and year fixed effects. Standard errors in parentheses are clustered at state level. Due to the low number of clusters (19), wild-bootstrapped p-values (WB) are shown in the table. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

Table 4: 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
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
Observations	135979	93227	103299	65344

Notes: The dependent variable is log of nominal daily wages. MW refers to nominal administrative minimum wages. Wage Quintiles, ranging from 1 to 5, sequentially represent 20% segments of wage earners, with the first being the lowest and the fifth, the base category, including the top 20%, all within each state and year. Controls include education, age-group, marital status, social group, religion, industry categories, district fixed effects, and year fixed effects. Formal workers (results presented in Panel A) are defined as those employed under written job contracts. Informal workers (results presented in Panel B) refer to those workers who do not have a written contract. Standard errors in parentheses are clustered at state level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 2004, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

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

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	0.010	0.002	0.034	0.031
	(0.05)	(0.05)	(0.05)	(0.04)
Low Skill=1	-1.219***	-1.213***	-1.054***	-1.057***
	(0.17)	(0.19)	(0.13)	(0.16)
Low Skill=1 × log MW	0.193***	0.189***	0.121***	0.118***
	(0.03)	(0.04)	(0.02)	(0.03)
Med Skill=1	-0.794***	-0.841***	-0.614***	-0.603***
	(0.12)	(0.12)	(0.10)	(0.13)
Med Skill=1 × log MW	0.127***	0.135***	0.060***	0.056**
	(0.02)	(0.02)	(0.02)	(0.03)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
WB (Low Skill=1 × log MW)	0.000	0.000	0.001	0.003
WB (Med Skill=1 × log MW)	0.000	0.000	0.022	0.075
R-Squared	0.78	0.79	0.71	0.72
Observations	249976	170515	203543	126073

Notes: The dependent variable is log of nominal daily wages. MW refers to nominal administrative minimum wages. 'Low Skill' workers refer to workers in elementary occupations such as laborers, skilled agricultural, and construction workers. 'Medium Skill' workers refer to those in clerical, administrative support, sales, and production roles. Controls include education, age-group, marital status, social group, religion, industry categories, district fixed effects, and year fixed effects. Standard errors in parentheses are clustered at state level. Wild-bootstrapped p-values (WB) related to the coefficients mentioned in brackets (differential impact of minimum wages on low and medium skilled workers) for each of the columns are shown in table rows. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

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

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	0.040	0.035	0.060	0.053
	(0.05)	(0.05)	(0.04)	(0.04)
Low Edu=1	-1.471***	-1.429***	-1.435***	-1.412***
	(0.18)	(0.20)	(0.09)	(0.10)
Low Edu=1 × log MW	0.173***	0.162***	0.083***	0.082***
	(0.04)	(0.04)	(0.02)	(0.02)
Med Edu=1	-1.053***	-1.014***	-0.858***	-0.866***
	(0.18)	(0.19)	(0.08)	(0.09)
Med Edu=1 × log MW	0.112***	0.103**	0.027	0.032*
	(0.03)	(0.04)	(0.02)	(0.02)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
WB (Low Edu=1 × log MW)	0.001	0.003	0.002	0.006
WB (Med Edu=1 × log MW)	0.009	0.021	0.185	0.140
R-Squared	0.78	0.78	0.69	0.69
Observations	250041	170556	203588	126108

Notes: The dependent variable is log of nominal daily wages. MW refers to nominal administrative minimum wages. 'Low Edu' denote workers with at most primary education and 'Medium Edu' indicate workers have more than primary but at most secondary education (class 10). Controls include age-group, marital status, social group, religion, industry categories, district fixed effects and year fixed effects. Standard errors in parentheses are clustered at state level. Wild-bootstrapped p-values (WB) related to the coefficients mentioned in brackets (differential impact of minimum wages on low and medium educated workers) for each of the columns are shown in table rows. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

Table 7: Effect of Minimum Wages on Wages at Different Wage Quintiles (After Controlling for NREGA, 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 (Wage Quintile=1 × log MW)	0.000	0.000	0.000
WB (Wage Quintile=2 × log MW)	0.000	0.000	0.000
WB (Wage Quintile=3 × log MW)	0.005	0.000	0.000
WB (Wage Quintile=4 × log MW)	0.066	0.010	0.010
R-Squared	0.90	0.95	0.95
Observations	132007	249976	249976

Notes: The dependent variable is log of nominal daily wages. MW refers to nominal administrative minimum wages. Wage Quintiles, ranging from 1 to 5, sequentially represent 20% segments of wage earners, with the first being the lowest and the fifth, the base category, including the top 20%, all within each state and year. Controls include education, age-group, marital status, social group, religion, industry categories, NREGA, district fixed effects and year fixed effects. In column 1, NREGA is controlled as a dummy varaible which takes value 1 for Phase 1 and Phase 2 districts where NREGA was implemented in the year 2007. Only data from years 1999, 2004 and 2007 have been utilised for the analysis in column 1. 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. The estimates presented are for rural India only, in line with the implementation scope of the NREGA policy. Standard errors in parentheses are clustered at state level. Wild-bootstrapped p-values (WB) related to the coefficients mentioned in brackets (differential impact of minimum wages by quintiles of wages) for each of the columns are shown in table rows. ***, **, * show significance at 1%, 5% and 10%, respectively.

Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

Table 8: Effect of Minimum Wages on Employment (Wage Work) by Education Level

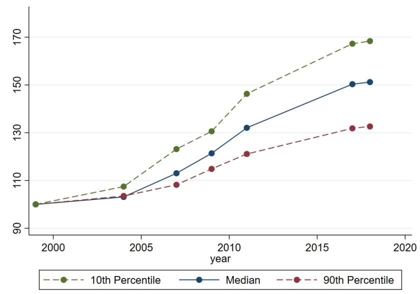
	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	-0.026	-0.028	0.003	-0.002
	(0.02)	(0.02)	(0.01)	(0.01)
Low Edu=1	0.070	0.046	-0.064*	-0.090**
	(0.06)	(0.06)	(0.03)	(0.04)
Low Edu=1 × log MW	-0.021	-0.016	-0.003	0.001
	(0.01)	(0.01)	(0.01)	(0.01)
Med Edu=1	-0.164***	-0.197***	-0.088**	-0.128***
	(0.04)	(0.05)	(0.03)	(0.03)
Med Edu=1 × log MW	0.013	0.019*	-0.008	-0.001
	(0.01)	(0.01)	(0.01)	(0.01)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
WB (Low Edu=1 × log MW)	0.141	0.255	0.639	0.893
WB (Med Edu=1 × log MW)	0.179	0.082	0.225	0.894
R-Squared	0.15	0.14	0.21	0.21
Observations	1130630	741754	749456	459256

Notes: The dependent variable is the proportion of days per week spent in casual workers or salaried work. MW refers to nominal administrative minimum wages. 'Low Edu' denote workers with at most primary education and 'Medium Edu' indicate workers have more than primary but at most secondary education (class 10). Controls include age-group, marital status, social group, religion, industry categories, district fixed effects and year fixed effects. Standard errors in parentheses are clustered at state level. Wild-bootstrapped p-values (WB) related to the coefficients mentioned in brackets (differential impact of minimum wages on low and medium educated workers) for each of the columns are shown in table rows. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

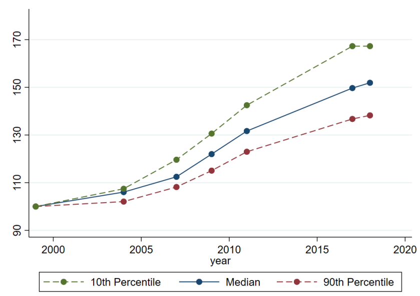
A Appendix

Figure A.1: Log of Nominal Daily Wages, 1999–2018 (Indexed 1999 = 100)

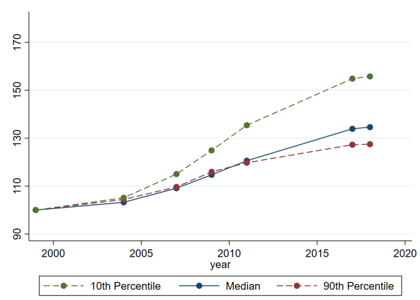
Panel A: All India



Panel B: Rural India



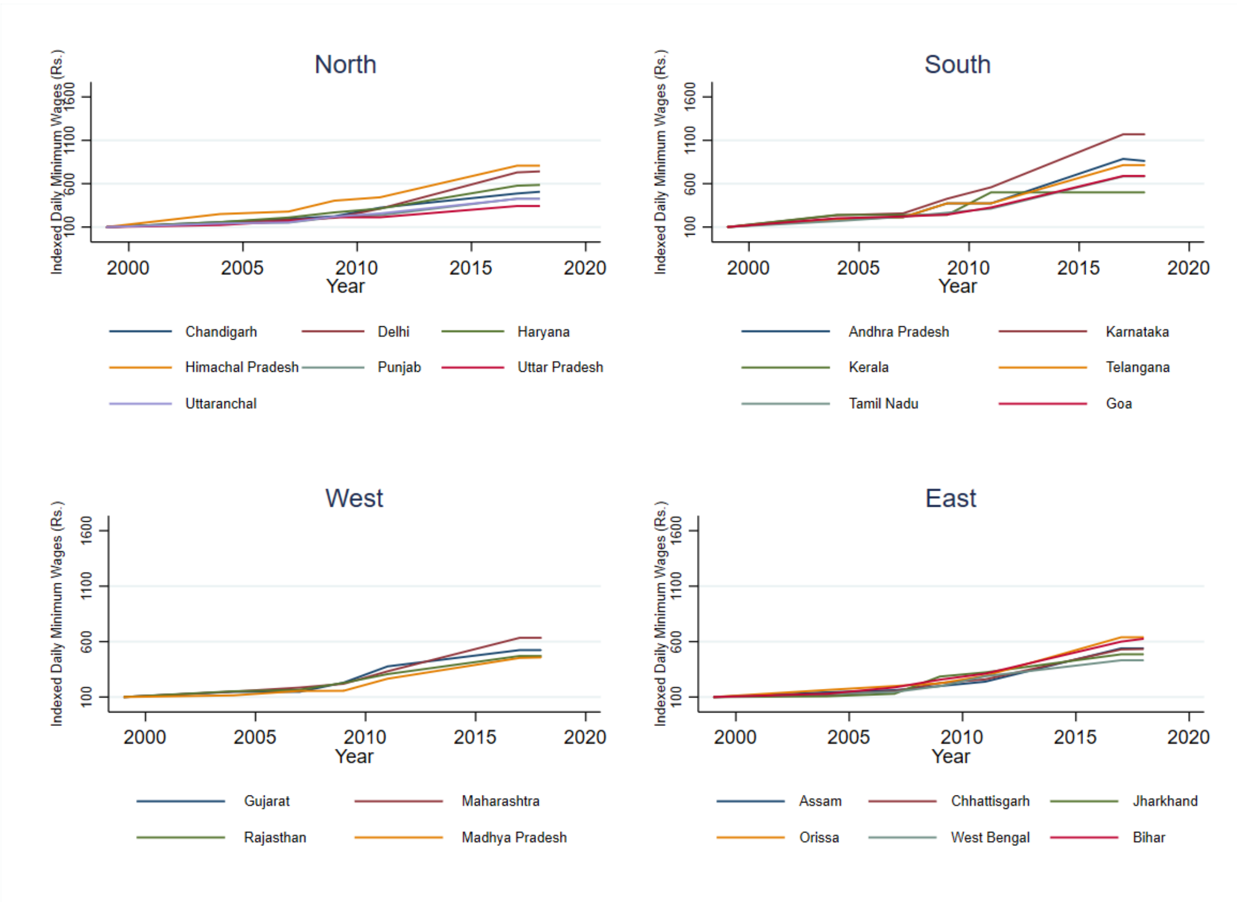
Panel C: Urban India



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

Source: Employment–Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017 and 2018.

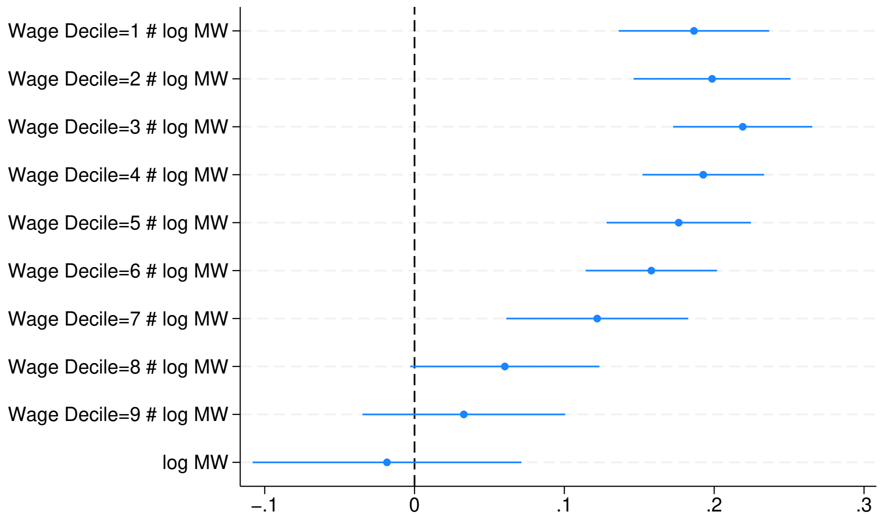
Figure A.2: Administrative Nominal Daily Minimum Wages in Agriculture, 1999–2018 (Indexed 1999 = 100)



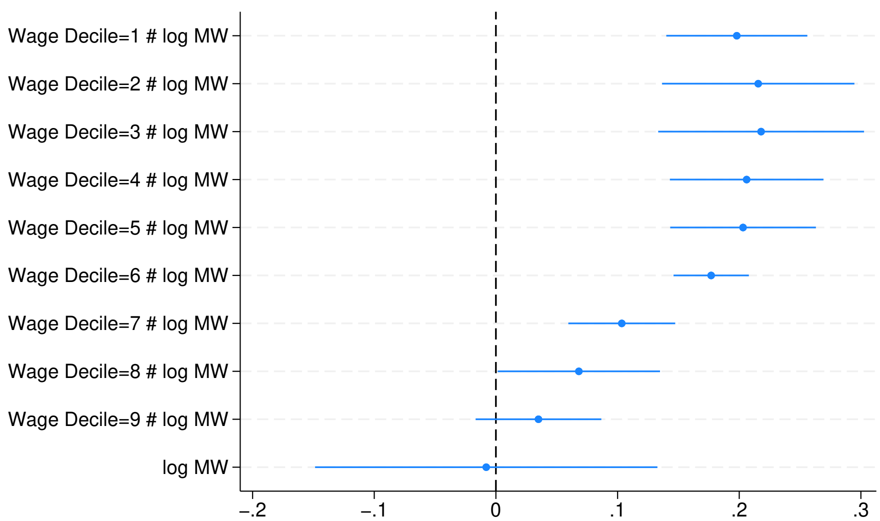
Notes: The administrative nominal daily MW for the agricultural sector for 1999 is indexed to 100 for each state.
Source: Labour Bureau.

Figure A.3: Effect of MW on Wages at Different Wage Deciles

Panel A: Rural India



Panel B: Urban India

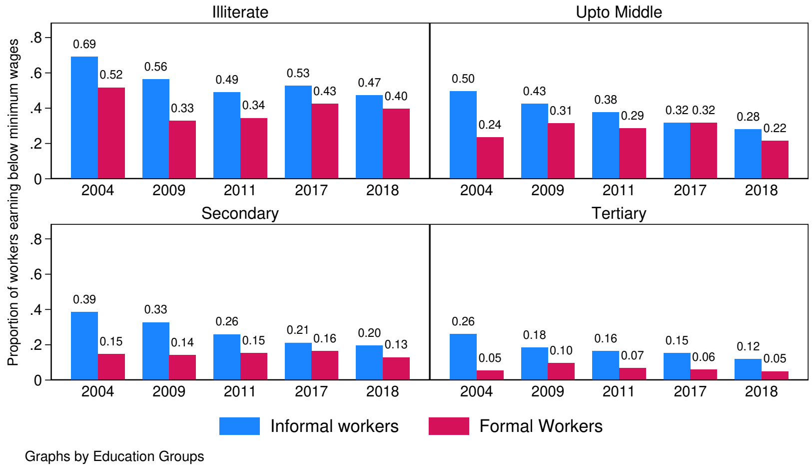


Notes: The dependent variable is log of nominal daily wages. MW refers to nominal administrative MW. Wage Deciles, ranging from 1 to 10, sequentially represent 10% segments of wage earners, with the first being the lowest and the tenth, the base category, including the top 10%, all within each state and year. Controls include education, age-group, marital status, social group, religion, industry categories, district fixed effects, and year fixed effects. Standard errors in parentheses are clustered at state level.

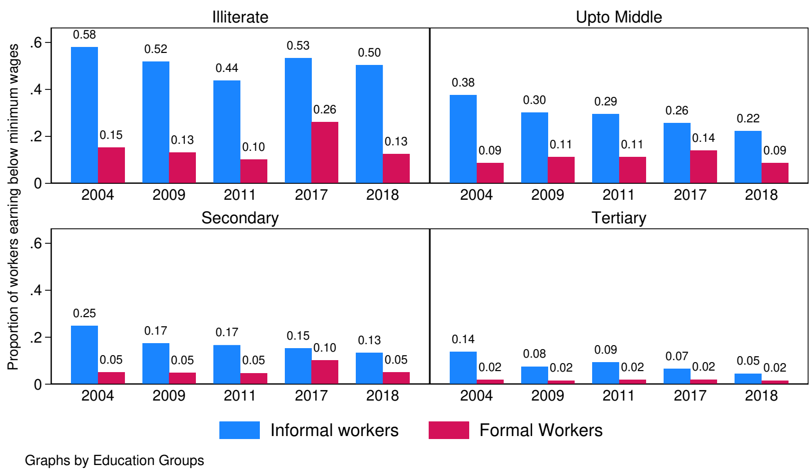
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. MW data are from Labour Bureau.

Figure A.4: Proportion of Formal and Informal Workers Earning Below Agriculture MW

Panel A: Rural India



Panel B: Urban India

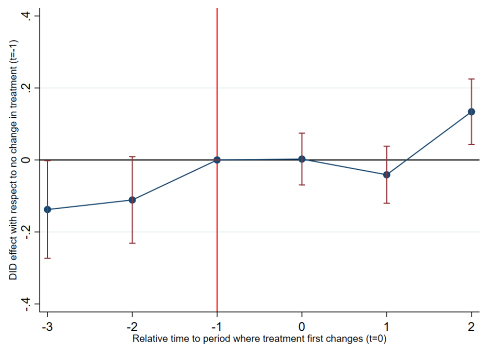


Notes: Formal workers are defined as those employed under written job contracts, and informal workers refer to those without written contracts.

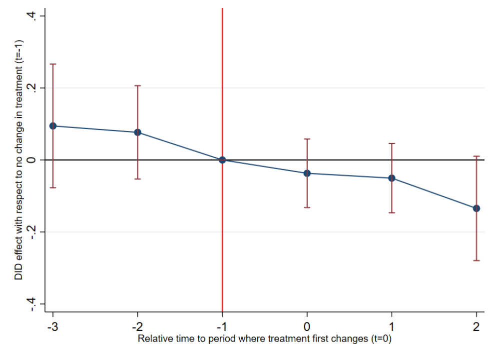
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 2004, 2009 and 2011, and PLFS rounds of 2017 and 2018. MW data are from the Labour Bureau.

Figure A.5: Staggered Difference-in-Differences: Impact of Changes in Minimum Wage on Wage Inequality at District level

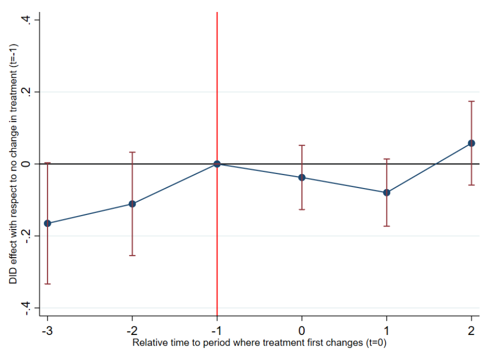
(a) Rural: ln90–ln50



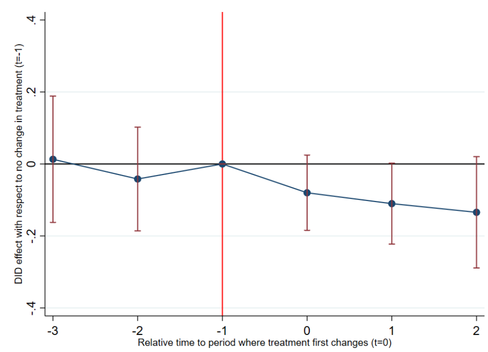
(b) Urban: ln90–ln50



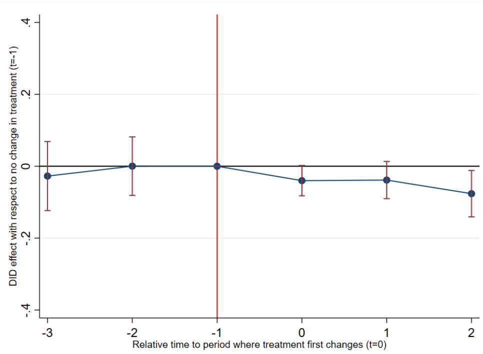
(c) Rural: ln90–ln10



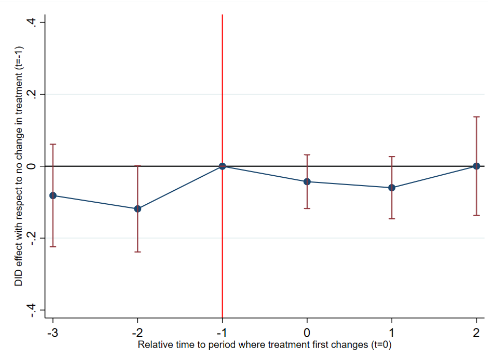
(d) Urban: ln90–ln10



(e) Rural: ln50–ln10



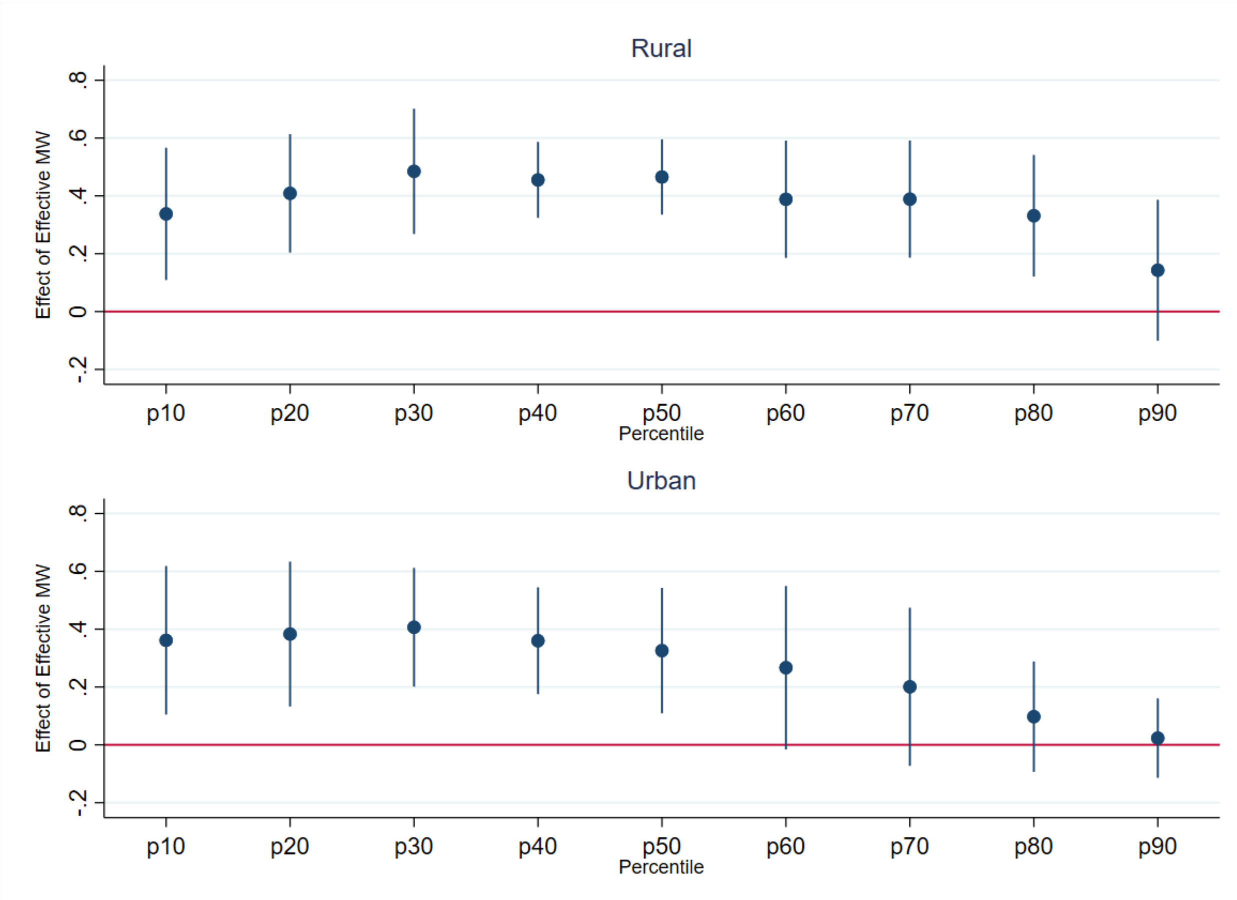
(f) Urban: ln50–ln10



Notes: The treatment variable is the log of the real MW (where the real MW is rounded to the nearest INR 50). Observations are at the district–sector–year level. The dependent variables, constructed at district–sector–year level, are measures of real wage inequality in both rural (panels a, c, and e) and urban areas (panels b, d, and f), quantified as the differences between the log 90th and log 50th percentiles (panels a and b), the log 90th and log 10th percentiles (panels c and d), and the log 50th and log 10th percentiles (panels e and f) of the real wage distribution. Real wages are obtained by deflating nominal wages using the CPI-IW and the CPI-AL in urban and rural areas, respectively. Administrative real MW are obtained by deflating the nominal minimum agricultural wages using the average of CPI-IW and CPI-AL. We deflate the wages since we use aggregate district-level measures of inequality here. The methodology employed for deriving estimates is the average dynamic DiD estimator for continuous treatment (De Chaisemartin *et al.* , 2019). Bars indicate 90% confidence intervals. Standard errors are clustered at the district level within each sector and bootstrapped with 200 resamples.

Source: Authors' calculations based on Employment–Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017 and 2018. MW data are from the Labour Bureau.

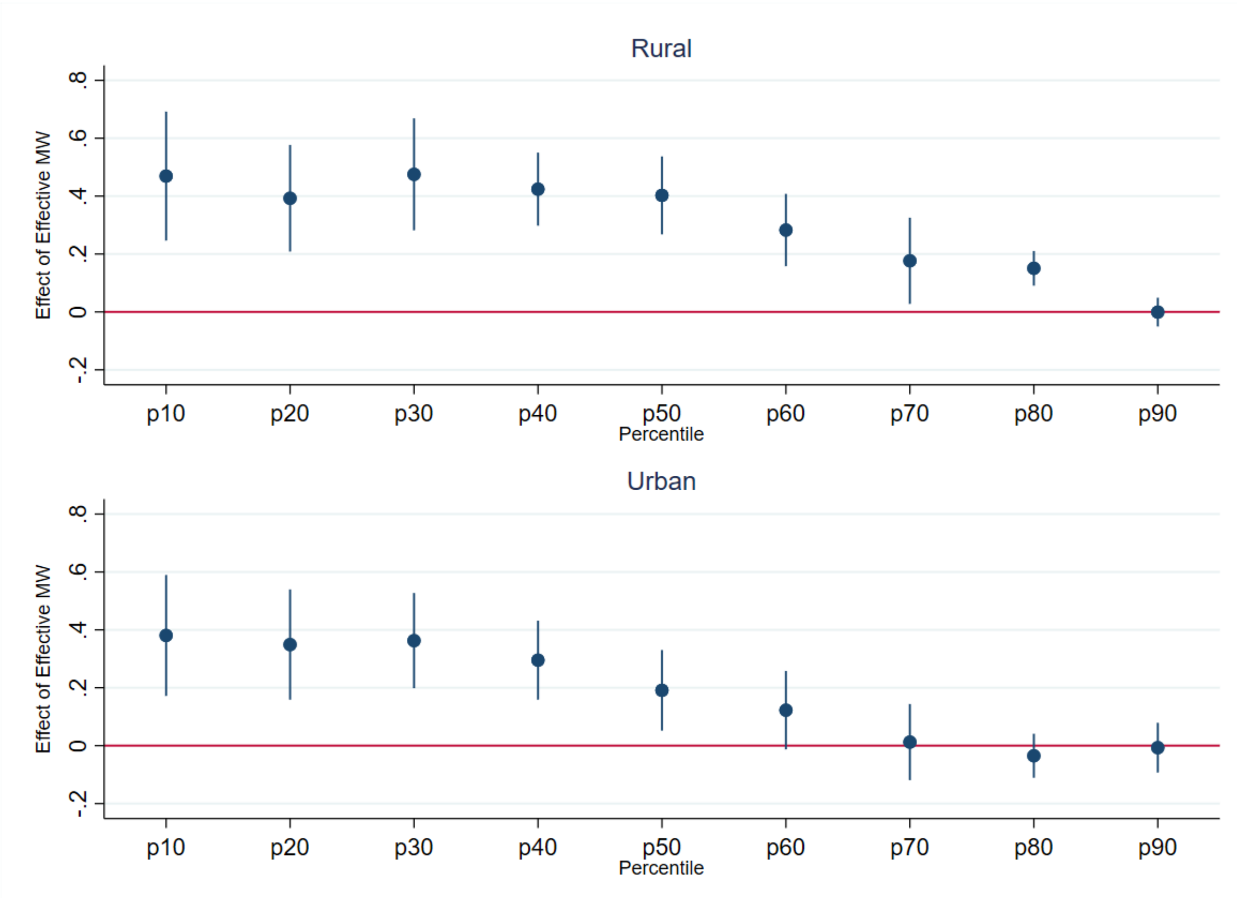
Figure A.6: Marginal Effects of MW on Wage Percentiles by Sector (Border Districts)



Notes: MW refers to the administrative MW. The estimation method is 2SLS, where the effective minimum wage (log(MW) - log(Average wages of high-skilled workers)) and its square are instrumented using the log(MW), the square of the log(MW), and the log(MW) interacted with the log(Average wages of high-skilled workers) at the state and sector levels. The x-axis shows the distance of a specific percentile (p) of the wage distribution from the average wages of high-skilled workers. The y-axis represents the marginal effects of effective minimum wage and its square on log(p) – log(Average wages of high-skilled workers) across states and years. Observations are at the state–year level. Regressions control for year fixed effects, state fixed effects and state trends. Standard errors are clustered at the state level. 95% confidence interval is represented by spikes.

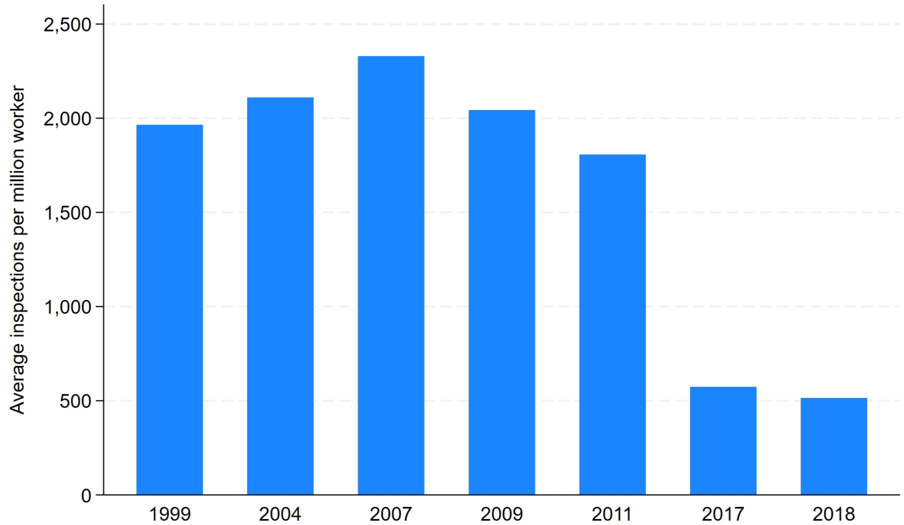
Source: Authors' calculations based on Employment–Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017 and 2018. MW data are from the Labour Bureau.

Figure A.7: Marginal Effects of MW on Wage Percentiles by Sector Relative to the 85th Percentile



Notes: MW refers to the administrative MW. The estimation method is 2SLS, where the effective minimum wage (log(MW) - log(Average wages at 85th percentile)) and its square are instrumented using the log(MW), the square of the log(MW), and the log(MW) interacted with the log(Average wages at 85th percentile) at the state and sector levels. The x-axis shows the distance of a specific percentile (p) of the wage distribution from the 85th percentile of the wage distribution. The y-axis represents the marginal effects of effective minimum wage and its square on log(p) – log(85th percentile of wage) across states and years. Observations are at the state–year level. Regressions control for year fixed effects, state fixed effects and state trends. Standard errors are clustered at the state -level. 95% confidence interval is represented by spikes.
Source: Authors' calculations based on Employment–Unemployment NSS rounds of 1999, 2004, 2007, 2009 and 2011, and PLFS rounds of 2017 and 2018. MW data are from the Labour Bureau.

Figure A.8: Labor Inspections per million worker, 1996–2018

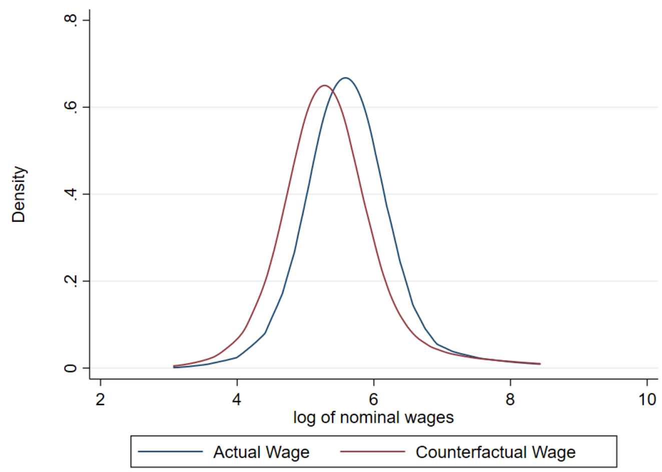


Notes: Data have been considered from 23 states in India: Andhra Pradesh, Assam, Bihar, Chandigarh, Chhattisgarh, Delhi, Goa, Gujarat, Haryana, Himachal Pradesh, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Orissa, Punjab, Rajasthan, Tamil Nadu, Telangana, Uttar Pradesh, Uttarakhand, and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

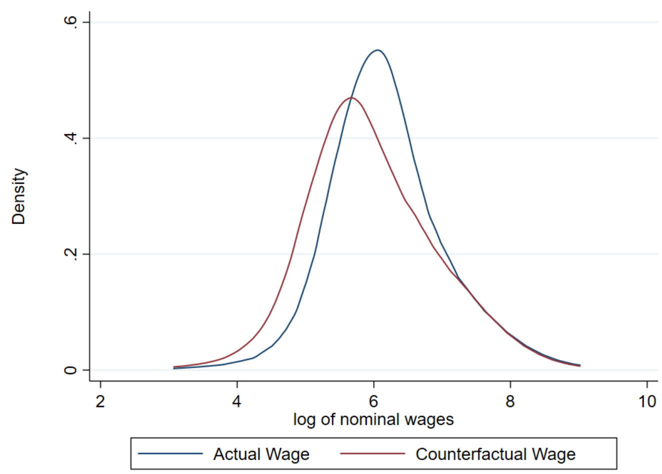
Source: Labour Bureau.

Figure A.9: 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 MW.

Source: Authors' calculations based on Employment–Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017 and 2018. MW data are from the Labour Bureau.

Table A.1: Trends in 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

Notes: Each row represents measures of nominal wage inequality measured via percentile log differences, Variance, and Gini of the log of nominal wage distribution.
Source: Authors' calculations based on NSS 1999, 2004, 2007, 2009, and 2011, and PLFS 2017, and 2018

Table A.2: Correlation between Agricultural and Other Sectoral 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: The independent variable is administrative minimum wages in agricultural sector. Dependent variables are administrative minimum wages of the industries presented in rows of the above table. All regression equations include state and year fixed effects.
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 A.3: Summary Statistics: Average Nominal Wage Distribution

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
Wages of All workers	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 nominal wages by different worker categories are provided in the table with their standard deviation in parentheses. 'Low-skilled workers' include workers in elementary occupations such as laborers, skilled agricultural, and construction workers. 'Medium-skilled workers' refer to those in clerical, administrative support, sales, and production roles. 'High-skilled workers' are those in professional, technical, and managerial positions. 'Low educated' denote workers with at most primary education, 'medium educated' indicate workers have more than primary but at most secondary education (class 10), and 'high educated' refers to those with more than secondary education. The wage distribution is segmented into quintiles, where the 'first quintile' represents the lowest 20% of wage earners and the 'fifth quintile' represents the top 20% of earners, all within each state and year.
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

Table A.4: 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)
Less-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 by skill and education (among those employed) are reported in the table with their standard deviation in parentheses. 'Low-skilled workers' include workers in elementary occupations such as laborers, skilled agricultural, and construction workers. 'Medium-skilled workers' refer to those in clerical, administrative support, sales, and production roles. 'High-skilled workers' are those in professional, technical, and managerial positions. 'Low educated' denote workers with at most primary education, 'medium educated' indicate workers have more than primary but at most secondary education (class 10), and 'high educated' refers to those with more than secondary education. The proportions are provided at sectoral level using all districts in columns (1) and (3) and only the border districts in columns (2) and (4).
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018.

Table A.5: Relationship between macro variables and minimum wages

	(1)	(2)	(3)	(4)
SGDP	0.994	0.742	0.873	-0.016
	(1.08)	(1.08)	(1.13)	(2.39)
Serv (% SGDP)	-0.000	0.002	0.001	0.005
	(0.01)	(0.01)	(0.01)	(0.01)
Agri (% SGDP)	0.007	0.009	0.009	0.010
	(0.01)	(0.01)	(0.01)	(0.01)
log Pop.	-0.882	-0.123	-0.520	-0.436
	(0.58)	(0.73)	(0.80)	(0.80)
CPI	0.000	0.000	0.000	0.000
	(0.00)	(0.00)	(0.00)	(0.00)
Fertility Rate		0.181	0.189	0.170
		(0.12)	(0.12)	(0.12)
Poverty Rate			0.004	0.004
			(0.00)	(0.00)
Literacy Rate			0.014	0.012
			(0.01)	(0.01)
Invested Capital				0.003
				(0.00)
Roads Length				-0.158
				(0.38)
Constant	12.661**	4.043	7.323	6.497
	(6.30)	(8.05)	(8.48)	(8.48)
State FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Joint F-test	1.47	1.82	1.65	1.39
Observations	192	192	192	192

Notes: The dependent variable is the log of nominal administrative minimum wages. Controls include state and year fixed effects. SGDP is constant at 2011 levels. Serv. and Agri. represent the percentage contributions of services and agriculture to SGDP, respectively. Population is logged. CPI pertains to the agricultural sector. Robust standard errors are reported in parentheses. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations are based on minimum wages data from the Labour Bureau; GDP, population, and fertility rate data from EPWRF; and poverty rate, invested capital, road length, and literacy rate data from the RBI.

Table A.6: Effect of Minimum Wages on Wages of Formal and Informal Workers at Different Wage Quintiles (Based on Provident Fund Eligibility of Workers)

	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
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
Observations	173864	118452	115685	71171

Notes: The dependent variable is log of nominal daily wages. MW refers nominal administrative minimum wages. Formal Worker refers to the workers eligible for Provident Fund benefits. This includes General Provident Fund (GPF), Contributory Provident Fund (CPF), and Public Provident Fund (PPF) benefits. Wage quintiles, ranging from 1 to 5, sequentially represent 20% segments of wage earners, with the first being the lowest and the fifth, the base category, including the top 20%, all within each state and year. Controls include education, age-group, marital status, social group, religion, industry categories, district fixed effects and year fixed effects. Standard errors in parentheses are clustered at state level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

Table A.7: Effect of Minimum Wages on Wages at Different Wage Quintiles (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 (Wage Quintile=1 × log MW)	0.000	0.000	0.000	0.000
WB (Wage Quintile=2 × log MW)	0.000	0.001	0.001	0.001
WB (Wage Quintile=3 × log MW)	0.000	0.002	0.001	0.002
WB (Wage Quintile=4 × log MW)	0.010	0.009	0.000	0.002
R-Squared	0.95	0.95	0.92	0.92
Observations	249976	170515	203543	126073

Notes: The dependent variable is log of nominal daily wages. MW refers to nominal administrative minimum wages. Wage quintiles, ranging from 1 to 5, sequentially represent 20% segments of wage earners, with the first being the lowest and the fifth, the base category, including the top 20%, all within each state and year. Controls include education, age-group, marital status, social group, religion, industry categories, district fixed effects, year fixed effects and district specific time trends. Standard errors in parentheses are clustered at state level. Wild-bootstrapped p-values (WB) related to the coefficients mentioned in brackets (differential impact of minimum wages by quintiles of wages) for each of the columns are shown in table rows. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

Table A.8: Effect of Minimum Wages on Wages at Different Wage Quintiles (Controlling for State Time Trends)

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	-0.054	-0.043	-0.042	-0.031
	(0.05)	(0.05)	(0.06)	(0.05)
Wage Quintile=1 × log MW	0.169***	0.176***	0.215***	0.200***
	(0.03)	(0.03)	(0.04)	(0.04)
Wage Quintile=2 × log MW	0.170***	0.166***	0.195***	0.164***
	(0.02)	(0.03)	(0.04)	(0.04)
Wage Quintile=3 × log MW	0.136***	0.152***	0.163***	0.155***
	(0.02)	(0.03)	(0.03)	(0.04)
Wage Quintile=4 × log MW	0.065***	0.094***	0.069***	0.087***
	(0.02)	(0.03)	(0.01)	(0.01)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
State Time Trends	✓	✓	✓	✓
WB (Wage Quintile=1 × log MW)	0.000	0.000	0.000	0.000
WB (Wage Quintile=2 × log MW)	0.000	0.001	0.001	0.001
WB (Wage Quintile=3 × log MW)	0.000	0.002	0.001	0.002
WB (Wage Quintile=4 × log MW)	0.008	0.008	0.000	0.002
R-Squared	0.95	0.95	0.92	0.92
Observations	249976	170515	203543	126073

Notes: The dependent variable is log of nominal daily wages. MW refers to nominal administrative minimum wages. Wage quintiles, ranging from 1 to 5, sequentially represent 20% segments of wage earners, with the first being the lowest and the fifth, the base category, including the top 20%, all within each state and year. Controls include education, age-group, sex, marital status, social group, religion , industry categories, district fixed effects, quarter-year fixed effects and state-time trends. Standard errors in parentheses are clustered at state level. Wild-bootstrapped p-values (WB) related to the coefficients mentioned in brackets (differential impact of minimum wages by quintiles of wages) for each of the columns are shown in table rows. ***, **, * show significance at 1%, 5% and 10%, respectively.

Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

Table A.9: Effect of Minimum Wages on Wages at Different Wage Quintiles (Controlling for Macrovariables)

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	0.010	-0.017	-0.010	-0.038
	(0.04)	(0.04)	(0.05)	(0.04)
Wage Quintile=1 × log MW	0.163***	0.167***	0.247***	0.246***
	(0.03)	(0.04)	(0.03)	(0.03)
Wage Quintile=2 × log MW	0.170***	0.165***	0.225***	0.206***
	(0.02)	(0.03)	(0.03)	(0.03)
Wage Quintile=3 × log MW	0.137***	0.151***	0.180***	0.186***
	(0.02)	(0.03)	(0.02)	(0.04)
Wage Quintile=4 × log MW	0.062***	0.089***	0.066***	0.092***
	(0.02)	(0.03)	(0.01)	(0.02)
Macro Controls	✓	✓	✓	✓
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
WB p-value of MW × 1.Wage Quintile	0.001	0.001	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	0.001	0.002	0.001	0.003
WB p-value of MW × 4.Wage Quintile	0.018	0.013	0.002	0.005
R-Squared	0.95	0.95	0.92	0.92
No. of Clusters	16	16	16	16
Observations	231403	154045	180205	105769

Notes: The dependent variable is log of nominal daily wages. MW refers to nominal administrative minimum wages. Wage Quintiles, ranging from 1 to 5, sequentially represent 20% segments of wage earners, with the first being the lowest and the fifth, the base category, including the top 20%, all within each state and year. Controls include macro variables: state income (GSDP), contributions of the agricultural and service sectors to GSDP, demographics (population), inflation, socioeconomic characteristics (fertility rate, poverty rate, literacy rate), and infrastructure (invested capital by factories, length of roads). Also, individual characteristics such as education, age group, marital status, social group, religion, industry categories, as well as district fixed effects and year fixed effects, are included. Standard errors in parentheses are clustered at state level. Due to the low number of clusters (19), wild-bootstrapped p-values (WB) are shown in the table. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

Table A.10: Effect of Minimum Wages on Wages at Different Wage Quintiles (Controlling for State-Year Fixed effects)

	Rural		Urban	
	(1)	(2)	(3)	(4)
	All	Border	All	Border
Wage Quintile=1 × log MW	0.183***	0.182***	0.249***	0.192***
	(0.03)	(0.03)	(0.03)	(0.02)
Wage Quintile=2 × log MW	0.175***	0.130***	0.216***	0.114***
	(0.03)	(0.02)	(0.04)	(0.02)
Wage Quintile=3 × log MW	0.139***	0.127***	0.178***	0.017
	(0.02)	(0.02)	(0.02)	(0.02)
Wage Quintile=4 × log MW	0.068***	0.107***	0.077***	-0.041*
	(0.02)	(0.02)	(0.01)	(0.02)
State-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	0.000	0.000	0.000
WB p-value of MW × 3.Wage Quintile	0.001	0.000	0.000	0.431
WB p-value of MW × 4.Wage Quintile	0.012	0.000	0.000	0.176
R-Squared	0.95	0.95	0.92	0.95
Observations	249976	170515	203543	126073

Notes: The dependent variable is log of nominal daily wages. MW refers to nominal administrative minimum wages. Wage quintiles, ranging from 1 to 5, sequentially represent 20% segments of wage earners, with the first being the lowest and the fifth, the base category, including the top 20%, all within each state and year. Controls include education, age-group, sex, marital status, social group, religion , industry categories, state-calendar year fixed effects. Standard errors in parentheses are clustered at state level. Wild-bootstrapped p-values (WB) related to the coefficients mentioned in brackets (differential impact of minimum wages by quintiles of wages) for each of the columns are shown in table rows. ***, **, * show significance at 1%, 5% and 10%, respectively.

Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

Table A.11: Effect of Minimum Wages on Wages at Different Wage Quintiles (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 (Wage Quintile=1 × log MW)	0.000	0.000	0.000	0.000
WB (Wage Quintile=2 × log MW)	0.000	0.001	0.001	0.001
WB (Wage Quintile=3 × log MW)	0.000	0.002	0.001	0.002
WB (Wage Quintile=4 × log MW)	0.010	0.010	0.000	0.002
R-Squared	0.95	0.95	0.92	0.92
Observations	249976	170515	203543	126073

Notes: The dependent variable is log of nominal daily wages. MW refers to nominal administrative minimum wages. Wage quintiles, ranging from 1 to 5, sequentially represent 20% segments of wage earners, with the first being the lowest and the fifth, the base category, including the top 20%, all within each state and year. Controls include education, age-group, sex, marital status, social group, religion , industry categories, district fixed effects and quarter-year fixed effects. Standard errors in parentheses are clustered at state level. Wild-bootstrapped p-values (WB) related to the coefficients mentioned in brackets (differential impact of minimum wages by quintiles of wages) for each of the columns are shown in table rows. ***, **, * show significance at 1%, 5% and 10%, respectively.

Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

Table A.12: Effect of Minimum Wages on Wages at Different Wage Quintiles: Border-Pair Robustness

	(1) Rural	(2) Urban
log MW	-0.108***	-0.024
	(0.03)	(0.02)
Wage Quintile=1 × log MW	0.157***	0.182***
	(0.02)	(0.02)
Wage Quintile=2 × log MW	0.165***	0.147***
	(0.02)	(0.02)
Wage Quintile=3 × log MW	0.142***	0.134***
	(0.02)	(0.02)
Wage Quintile=4 × log MW	0.091***	0.087***
	(0.02)	(0.01)
Border District Pair-Year FE	✓	✓
R-Squared	0.96	0.93
No. of Clusters	87	87
Observations	371292	294633

Notes: We generate unique border district pairs for each employed person in a year, where individual data is repeated for those residing in a district sharing a border with more than one district in the neighboring states. The dependent variable is log of nominal daily wages. MW refers to nominal administrative minimum wages. Wage quintiles, ranging from 1 to 5, sequentially represent 20% segments of wage earners, with the first being the lowest and the fifth, the base category, including the top 20%, all within each state and year. Controls include education, age-group, sex, marital status, social group, religion , industry categories, district border-pair-year fixed effects. Standard errors in parentheses are clustered at the cross-state border segment, including all districts on both sides of a border between two states. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

Table A.13: Effect of Real Minimum Wages on Real Wages at Different 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 (Wage Quintile=1 × log MW)	0.002	0.004	0.012	0.023
WB (Wage Quintile=2 × log MW)	0.002	0.004	0.012	0.038
WB (Wage Quintile=3 × log MW)	0.006	0.009	0.011	0.023
WB (Wage Quintile=4 × log MW)	0.062	0.044	0.006	0.006
R-Squared	0.95	0.95	0.92	0.92
Observations	249976	170515	203543	126073

Notes: The dependent variable is log of real daily wages. MW refers to real administrative minimum wages. Wage quintiles, ranging from 1 to 5, sequentially represent 20% segments of wage earners, with the first being the lowest and the fifth, the base category, including the top 20%, all within each state and year. Controls include education, age-group, sex, marital status, social group, religion, industry categories, district fixed effects and year fixed effects. Real wages are obtained by deflating nominal wages using the Consumer Price Index for Industrial Workers (CPI-IW) and the Consumer Price Index for Agricultural Laborers (CPI-AL) in urban and rural areas, respectively. Administrative real minimum wages are obtained by deflating the nominal minimum agricultural wages using the average of CPI-IW and CPI-AL. Standard errors in parentheses are clustered at state level. Wild-bootstrapped p-values (WB) related to the coefficients mentioned in brackets (differential impact of minimum wages by quintiles of wages) for each of the columns are shown in table rows. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

Table A.14: Effect of Minimum Wages on Wages at State-Sector-Year Defined Wage Quintiles

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	0.026	-0.001	-0.000	0.003
	(0.05)	(0.05)	(0.06)	(0.05)
Wage Quintile=1 × log MW	0.130***	0.136***	0.217***	0.218***
	(0.03)	(0.04)	(0.01)	(0.03)
Wage Quintile=2 × log MW	0.131***	0.129***	0.166***	0.164***
	(0.03)	(0.03)	(0.02)	(0.03)
Wage Quintile=3 × log MW	0.112***	0.128***	0.074***	0.065***
	(0.02)	(0.02)	(0.02)	(0.02)
Wage Quintile=4 × log MW	0.088***	0.105***	-0.010	-0.007
	(0.02)	(0.02)	(0.02)	(0.02)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
WB (Wage Quintile=1 × log MW)	0.002	0.002	0.000	0.000
WB (Wage Quintile=2 × log MW)	0.001	0.002	0.000	0.000
WB (Wage Quintile=3 × log MW)	0.001	0.001	0.005	0.013
WB (Wage Quintile=4 × log MW)	0.006	0.003	0.631	0.730
R-Squared	0.93	0.93	0.94	0.94
Observations	249976	170515	203543	126073

Notes: The dependent variable is log of nominal daily wages. MW refers to nominal administrative minimum wages. Wage Quintiles, ranging from 1 to 5, sequentially represent 20% segments of wage earners, with the first being the lowest and the fifth, the base category, including the top 20%, all within each state, sector and year. Controls include education, age-group, marital status, social group, religion, industry categories, district fixed effects, and year fixed effects. Standard errors in parentheses are clustered at state level. Due to the low number of clusters (19), wild-bootstrapped p-values (WB) are shown in the table. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

Table A.15: 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 (Earning Quintile=1 × log MW)	0.000	0.000	0.000	0.001
WB (Earning Quintile=2 × log MW)	0.000	0.000	0.000	0.001
WB (Earning Quintile=3 × log MW)	0.000	0.000	0.000	0.001
WB (Earning Quintile=4 × log MW)	0.002	0.004	0.000	0.001
R-Squared	0.92	0.92	0.91	0.91
Observations	249976	170515	203543	126073

Notes: The dependent variable is log of nominal weekly earnings. MW refers to nominal administrative minimum wages. Earnings quintiles, ranging from 1 to 5, sequentially represent 20% segments of weekly earners, with the first being the lowest and the fifth, the base category, including the top 20%, all within each state and year. Controls include education, age-group, sex, marital status, social group, religion, industry categories, district fixed effects and year fixed effects. Standard errors in parentheses are clustered at state level. Wild-bootstrapped p-values (WB) related to the coefficients mentioned in brackets (differential impact of minimum wages by quintiles of wages) for each of the columns are shown in table rows. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

Table A.16: Average Dynamic Effect of Minimum Wages on Wage Inequality (Staggered DID Estimates)

	(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). The dependent variables are measures of real wage inequality in both rural and urban areas, quantified as the differences between the log 90th and log 50th percentiles, the log 90th and log 10th percentiles, and the log 50th and log 10th percentiles of the real wage distribution. The methodology employed for deriving estimates is the average dynamic DiD estimator for continuous treatment. Observations (N) are at the district-sector-year level. Switchers are the states that change their minimum wages over time. Real wages are obtained by deflating nominal wages using the Consumer Price Index for Industrial Workers (CPI-IW) and the Consumer Price Index for Agricultural Laborers (CPI-AL) in urban and rural areas, respectively. Administrative real minimum wages are obtained by deflating the nominal minimum agricultural wages using the average of CPI-IW and CPI-AL. 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 Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

Table A.17: Effect of Minimum Wages on the Highest Skilled and Educated Workers

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
Panel A: High Skilled Workers				
log MW	0.032	0.009	0.015	0.058
	(0.07)	(0.08)	(0.06)	(0.08)
WB (log MW)	0.726	0.923	0.826	0.486
R-Squared	0.62	0.63	0.57	0.58
Observations	26925	18405	48813	30483
Panel B: High Educated Workers				
log MW	0.036	0.025	0.007	0.035
	(0.10)	(0.11)	(0.05)	(0.06)
WB (log MW)	0.749	0.849	0.900	0.665
R-Squared	0.55	0.56	0.50	0.50
Observations	22398	15113	56205	35131
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓

Notes: The dependent variable is log of nominal daily wages. Panel A keeps only high skilled workers (i.e., workers in professional, technical, and managerial positions) while Panel B keeps only high educated workers (i.e., workers having completed at least college or graduate degree). MW refers to nominal administrative minimum wages. Controls include education, age-group, marital status, social group, religion, industry categories, district fixed effects and year fixed effects. Standard errors in parentheses are clustered at state level. Wild-bootstrapped p-values (WB) related to the impact of log MW on worker wages for each of the columns are shown in table rows. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

Table A.18: Effect of Minimum Wages on Wages at Different Wage Quintiles (Controlling for NREGA in Rural India's Border Districts)

	(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 (Wage Quintile=1 × log MW)	0.000	0.000	0.000
WB (Wage Quintile=2 × log MW)	0.000	0.001	0.001
WB (Wage Quintile=3 × log MW)	0.000	0.002	0.002
WB (Wage Quintile=4 × log MW)	0.003	0.010	0.010
R-Squared	0.90	0.95	0.95
Observations	89327	170515	170515

Notes: The dependent variable is log of nominal daily wages. MW refers to nominal administrative minimum wages. Wage quintiles, ranging from 1 to 5, sequentially represent 20% segments of wage earners, with the first being the lowest and the fifth, the base category, including the top 20%, all within each state and year. Controls include education, age-group, marital status, social group, religion, industry categories, NREGA, district fixed effects and year fixed effects. In column 1, NREGA is controlled as a dummy varaible which takes value 1 for Phase 1 and Phase 2 districts where NREGA was implemented in the year 2007. Only data from years 1999, 2004 and 2007 have been utilised for the analysis in column 1. 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. The estimates presented are for rural India only, in line with the implementation scope of the NREGA policy. Standard errors in parentheses are clustered at state level. Wild-bootstrapped p-values (WB) related to the coefficients mentioned in brackets (differential impact of minimum wages by quintiles of wages) for each of the columns are shown in table rows. ***, **, * show significance at 1%, 5% and 10%, respectively.

Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

Table A.19: Effect of Minimum Wages on Wages at Different Wage Quintiles (Controlling for Enforcement)

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	-0.007	-0.020	0.008	-0.008
	(0.05)	(0.05)	(0.07)	(0.05)
Wage Quintile=1 × log MW	0.179***	0.187***	0.221***	0.201***
	(0.03)	(0.03)	(0.04)	(0.04)
Wage Quintile=2 × log MW	0.176***	0.174***	0.196***	0.168***
	(0.02)	(0.03)	(0.04)	(0.04)
Wage Quintile=3 × log MW	0.146***	0.163***	0.165***	0.160***
	(0.02)	(0.03)	(0.03)	(0.04)
Wage Quintile=4 × log MW	0.073***	0.102***	0.067***	0.089***
	(0.02)	(0.03)	(0.01)	(0.01)
log Enforc.	-0.022	-0.014	0.013	0.020**
	(0.01)	(0.01)	(0.01)	(0.01)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R-Squared	0.94	0.94	0.92	0.92
Observations	249976	170515	203543	126073

Notes: The dependent variable is log of nominal daily wages. MW refers to nominal administrative minimum wages. Enforc. refers to the enforcement variable, calculated as the number of labor inspections per million workers. Wage Quintiles, ranging from 1 to 5, sequentially represent 20% segments of wage earners, with the first being the lowest and the fifth, the base category, including the top 20%, all within each state and year. Controls include enforcement, education, age-group, marital status, social group, religion, sex, industry categories, district fixed effects, and year fixed effects. Standard errors in parentheses are clustered at state level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

Table A.20: Effect of Minimum Wages and Enforcement on Wages

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	0.039	0.068	0.041	0.091
	(0.08)	(0.07)	(0.07)	(0.08)
log Enforc.	-0.108**	-0.080*	-0.037	0.003
	(0.05)	(0.05)	(0.04)	(0.05)
log MW × log Enforc.	0.018*	0.013	0.008	0.000
	(0.01)	(0.01)	(0.01)	(0.01)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R-Squared	0.78	0.78	0.70	0.70
Observations	249976	170515	203543	126073

Notes: The dependent variable is log of nominal daily wages. MW refers to nominal administrative minimum wages. Enforc. refers to the enforcement variable, measured as the number of inspections per million workers. Controls include education, age-group, marital status, social group, religion, sex, industry categories, district fixed effects, and year fixed effects. Standard errors in parentheses are clustered at state level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.

Table A.21: Effect of Minimum Wages and Enforcement on Wages at Different Wage Quintiles

	Rural		Urban	
	(1) All	(2) Border	(3) All	(4) Border
log MW	-0.556***	-0.384**	-0.365**	-0.229**
	(0.10)	(0.16)	(0.13)	(0.10)
Wage Quintile=1 × log MW	0.539**	0.428*	0.302**	0.205
	(0.19)	(0.21)	(0.14)	(0.13)
Wage Quintile=2 × log MW	0.497***	0.409**	0.301*	0.177
	(0.13)	(0.18)	(0.15)	(0.16)
Wage Quintile=3 × log MW	0.465***	0.317*	0.321*	0.169
	(0.09)	(0.16)	(0.17)	(0.15)
Wage Quintile=4 × log MW	0.247**	0.195	0.199	0.130
	(0.09)	(0.16)	(0.15)	(0.11)
log Enforc.	-0.398***	-0.265**	-0.243**	-0.134*
	(0.07)	(0.11)	(0.09)	(0.07)
log MW × log Enforc.	0.068***	0.043**	0.049**	0.027*
	(0.01)	(0.02)	(0.02)	(0.01)
Wage Quintile=1 × log MW × log Enforc.	-0.047	-0.031	-0.012	-0.001
	(0.03)	(0.03)	(0.02)	(0.02)
Wage Quintile=2 × log MW × log Enforc.	-0.038*	-0.027	-0.014	0.000
	(0.02)	(0.02)	(0.02)	(0.02)
Wage Quintile=3 × log MW × log Enforc.	-0.036***	-0.013	-0.019	0.004
	(0.01)	(0.02)	(0.02)	(0.02)
Wage Quintile=4 × log MW × log Enforc.	-0.017	-0.003	-0.015	-0.000
	(0.01)	(0.02)	(0.02)	(0.01)
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
R-Squared	0.95	0.95	0.92	0.92
Observations	249976	170515	203543	126073

Notes: The dependent variable is log of nominal daily wages. MW refers to nominal administrative minimum wages. Enforc. refers to the enforcement variable, measured as the number of inspections per million workers. Controls include education, age-group, marital status, social group, religion, sex, industry categories, district fixed effects, and year fixed effects. Standard errors in parentheses are clustered at state level. ***, **, * show significance at 1%, 5% and 10%, respectively.
Source: Authors' calculations based on Employment-Unemployment NSS rounds of 1999, 2004, 2007, 2009, and 2011, and PLFS rounds of 2017, and 2018. Minimum Wages data are from Labour Bureau.