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ARTICLE

Population Adjustment to Asymmetric Labour Market Shocks in India: A Comparison to Europe and the United States at Two Different Regional Levels

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Abstract

This paper uses Indian EUS-NSSO data on 32 states/union territories and 570 districts for a bi-annual panel with 5 waves to estimate how regional population reacts to asymmetric shocks. These shocks are measured by non-employment rates, unemployment rates, and wages in fixed-effects regressions which effectively use changes in these indicators over time within regions as identifying information. Because we include region and time effects, we interpret regression-adjusted population changes as proxies for regional migration. Comparing the results with those for the United States (US) and the European Union (EU), the most striking difference is that, in India, we do not find any significant reactions to asymmetric non-employment shocks at the state level, only at the district level, whereas the estimates are statistically significant and of similar size for the state/NUTS-1 (Classification of Territorial Units for Statistics (NUTS, the French abbreviation for "nomenclature d'unités territoriales 21 statistiques")) and district level in both the US and Europe. We find that Indian workers react to asymmetric regional shocks by adjusting up to a third of a regional non-employment shock through migration within 2 years. This is somewhat higher than the response to non-employment shocks in the US and the EU but somewhat lower than the response to unemployment shocks in these economies. In India, the unemployment rate does not seem to be a reliable measure of regional shocks, at least we find no significant effects for it. However, we find a significant population response to regional wage differentials in India at both the state and district level.

Keywords Migration · Population · Regional convergence · Non-employment · Unemployment · Wages

JEL Classification J61

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1 Introduction

Internal migration can be an important component for adjusting asymmetric regional labour market shocks. For a fast-developing economy like India, which is also experiencing rapid population growth, efficient internal migration of labour may be even more important (Lagakos 2020). Still, in a large country such as India with different language groups, internal migration may also face political and administrative barriers as documented in Aggarwal et al. (2020), Bhagat (2012), Borhade (2012) and Kone et al. (2018).

In this paper, we estimate how net migration, proxied by regression-controlled population change in a region, reacts to regional labour market shocks in India. We measure asymmetric regional labour market shocks by changes in the ratio of the regional non-employment rate to the average non-employment rate of all Indian regions as well as by changes in the ratio of the average full-time wage in a region to the average wage of all Indian regions. We use both states/union territories and districts as regional units.[1] Based on regressions using regional and year fixed effects, we find that Indian workers respond to asymmetric regional labour market conditions. Indeed, when comparing our results to those obtained for the United States (US) and the European Union (EU) applying the same methodology as in Jauer et al. (2019), we find that regional adjustment in India occurs primarily at the district level but not at the state level, whereas it occurs at both of these levels in the US and in Europe. This finding is not inconsistent with concerns raised in the literature on barriers to mobility: maybe the dynamics of the Indian economy requires much more labour mobility for India to unleash its economic potential.

During the last two decades, India has seen significant macroeconomic and labour market changes: India has seen larger population growth since the year 2000 than the US, the EU, or China, but its GDP growth has been below the one of China since the late 2000s (see Figs. 1 and 2). This raises the question whether India is making full use of its labour market potential. Indeed, the employment to population ratio for people older than 15 years of age has been decreasing for the last two decades in India and is now below the one of the US, the EU, and China (Fig. 3), see also Verick (2014). The unemployment rate has increased recently (Fig. 4), although—given the lack of a European or the US style unemployment benefit system—we have doubts whether it is as meaningful as a statistic here as the non-employment rate, which will be our preferred statistic to measure (the inverse of) labour market tightness. For the employed, there have been significant structural shifts: India has experienced a decrease in the (still high) share of agricultural employment. This is not only reflected in an increase in the share of service employment: in striking contrast to the US and the EU, India and China have experienced industrialisation of their workforces in the first decade of the 21st century and slightly beyond

[1] In the following, when we refer to states this is supposed to include the union territories.

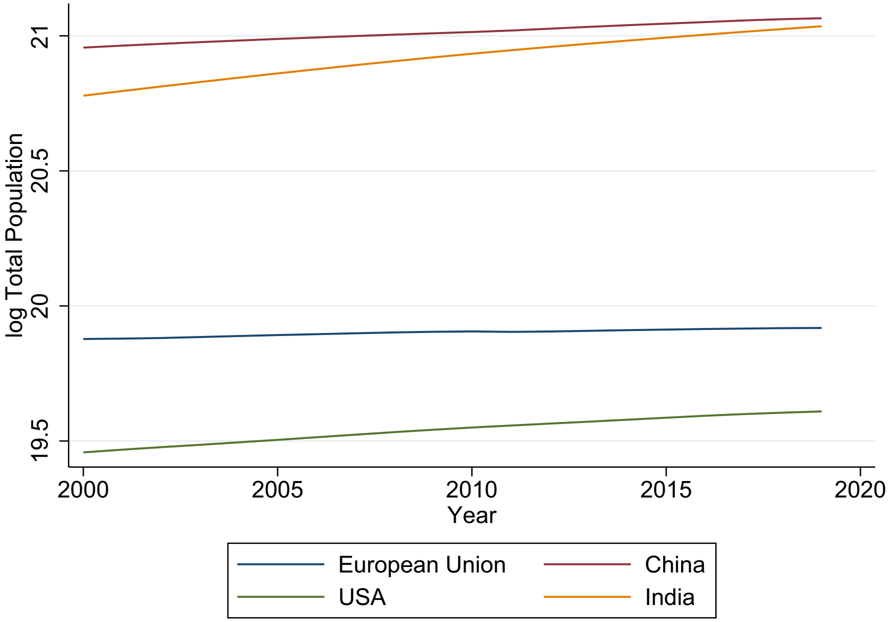

Fig. 1 Population by country. Data Source: https://data.worldbank.org

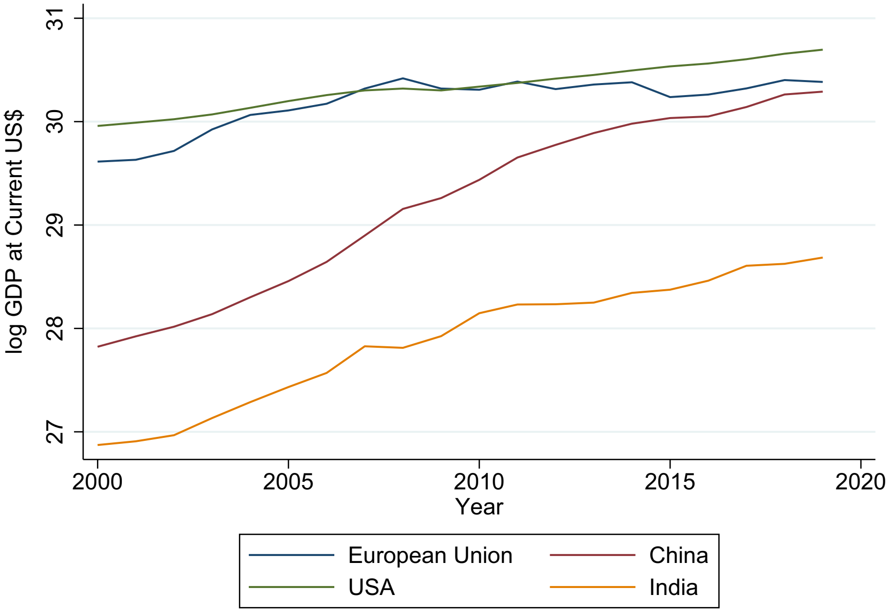

Fig. 2 GDP by country. Data Source: https://data.worldbank.org

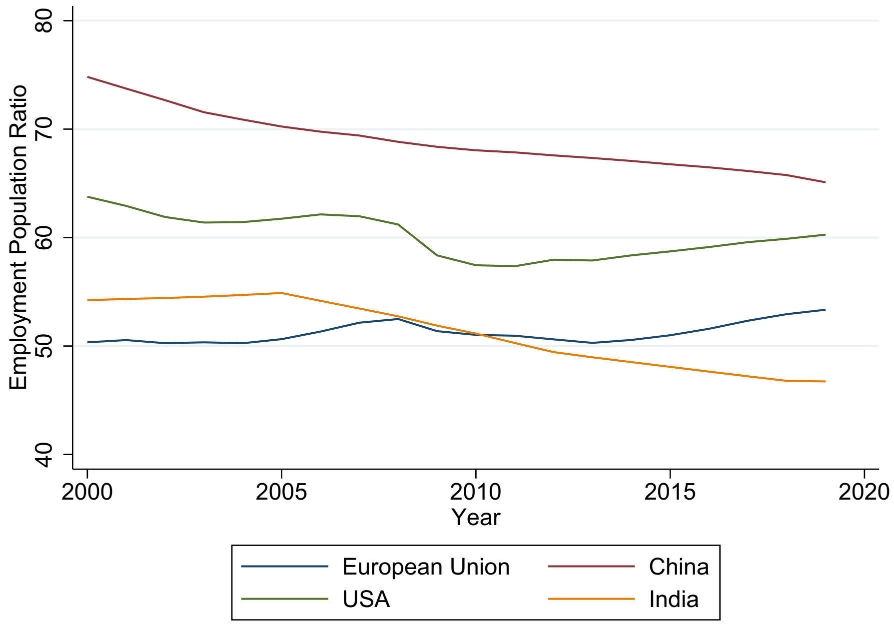

Fig. 3 Employment to population ratio by country. Data Source: https://data.worldbank.org

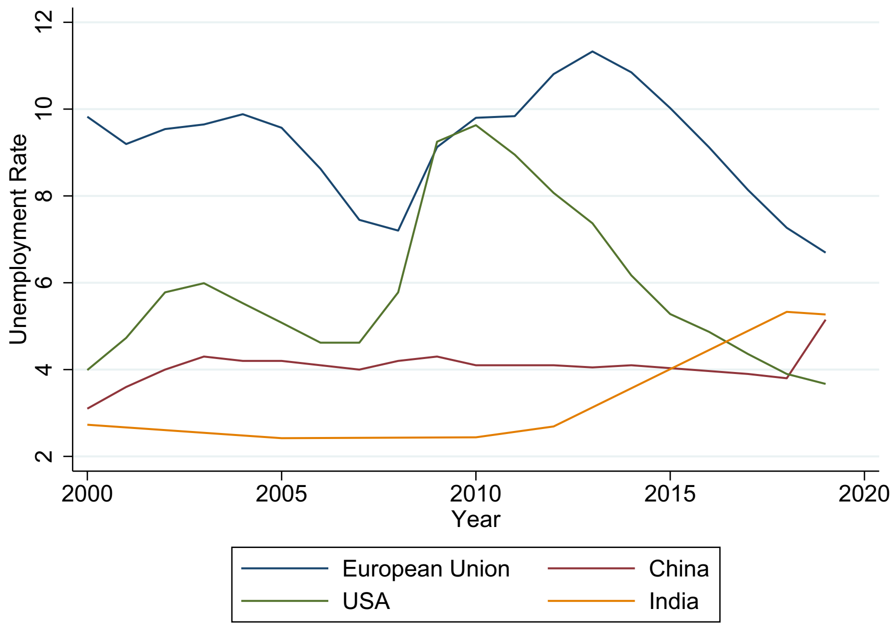

Fig. 4 Unemployment rates by country. Data Source: https://data.worldbank.org

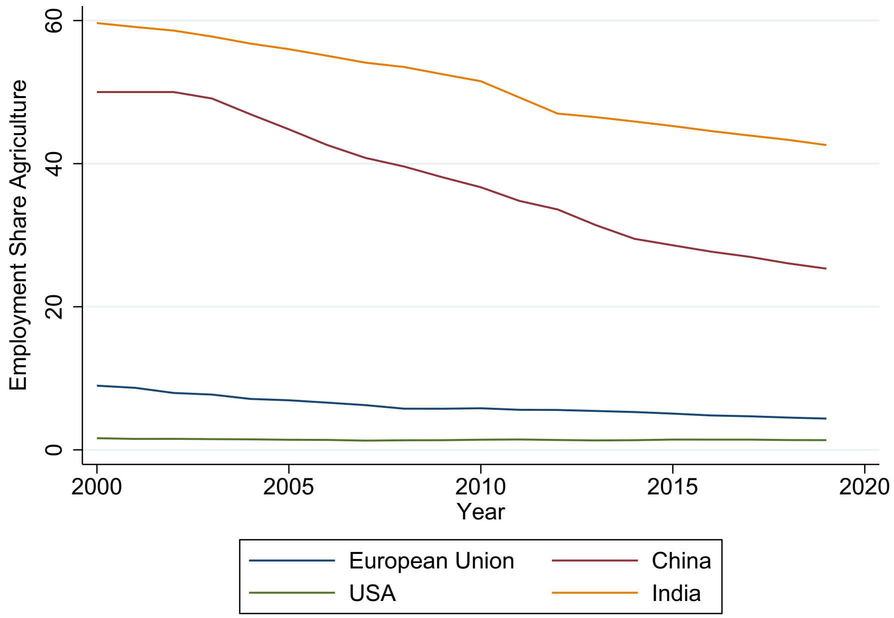

Fig. 5 Employment share agriculture by country. Data Source: https://data.worldbank.org

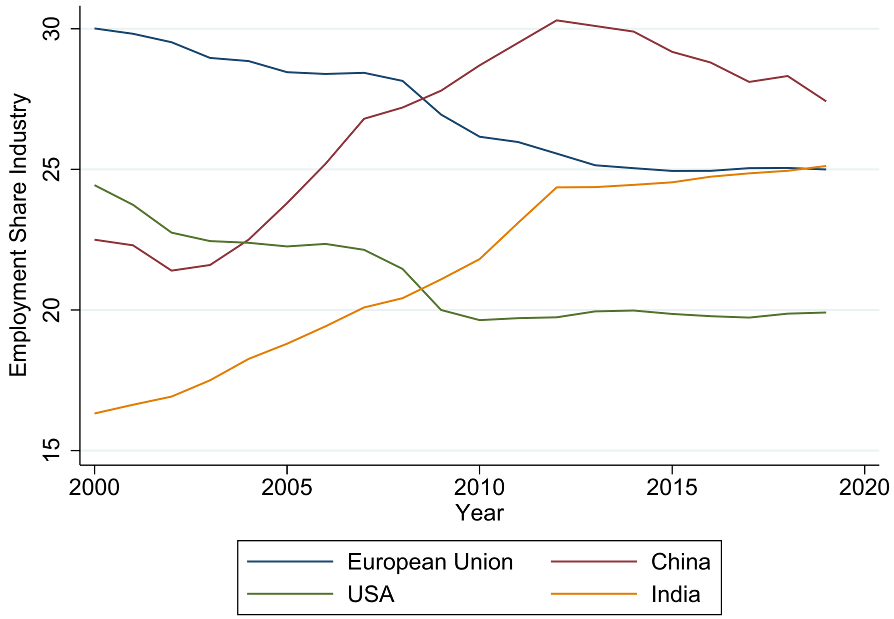

Fig. 6 Employment share industry by country. Data Source: https://data.worldbank.org

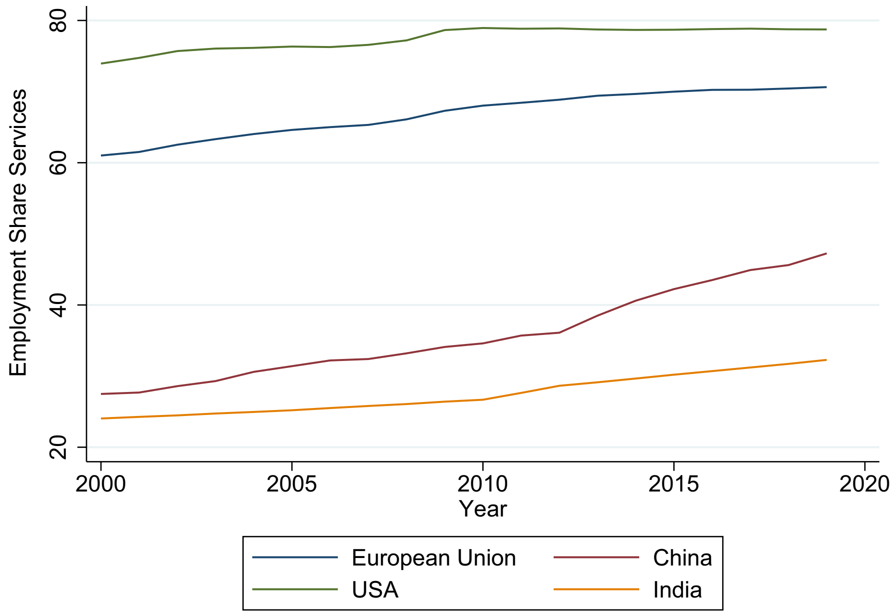

Fig. 7 Employment share services by country. Data Source: https://data.worldbank.org

(Figs. 5, 6 and 7). India may thus experience a form of development similar to the Lewis (1954) model, for which internal migration is a crucial component.

The paper is structured as follows. Section 2 describes our data set and presents descriptive statistics in the form of graphs. Section 3 presents the regression results. Section 4 concludes.

2 Data and Descriptive Statistics

We use individual-level survey data from the Employment and Unemployment Survey (EUS) by the National Sample Survey Office (NSSO) of India, rounds 60 (collected from January 2004 to June 2004), 62 (collected from July 2005 to June 2006), 64 (collected from July 2007 to June 2008), 66 (collected from July 2009 to June 2010), and 68 (latest available, collected from July 2011 to June 2012). Because round 60 was only collected during 6 instead of 12 months, we will check the sensitivity of our results with respect to exclusion or inclusion of round 60. Round 61 is excluded because our estimating equation will contain a lag structure and we want to maintain a similar (2-year) lag throughout the sample.

Using sampling weights, we build regional-level data (at the state/union territory or district level) for the population growth factor, the non-employment rate (1 minus the employment-population ratio), and the unemployment rate. In doing that, we only consider people of working age (15–64 years). Using sampling weights, we also generate the average wage per region as a proxy for earnings potential. Because

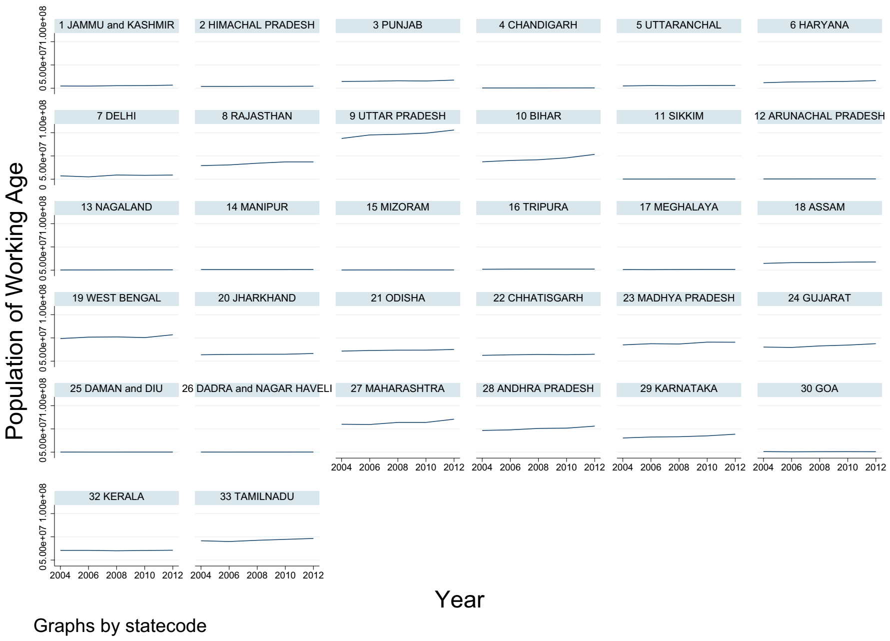

Fig. 8 Population by state. Data Source: EUS by NSSO, Rounds 60 and 62–68

we do not have information on hours of work, we only use full-time workers who usually work at least 5 days per week full-time.

We exclude the following small union territories: Andaman and Nicobar Islands, Lakshadweep (both islands), and Puducherry (set of geographically disconnected territories). Because of changes to districts and inconsistencies in the data, Delhi and Goa are treated as a single entity in the district data. The following districts are excluded due to lack of wage information: Lakhisarai (Bihar), Upper Siang (Arunachal Pradesh), and Tamenglong (Manipur). We also excluded Leh Ladakh, Kargil, and Punch (all in Jammu and Kashmir), because data for these districts are only available in round 68 (collected from July 2011 to June 2012) of the EUS survey. This leaves us with 32 states/union territories and 570 districts, which we observe bi-annually in 5 different years over a time period of about 8 years.[2]

The size of the population is heterogeneous across states and districts as exhibited in Figs. 8 and 9. Average wages increased in virtually all states after 2008 (Fig. 10). However, the increase in wages was also accompanied by regional diversion from 2008 to 2012, whereas there seems to have been regional wage conversion between

[2] District-level territorial reforms in the period under consideration were taken into account as follows: we used the districts from round 60 of the EUS-NSSO as a basis. In most cases, it was clear from which district the new district had been created and we assigned it to the original district. Exceptions are the district of Mewat (state: Haryana) and the district of Baksa (state: Assam), where the district of origin was not clearly identifiable. Here we have merged the new districts and all the original districts. A detailed list can be requested from the authors.

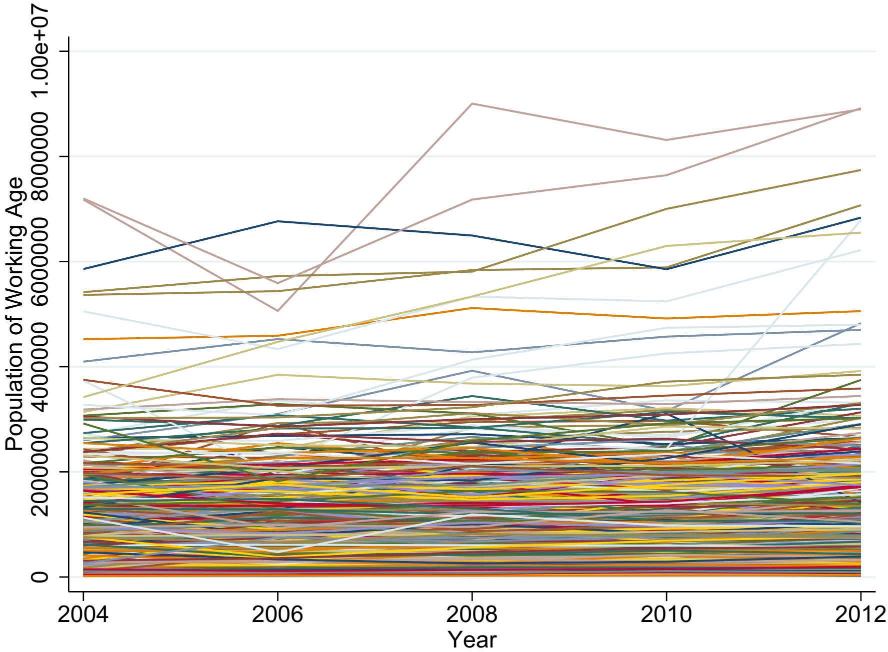

Fig. 9 Population by district. Data Source: EUS by NSSO, Rounds 60 and 62–68

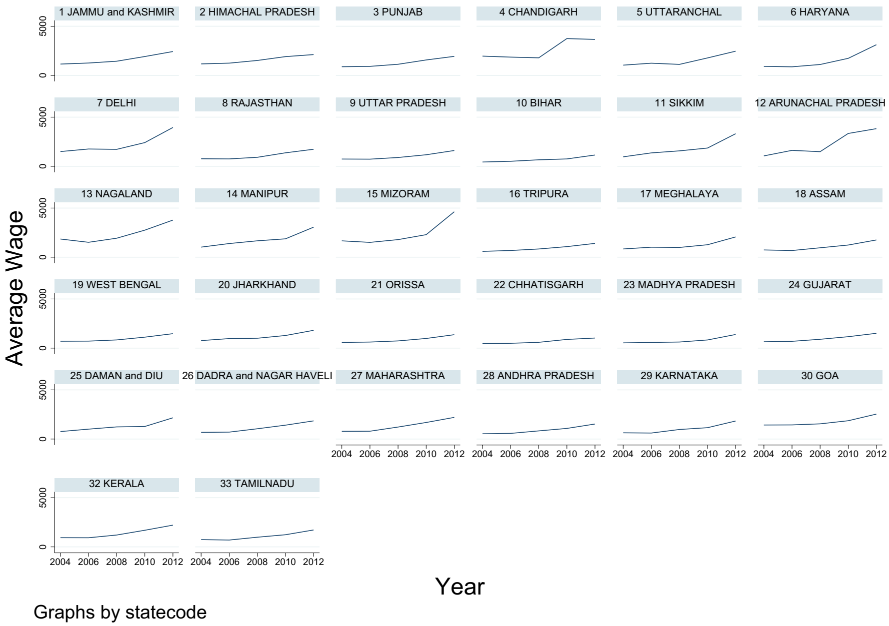

Fig. 10 Average wage by state. Data Source: EUS by NSSO, Rounds 60 and 62–68

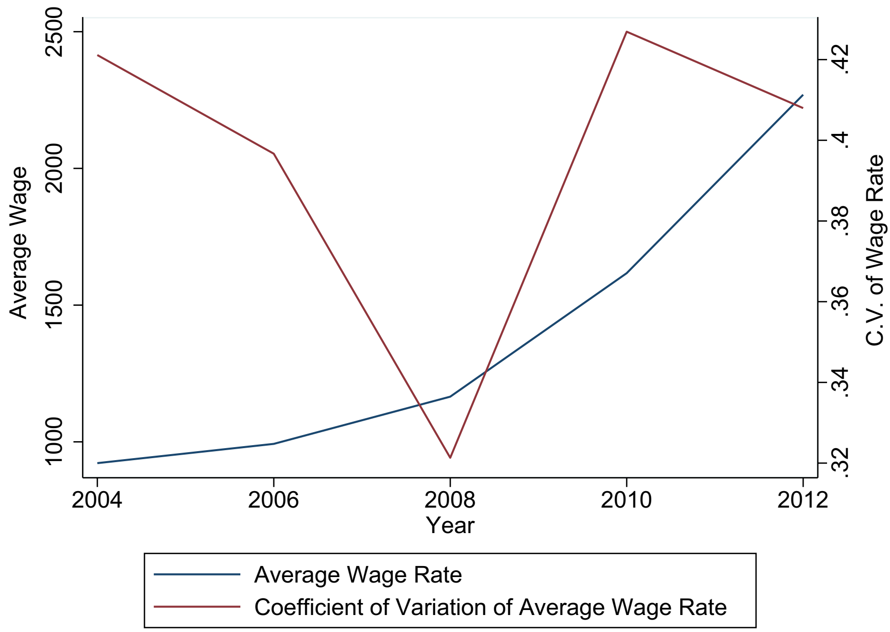

Fig. 11 Average wage and coefficient of variation of the average wage over states. Data Source: EUS by NSSO, Rounds 60 and 62–68

2004 and 2008, see the corresponding coefficients of variation in Fig. 11. When considering wages by district, there also seems to be increasing diversion together with wage increases after 2008 (even when ignoring the outlier, see Fig. 12 and the corresponding coefficients of variation in Fig. 13). Himanshu (2017) also reports a "rapid acceleration" of wages "during 2008–2013" (p. 309).

On the other hand, there seems to be a convergence in the non-employment rates by both states and districts, despite of rising non-employment rates (Figs. 14 and 15, for the corresponding coefficients of variation, see Figs. 16 and 17). The dispersion of the regional unemployment rate seems to move more erratically over time, especially when plotted by district (Figs. 18 and 19). There appears to be an increase in the dispersion when plotted by state (Fig. 18), but we consider the non-employment statistic to be more reliable than the unemployment statistic. Indeed, as Figs. 20 and 21 show, there is a clear increase in the non-employment rate over time (when averaged over states and districts), whereas there is no such clear trend for the unemployment rate.

3 Methodology and Results

Following Jauer et al. (2019), we estimate the following regression with the regional population growth factor on the left hand side and the region's ratio of its unemployment/non-employment rate (*ur*) to the national average as well as the ratio of the

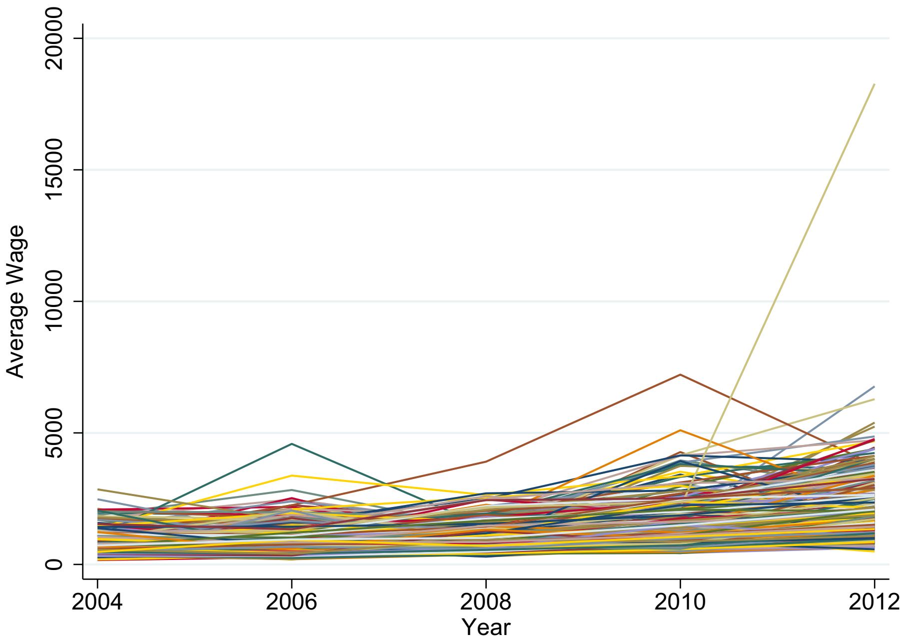

Fig. 12 Average wage by district. Data Source: EUS by NSSO, rounds 60 and 62–68

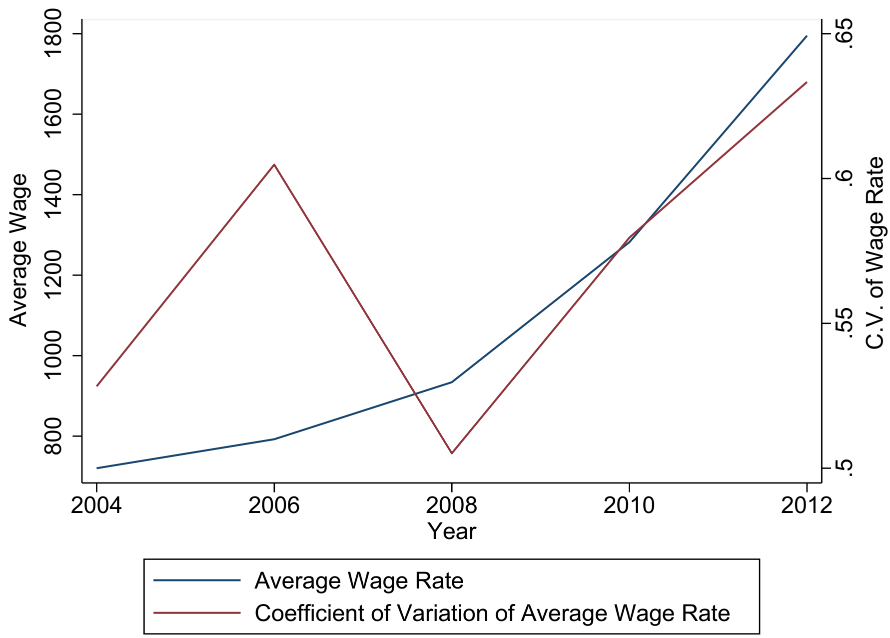

Fig. 13 Average wage and coefficient of variation of the average wage over districts. Data Source: EUS by NSSO, Rounds 60 and 62–68

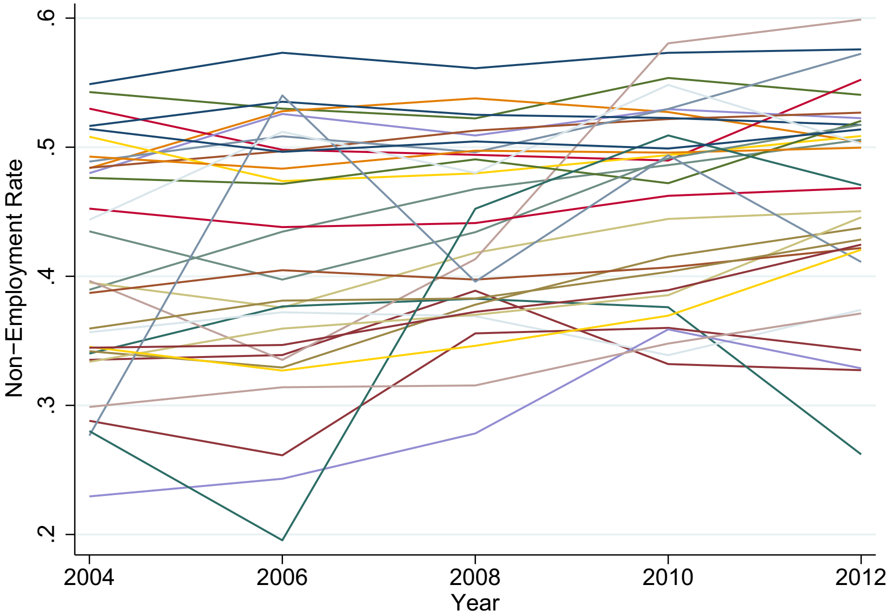

Fig. 14 Non-employment rate by state. Data Source: EUS by NSSO, Rounds 60 and 62–68

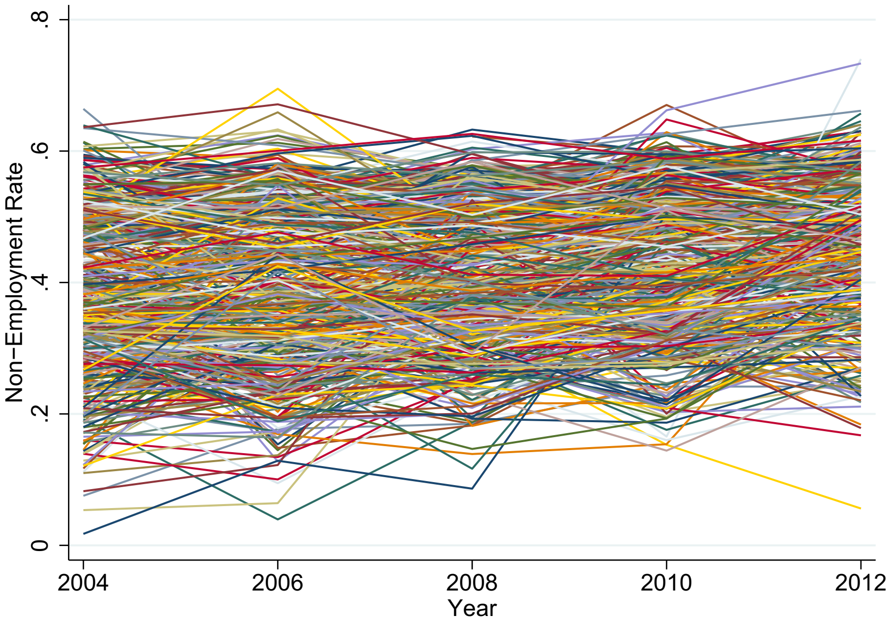

Fig. 15 Non-employment rate by district. Data Source: EUS by NSSO, Rounds 60 and 62–68

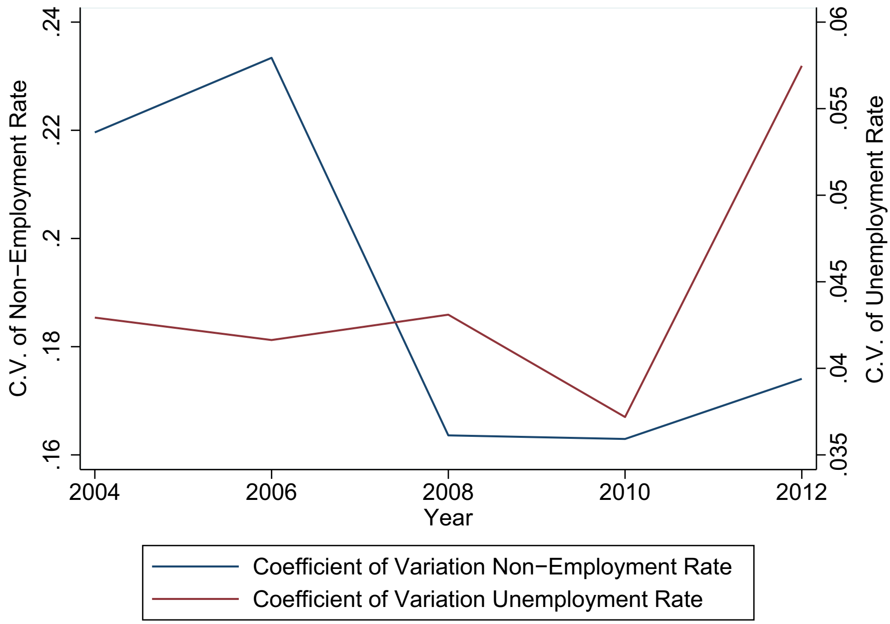

Fig. 16 Coefficient of variation of the non-employment and unemployment rates by states. Data Source: EUS by NSSO, Rounds 60 and 62–68

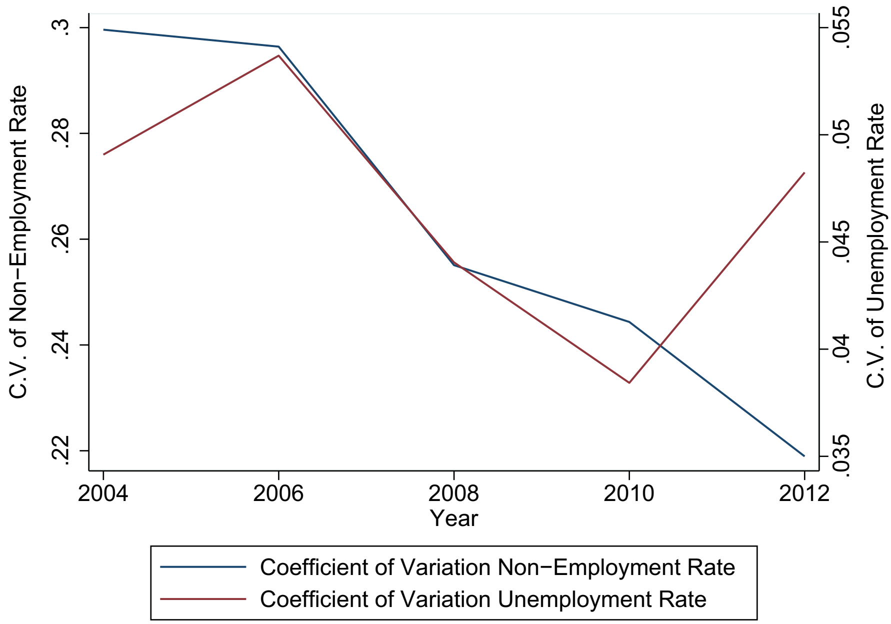

Fig. 17 Coefficient of variation of the non-employment and unemployment rates by districts. Data Source: EUS by NSSO, Rounds 60 and 62–68

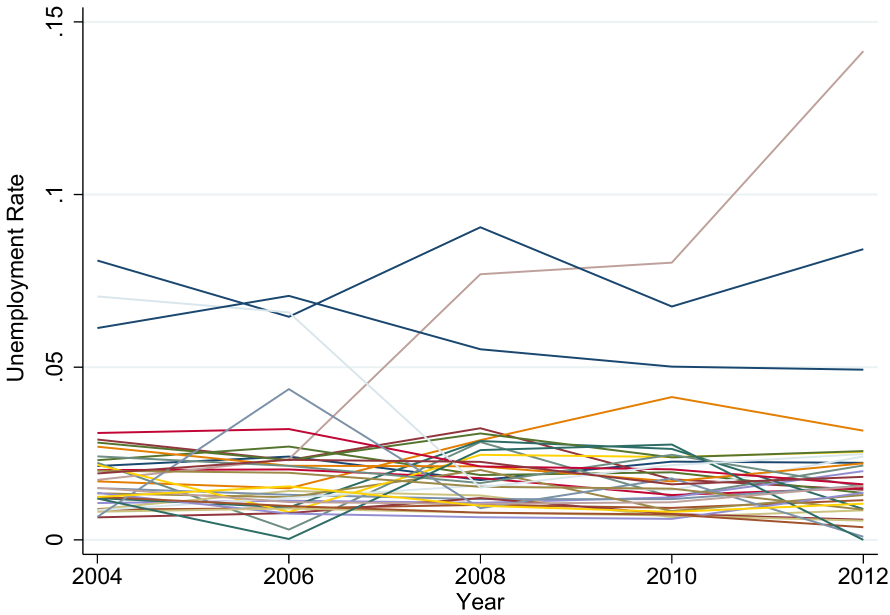

Fig. 18 Unemployment rate by state. Data Source: EUS by NSSO, Rounds 60 and 62–68

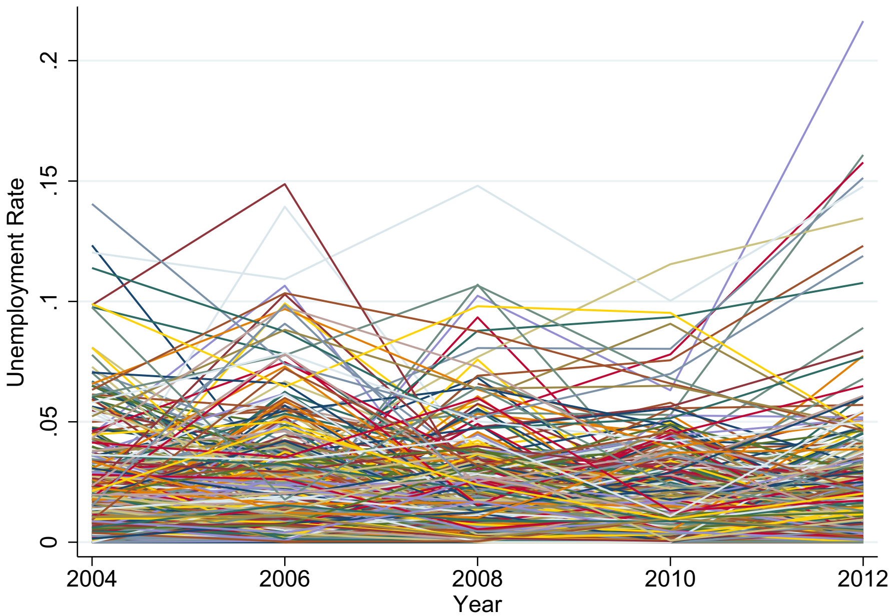

Fig. 19 Unemployment rate by district. Data Source: EUS by NSSO, Rounds 60 and 62–68

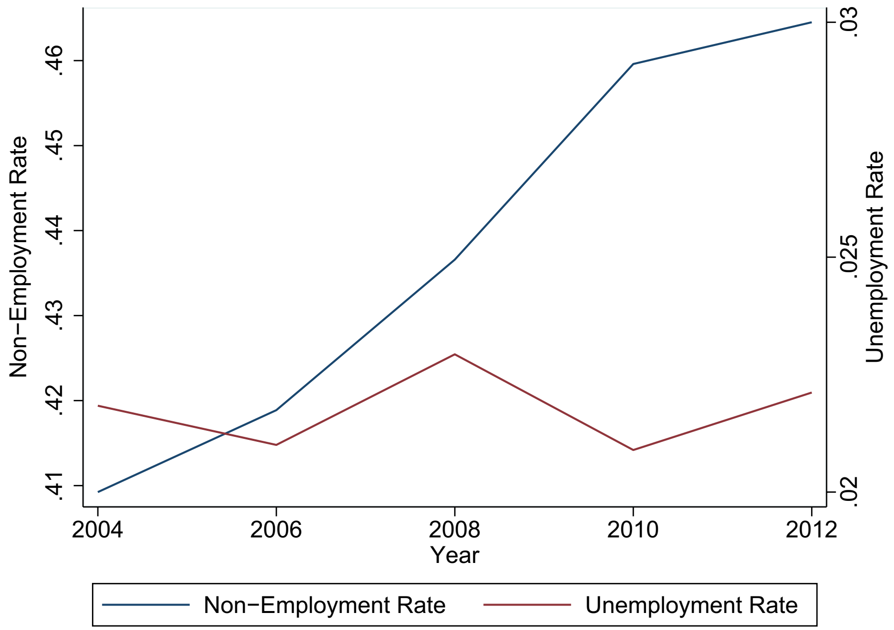

Fig. 20 Unemployment rate and non-employment rate averaged over states. Data Source: EUS by NSSO, Rounds 60 and 62–68

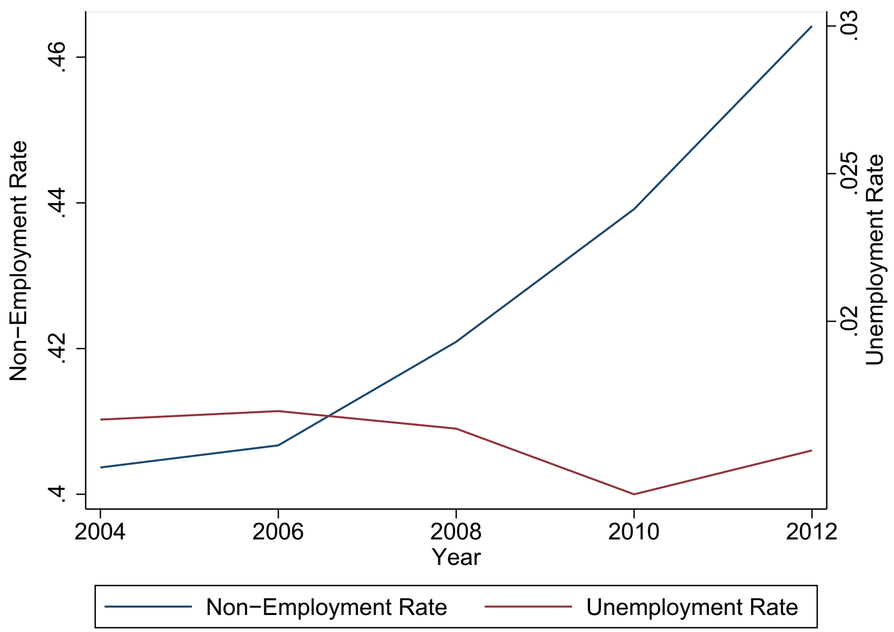

Fig. 21 Unemployment rate and non-employment rate averaged over districts. Data Source: EUS by NSSO, Rounds 60 and 62–68

region's wage rate (y) to the national average on the right hand side. The estimating equation is:

$$\ln\left(\frac{\text{pop}_{\text{it}}}{\text{pop}_{\text{it}-2}}\right) = \alpha_0 + \alpha_1 \ln\left(\frac{\text{ur}_{\text{it}-2}}{\text{ur}_{\text{nt}-2}}\right) + \ln\left(\frac{y_{\text{it}-2}}{y_{\text{nt}-2}}\right) + \eta_t + \mu_i + \varepsilon_{\text{it}} \tag{1}$$

Because we have bi-annual regional panel data, we include both region and time fixed effects (FE), μ_i and η_t, respectively. Because the national averages in the denominators on the right hand side are constant between regions, they are taken account of by the year fixed effects. If the region and time fixed effects take account of natural population growth, using the population growth factor on the left hand side—regression-adjusted by region and time effects—will effectively measure population change due to net migration.[3]

$$\begin{aligned}\ln\left(\frac{\text{pop}_{\text{it}}}{\text{pop}_{\text{it}-2}}\right) - \eta_t - \mu_i &= \ln\left(\frac{\Delta_{t-2}^{t}\text{pop}_{\text{it}} + \text{pop}_{\text{it}-2}}{\text{pop}_{\text{it}-2}}\right) - \eta_t - \mu_i \\ &\approx \ln\left(\frac{\text{mig}_{\text{it},t-2} + \text{pop}_{\text{it}-2}}{\text{pop}_{\text{it}-2}}\right)\end{aligned} \tag{2}$$

Under these assumptions, we follow Jauer et al. (2019) and interpret the coefficients on the unemployment/non-employment rate and on the wage as the reactions of net migration to regional labour market shocks. Because of the log–log specification, the coefficient on the wage can be interpreted as an elasticity. Similarly, the coefficient on the unemployment/non-employment rate is an elasticity, but here we are more interested in how much of an increase in non-employment in a region can possibly be adjusted by net migration (discussed below).

Table 1 shows ordinary least squares (OLS, first two columns, the latter restricted to the population up to age 50) and fixed-effects (FE, last two columns, the latter restricted to the population up to age 50) regression results at the state level. The upper panel of the table presents the specifications with lagged relative unemployment and the lower panel the specifications with lagged relative non-employment as measure of labour market tightness. Within these panels the upper (lower) block refers to rounds 62 (60) to 68 of the EUS, hence years 2005 (2004) to 2012. In the OLS results without region fixed effects, which exploit both within- and between-state variation in the impact variables, none of the unemployment, non-employment nor wage variables are statistically significant. Still, the coefficients have the expected signs.

[3] We have also experimented with proxying bi-annual natural population growth by adding the number of people aged 13 and 14 years of age and subtracting the number of people aged 63 and 64 years of age at the state and district level for the base year. Subtracting our natural population growth proxy from the observed population growth–and taking this difference as dependent variable–hardly makes any difference to our point estimates of the coefficients of the unemployment/non-employment rate or the wage rate in the fixed-effects regressions. This supports our working hypothesis that region and time fixed effects together act as an adequate control for natural population growth in our model during our observation period.

Table 1 Regressions at the state level

	OLS	OLS U50	FE	FE U50
Specifications with lagged relative unemployment				
Unemployment, rounds 62–68				
Log rel. unemp	− 0.011	− 0.010	0.008	0.013
(s.e.)	(0.010)	(0.011)	(0.020)	(0.019)
Log rel. wage	0.007	0.008	0.449***	0.502***
(s.e.)	(0.005)	(0.005)	(0.126)	(0.120)
Constant	0.072***	0.064***	− 0.412***	− 0.472***
(s.e.)	(0.021)	(0.022)	(0.139)	(0.131)
R2/R2 within	0.065	0.054	0.398	0.466
No. regions	32	32	32	32
No. observations	96	96	96	96
Unemployment, rounds 60–68				
Log rel. unemp	− 0.010	− 0.007	0.003	0.010
(s.e.)	(0.013)	(0.013)	(0.023)	(0.021)
Log rel. wage	0.003	0.003	0.456***	0.510***
(s.e.)	(0.005)	(0.005)	(0.099)	(0.101)
Constant	0.077***	0.070***	− 0.421***	− 0.482***
(s.e.)	(0.022)	(0.023)	(0.102)	(0.102)
R2/R2 within	0.059	0.041	0.349	0.400
No. regions	32	32	32	32
No. observations	128	128	128	128
Specifications with lagged relative non-employment				
Non-employment, rounds 62–68				
Log rel. non-emp	− 0.018	− 0.019	− 0.096	− 0.069
(s.e.)	(0.053)	(0.051)	(0.130)	(0.124)
Log rel. wage	0.007	0.008	0.441***	0.496***
(s.e.)	(0.005)	(0.006)	(0.131)	(0.124)
Constant	0.074***	0.066***	− 0.408***	− 0.471***
(s.e.)	(0.022)	(0.023)	(0.143)	(0.134)
R2/R2 within	0.058	0.049	0.406	0.465
No. regions	32	32	32	32
No. observations	96	96	96	96
Non-employment, rounds 60–68				
Log rel. non-emp	0.001	0.024	− 0.033	0.009
(s.e.)	(0.048)	(0.048)	(0.138)	(0.128)
Log rel. wage	0.003	0.003	0.456***	0.506***
(s.e.)	(0.005)	(0.006)	(0.101)	(0.103)
Constant	0.079***	0.073***	− 0.422***	− 0.478***
(s.e.)	(0.022)	(0.024)	(0.107)	(0.106)
R2/R2 within	0.054	0.041	0.350	0.398
No. regions	32	32	32	32
No. observations	128	128	128	128

Regressions are estimated by pooled ordinary least squares (OLS) and fixed effects (FE). U50 refers to a sub-sample not older than 50 years of age. Standard errors clustered at the state level appear in

Table 1 (continued) parentheses. All regressions include year fixed effects. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Data Source: Indian EUS-NSSO

In the fixed-effects regressions, the coefficients for state unemployment and non-employment are still statistically insignificant, but the wage rate is statistically significant. The interpretation for the FE coefficients in the third column of Table 1 is that a 1.0% increase in the wage of a region increases the population growth factor by approximately 0.45% (coefficients are rather similar across the panels in the third column). This estimate is larger than the estimates reported by Jauer et al. (2019) for the USW and the EU, which are statistically insignificant in many cases. However, these authors have a 1-year time lag. Hence, in order to produce comparable results for the US and the EU, in Appendix Table 7 we use the data of Jauer et al. (2019) and re-estimate their main models with a 2-year lag. Still, the wage effect estimates for the US and the EU remain smaller than the ones for India. When we add round 62 and the lagged variables from round 60 to the sample as a robustness check (the second blocks in the panels of Table 1), we mostly obtain similar results for both OLS and FE estimates.

Using Indian districts instead of states as units of analysis (Table 2), the coefficient of the non-employment rate becomes statistically significant, although the coefficient of the unemployment rate is still statistically insignificant with a point estimate close to zero. Again, results are qualitatively robust to the inclusion of round 62 and the lagged variables from round 60.

Results in general are also qualitatively and quantitatively similar when restricting the sample to the population up to age 50 (Table 1, columns 2 and 4 at the state level and Table 2 columns 2 and 4 at the district level), which might be more mobile. The coefficients are only a bit larger in most cases. This might be explained by India being a young country, so that the cohorts above age 50 are comparatively small, which lessens their influence on the estimates for the total working age population.[4]

How can we interpret the size of the estimate for the unemployment or non-employment rate? In order to simulate how much of an increase in non-employment in a region can possibly be adjusted by net migration, Tables 3 and 4 show what a one per cent increase in unemployment or non-employment amounts to in absolute numbers and set this in relation to the migration-induced population change of

[4] At the district level, we also conducted the analysis by gender. Results can be found in Appendix B, Tables 8 and 9. Again, only coefficients of the fixed-effects regressions for non-employment are significant. Comparing men and women, point estimates for women are somewhat lower in absolute terms than for men using the whole sample (Table 8), but for non-employment (but not for the wage) slightly larger when restricting the sample to the population up to age 50 (Table 9). In Appendix C, we also report separate estimates for population changes by social background, where disadvantaged "classes" (abbreviated OBC in the EUS-NSSO), "scheduled tribes" (ST) and "scheduled casts" (SC), again as defined in the EUS-NSSO, all together form the disadvantaged group, which amounts to about two thirds of the Indian population according to unweighted survey statistics, and "others", as defined in the EUS-NSSO, form the alternative group. The point estimates shown in Table 10 show that although both groups react to district non-employment and wage differentials, the point estimates for the disadvantaged groups are larger than for the "other" group.

Table 2 Regressions at the district level

	OLS	OLS U50	FE	FE U50
Specifications with lagged relative unemployment				
Unemployment, rounds 62–68				
Log rel. unemp	− 0.002	− 0.001	− 0.001	0.001
(s.e.)	(0.003)	(0.003)	(0.005)	(0.005)
Log rel. wage	0.013***	0.013***	0.229***	0.259***
(s.e.)	(0.004)	(0.004)	(0.022)	(0.022)
Constant	0.037***	0.029***	− 0.005	− 0.021**
(s.e.)	(0.008)	(0.008)	(0.008)	(0.008)
R2/R2 within	0.013	0.013	0.132	0.151
No. regions	570	570	570	570
No. observations	1590	1587	1590	1587
Unemployment, rounds 60–68				
Log rel. unemp	− 0.004	− 0.003	− 0.002	0.001
(s.e.)	(0.003)	(0.003)	(0.004)	(0.005)
Log rel. wage	0.026***	0.027***	0.351***	0.373***
(s.e.)	(0.006)	(0.006)	(0.035)	(0.036)
Constant	0.049***	0.057***	− 0.034***	− 0.027**
(s.e.)	(0.014)	(0.015)	(0.011)	(0.011)
R2/R2 within	0.024	0.025	0.252	0.266
No. regions	570	570	570	570
No. observations	2081	2078	2081	2078
Specifications with lagged relative non-employment				
Non-employment, rounds 62–68				
Log rel. non-emp	− 0.019	− 0.025*	− 0.126***	− 0.138***
(s.e.)	(0.014)	(0.015)	(0.030)	(0.032)
Log rel. wage	0.014***	0.014***	0.235***	0.266***
(s.e.)	(0.004)	(0.004)	(0.022)	(0.023)
Constant	0.039***	0.028***	− 0.024***	− 0.042***
(s.e.)	(0.008)	(0.008)	(0.009)	(0.009)
R2/R2 within	0.016	0.015	0.151	0.169
No. regions	570	570	570	570
No. observations	1708	1707	1708	1707
Non-employment, rounds 60–68				
Log rel. non-emp	− 0.021	− 0.020	− 0.162***	− 0.153***
(s.e.)	(0.017)	(0.017)	(0.026)	(0.026)
Log rel. wage	0.028***	0.029***	0.360***	0.388***
(s.e.)	(0.006)	(0.006)	(0.031)	(0.033)
Constant	0.064***	0.070***	− 0.049***	− 0.048***
(s.e.)	(0.014)	(0.014)	(0.012)	(0.012)
R2/R2 within	0.031	0.032	0.271	0.292
No. regions	570	570	570	570
No. observations	2273	2272	2273	2272

Regressions are estimated by pooled ordinary least squares (OLS) and fixed effects (FE). U50 refers to a sub-sample not older than 50 years of age. Standard errors clustered at the district level appear in paren-

Table 2 (continued) theses. All regressions include year fixed effects. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Data Source: Indian EUS-NSSO

α_1 per cent. The inverse ratio between these two is the fraction of the unemployment or non-employment change that can at most be adjusted by migration (population change). This upper bound would only be reached if all migration (population change) were labour market related and actually offset the asymmetric shock. Tables 5 and 6 present the corresponding results for the US and the EU based on the data used in Jauer et al. (2019), but with a 2-year lag structure, as we have in the data for India. The regression results on which these simulations are based are reported in Table 7.

In Table 3, which reports simulations at the state level, none of the coefficients underlying the simulations is statistically significant and the simulated per cent of the shock adjusted due to migration changes sign. However, when considering the district level, the simulated adjustments based on the statistically significant coefficients, which are exclusively the coefficients of non-employment, are consistently between 28 per cent and 37 per cent. When comparing the results for India with those for the US and the EU in Tables 5 and 6, we make two key observations. First, whereas none of the estimates at the state level are statistically significant for India, for the US and Europe, all the estimates both at the state/NUTS-1 and the district level are statistically significant and the adjustments are of similar size, even larger at the state than at the district level. This is consistent with limited adjustment to non-employment disparities across state boundaries in India when compared to the US and the EU. Second, whereas we only observe an adjustment to non-employment, but not to unemployment disparities in India, in the US and in Europe, the adjustment is larger with respect to unemployment than with respect to non-employment.

4 Conclusion

In this paper, we have used the EUS-NSSO data to create regional panel data sets for both Indian states and districts. Based on this panel, we have estimated how the population in these regions adjusts to asymmetric labour market shocks within a 2-year time period. These asymmetric labour market shocks have been proxied from the same data source using the average wage and unemployment or non-employment rate in the state or district, lagged by 2 years.

Based on fixed-effects models, we find that Indian workers migrate (proxied by regression-adjusted population change) in response to wage and non-employment shocks. However, the unemployment rate does not seem to be a very reliable statistic in this context. When compared with results applying the same methodology using data for the US and the EU for a similar time period (Jauer et al. 2019), we find no significant response of Indian workers to non-employment disparities across Indian states, but only to Indian districts, whereas the response to disparities is similar across states/NUTS-1 regions and districts in the US and in Europe.

Table 3 Simulated unemployment/non-employment adjustment due to migration at the state level (based on fixed-effect estimates)

Specification	Coefficient	Standard Error	Average number of unemp./non-emp.	Average population	1 % Change in unemp./non-emp.	Migration induced pop. change	UE/NON-E Adj. due to mig. (%)
Unemployment							
Rounds 60–68	(0.003)	0.023	319,437	20,416,288	3194	(− 524)	(− 16)
Rounds 60–68, U50	(0.010)	0.021	314,671	17,721,014	3147	(− 1711)	(− 54)
Rounds 62–68	(0.008)	0.020	312,383	20,877,478	3124	(− 1745)	(− 56)
Rounds 62–68, U50	(0.013)	0.019	308,319	18,084,318	3083	(− 2424)	(− 79)
Non-employment							
Rounds 60–68	(− 0.033)	0.138	9,073,555	20,416,288	90,736	(6649)	(7)
Rounds, 60–68, U50	(0.009)	0.128	8,017,520	17,721,014	80,175	(− 1611)	(− 2)
Rounds 62–68	(− 0.096)	0.130	9,426,386	20,877,478	94,264	(19,997)	(21)
Rounds 62–68, U50	(− 0.069)	0.124	8,319,259	18,084,318	83,193	(12,462)	(15)

The rows contain results based on regressions using either the unemployment (Unemp., UE) or non-employment (non-emp., NON-E) rate as explanatory variable. Rounds 60–68 and Rounds 62–68 stand for results based on using the EUS-NSSO rounds 60–68 and 62–68, respectively (including lagged variables). U50 refers to samples of individuals aged 15–50, whereas the default sample uses the working-age population aged 15–64. Because none of the coefficients is significant, the simulated changes/adjustments appear in parentheses. Data Source: EUS-NSSO

Table 4 Simulated unemployment/non-employment adjustment due to migration at the district level (based on fixed-effect estimates)

Specification	Coefficient	Standard error	Average number of unemp./non-emp.	Average population	1 % Change in unemp./non-emp.	Migration induced pop. change	UE/NON-E adj. due to mig. (%)
Unemployment							
Rounds 60–68	(− 0.002)	0.004	19,102	1,190,959	191	(29)	(15)
Rounds 60–68, U50	(0.001)	0.005	18,844	1,033,651	188	(− 11)	(− 6)
Rounds 62–68	(− 0.001)	0.005	18,361	1,201,157	184	(14)	(7)
Rounds 62–68, U50	(0.001)	0.005	18,145	1,040,755	181	(− 10)	(− 5)
Non-employment							
Rounds 60–68	− 0.162	0.026	510,440	1,148,707	5104	1864	37
Rounds 60–68, U50	− 0.153	0.026	451,154	997,302	4512	1527	34
Rounds 62–68	− 0.126	0.030	529,332	1,172,602	5293	1482	28
Rounds 62–68, U50	− 0.138	0.032	467,347	1,016,076	4673	1400	30

The rows contain results based on regressions using either the unemployment (Unemp., UE) or non-employment (non-emp., NON-E) rate as explanatory variable. Rounds 60–68 and Rounds 62–68 stand for results based on using the EUS-NSSO rounds 60–68 and 62–68, respectively (including lagged variables). U50 refers to samples of individuals aged 15–50, whereas the default sample uses the working-age population aged 15–64. Results based on insignificant coefficients are presented in parentheses. Data Source: EUS-NSSO

Table 5 Simulated unemployment/non-employment adjustment due to migration at the district level (based on fixed-effect estimates), EU-27, Eurozone, and USA, larger regions 2006–2016

Specification	Coefficient	Average number of unemp./non-emp.	Average population	1 % Change in unemp./non-emp.	Migration induced pop. change	UE/NON-E adj. due to mig. (%)
Unemployment						
EU-27/EFTA NUTS-1	− 0.030	222,675	3,423,717	2227	1027	46
Eurozone NUTS-1	− 0.028	253,040	3,512,915	2530	984	39
USA States	− 0.021	242,253	4,034,056	2423	847	35
Non-employment						
EU-27/EFTA NUTS-1	− 0.058	1,383,131	4,091,638	13,831	2373	17
Eurozone NUTS-1	− 0.095	1,199,681	3,492,804	11,997	3318	28
USA States	− 0.077	1,358,869	4,034,056	13,589	3095	23

The rows contain results based on regressions using either the unemployment (Unemp., UE) or non-employment (non-emp., NON-E) rate as explanatory variable. All coefficients presented in this table are statistically significant. Data Source: European Labour Force Survey, Eurostat Regional Database, American Community Survey

Table 6 Simulated unemployment/non-employment adjustment due to migration at the district level (based on fixed-effect estimates), EU-27, Eurozone, and USA, smaller regions 2006–2016

Specification	Coefficient	Average number of unemp./non-emp.	Average population	1 % Change in unemp./non-emp.	Migration induced pop. change	UE/NON-E adj. due to mig. (%)
Unemployment						
EU-27/EFTA NUTS-2	– 0.027	83,125	1,277,951	831	345	42
Eurozone NUTS-2	– 0.026	92,067	1,277,911	921	332	36
USA SuperPUMA	– 0.015	53,717	907,276	537	136	25
Non-employment						
EU-27/EFTA NUTS-2	– 0.096	427,119	1,274,914	4271	1224	29
Eurozone NUTS-2	– 0.088	437,531	1,273,134	4375	1120	26
USA SuperPUMA	– 0.034	306,694	907,276	3067	308	10

The rows contain results based on regressions using either the unemployment (Unemp., UE) or non-employment (non-emp., NON-E) rate as explanatory variable. All coefficients presented in this table are statistically significant

Data Source: European Labour Force Survey, Eurostat Regional Database, American Community Survey

Appendix A

See Table 7.

Table 7 Unemployment, non-employment, and population change, EU-27, Eurozone, and the US, 2006–2016

	OLS EU-27/EFTA	OLS Eurozone	OLS USA	FE EU-27/EFTA	FE Eurozone	FE USA
Specifications with lagged relative unemployment						
NUTS-1/states						
Log rel. unemp	− 0.010***	− 0.011**	− 0.005	− 0.030***	− 0.028***	− 0.021***
(s.e.)	(0.003)	(0.005)	(0.007)	(0.003)	(0.004)	(0.007)
Log rel. income	0.013***	0.010	0.021***	− 0.017**	0.036*	0.023
(s.e.)	(0.002)	(0.007)	(0.007)	(0.009)	(0.021)	(0.014)
R2/R2 within	0.200	0.124	0.430	0.162	0.195	0.559
No. regions	98	61	51	98	61	51
No. time periods	11	11	11	11	11	11
No. observations	1’068	661	510	1’068	661	510
NUTS-2/SuperPUMA						
Log rel. unemp	− 0.005**	− 0.006**	− 0.007**	− 0.027***	− 0.026***	− 0.015***
(s.e.)	(0.002)	(0.003)	(0.003)	(0.002)	(0.002)	(0.005)
Log rel. income	0.012***	0.006	0.010	− 0.025***	0.014	0.005
(s.e.)	(0.001)	(0.004)	(0.007)	(0.006)	(0.010)	(0.016)
R2/R2 within	0.144	0.102	0.170	0.125	0.195	0.214
No. regions	263	168	230	263	168	230
No. time periods	11	11	11	11	11	11
No. observations	2’856	1’813	2’300	2’856	1’813	2’300
Specifications with lagged relative non-employment						
NUTS-1/states						
Log rel. non-emp	− 0.001	0.001	0.012	− 0.109***	− 0.095***	− 0.058**
(s.e.)	(0.003)	(0.007)	(0.008)	(0.012)	(0.016)	(0.023)
Log rel. income	0.008***	0.016***	0.019***	− 0.013	0.043**	0.036***
(s.e.)	(0.001)	(0.002)	(0.006)	(0.009)	(0.021)	(0.013)
R2/R2 within	0.177	0.102	0.432	0.162	0.186	0.556
No. regions	98	61	51	98	61	51
No. time periods	11	11	11	11	11	11
No. observations	1’072	665	510	1’072	665	510
NUTS-2/SuperPUMA						
Log rel. non-emp	0.000	0.008	− 0.000	− 0.096***	− 0.088***	− 0.034**
(s.e.)	(0.005)	(0.006)	(0.007)	(0.008)	(0.009)	(0.015)
Log rel. income	0.014***	0.013***	0.011*	− 0.020***	0.018*	0.014
(s.e.)	(0.002)	(0.004)	(0.006)	(0.006)	(0.009)	(0.016)
R2/R2 within	0.135	0.090	0.165	0.119	0.167	0.212
No. regions	263	168	230	263	168	230
No. time periods	11	11	11	11	11	11
No. observations	2’864	1’821	2’300	2’864	1’821	2’300

Pooled ordinary least squares (OLS) and region fixed effects (FE) regressions. Standard errors clustered at the regional level appear in parentheses. All regressions include year fixed effects. $^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Source: European Labour Force Survey, Eurostat Regional Database, American Community Survey

Appendix B

See Tables 8 and 9.

Table 8 Regressions at the district level by gender

	OLS (w)	OLS (m)	FE (w)	FE (m)
Specifications with lagged relative unemployment				
Unemployment, rounds 62–68				
Log rel. unemp	− 0.001	− 0.001	− 0.002	0.000
(s.e.)	(0.002)	(0.002)	(0.003)	(0.003)
Log rel. wage	0.006***	0.007***	0.098***	0.135***
(s.e.)	(0.002)	(0.002)	(0.012)	(0.013)
Constant	0.028***	0.016***	0.009*	− 0.008*
(s.e.)	(0.005)	(0.005)	(0.004)	(0.005)
R2/R2 within	0.016	0.012	0.094	0.129
No. regions	570	570	570	570
No. observations	1590	1590	1590	1590
Unemployment, rounds 60–68				
Log rel. unemp	− 0.002	− 0.002	− 0.000	− 0.000
(s.e.)	(0.002)	(0.002)	(0.003)	(0.003)
Log rel. wage	0.015***	0.016***	0.187***	0.208***
(s.e.)	(0.004)	(0.004)	(0.028)	(0.027)
Constant	0.034***	0.037***	− 0.009	− 0.012*
(s.e.)	(0.008)	(0.008)	(0.006)	(0.006)
R2/R2 within	0.028	0.028	0.231	0.248
No. regions	570	570	570	570
No. observations	2081	2081	2081	2081
Specifications with lagged relative non-employment				
Non-employment, rounds 62–68				
Log rel. non-emp	− 0.007	− 0.011	− 0.057***	− 0.070***
(s.e.)	(0.008)	(0.008)	(0.016)	(0.018)
Log rel. wage	0.008***	0.007***	0.105***	0.134***
(s.e.)	(0.002)	(0.002)	(0.012)	(0.013)
Constant	0.029***	0.017***	0.001	− 0.019***
(s.e.)	(0.004)	(0.005)	(0.005)	(0.005)
R2/R2 within	0.020	0.012	0.114	0.136
No. regions	1708	1708	1708	1708
No. observations	570	570	570	570
Non-employment, rounds 60–68				
Log rel. non-emp	− 0.008	− 0.008	− 0.082***	− 0.085***
(s.e.)	(0.010)	(0.010)	(0.017)	(0.015)
Log rel. wage	0.017***	0.018***	0.197***	0.211***
(s.e.)	(0.004)	(0.004)	(0.024)	(0.024)
Constant	0.041***	0.048***	− 0.020***	− 0.017**
(s.e.)	(0.008)	(0.008)	(0.007)	(0.007)
R2/R2 within	0.037	0.036	0.254	0.258
No. regions	570	570	570	570
No. observations	2273	2273	2273	2273

Regressions are estimated by pooled ordinary least squares (OLS) and fixed effects (FE). (w) and (m) denote the female and male population, respectively. Standard errors clustered at the district level appear in parentheses. All regressions include year fixed effects. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Data Source: Indian EUS-NSSO

Table 9 Regressions at the district level by gender, working age population younger than 50

	OLS (w)	OLS (m)	FE (w)	FE (m)
Specifications with lagged relative unemployment				
Unemployment, rounds 62–68				
Log rel. unemp	− 0.001	− 0.001	− 0.001	0.002
(s.e.)	(0.002)	(0.002)	(0.003)	(0.003)
Log rel. wage	0.007***	0.008***	0.110***	0.155***
(s.e.)	(0.002)	(0.002)	(0.012)	(0.013)
Constant	0.024***	0.011**	0.002	− 0.018***
(s.e.)	(0.005)	(0.005)	(0.005)	(0.005)
R2/R2 within	0.013	0.014	0.102	0.150
No. regions	570	570	570	570
No. observations	1587	1587	1587	1587
Unemployment, rounds 60–68				
Log rel. unemp	− 0.001	− 0.001	0.001	0.002
(s.e.)	(0.002)	(0.002)	(0.003)	(0.003)
Log rel. wage	0.016***	0.017***	0.198***	0.222***
(s.e.)	(0.004)	(0.004)	(0.030)	(0.028)
Constant	0.040***	0.041***	− 0.004	− 0.009
(s.e.)	(0.009)	(0.009)	(0.006)	(0.006)
R2/R2 within	0.029	0.030	0.237	0.261
No. regions	570	570	570	570
No. observations	2078	2078	2078	2078
Specifications with lagged relative non-employment				
Non-employment, rounds 62–68				
Log rel. non-emp	− 0.012	− 0.013	− 0.070***	− 0.069***
(s.e.)	(0.008)	(0.009)	(0.017)	(0.019)
Log rel. wage	0.008***	0.008***	0.118***	0.154***
(s.e.)	(0.002)	(0.003)	(0.012)	(0.014)
Constant	0.025***	0.011**	− 0.007	− 0.029***
(s.e.)	(0.005)	(0.005)	(0.005)	(0.005)
R2/R2 within	0.017	0.014	0.127	0.154
No. regions	570	570	570	570
No. observations	1707	1707	1707	1707
Non-employment, rounds 60–68				
Log rel. non-emp	− 0.009	− 0.007	− 0.080***	− 0.078***
(s.e.)	(0.010)	(0.010)	(0.017)	(0.015)
Log rel. wage	0.018***	0.018***	0.213***	0.228***
(s.e.)	(0.004)	(0.004)	(0.027)	(0.025)
Constant	0.045***	0.051***	− 0.019**	− 0.018**
(s.e.)	(0.008)	(0.008)	(0.007)	(0.007)
R2/R2 within	0.037	0.037	0.272	0.278
No. regions	570	570	570	570
No. observations	2272	2272	2272	2272

Regressions are estimated by pooled ordinary least squares (OLS) and fixed effects (FE). (w) and (m) denote the female and male population, respectively. Standard errors clustered at the district level appear in parentheses. All regressions include year fixed effects. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Data Source: Indian EUS-NSSO

Appendix C

See Table 10.

Table 10 Regressions at the district level for (1) "Others" and (2) "Disadvantaged groups"

	OLS (1)	OLS (2)	FE (1)	FE (2)
Specifications with lagged relative unemployment				
Unemployment, rounds 62–68				
Log rel. unemp	0.019***	− 0.017***	0.001	− 0.003
(s.e.)	(0.003)	(0.003)	(0.002)	(0.003)
Log rel. wage	− 0.002	0.005	0.038***	0.103***
(s.e.)	(0.004)	(0.004)	(0.009)	(0.011)
Constant	0.259***	0.540***	0.240***	0.537***
(s.e.)	(0.008)	(0.007)	(0.003)	(0.004)
R2/R2 within	0.026	0.027	0.020	0.109
No. regions	565	565	565	565
No. observations	1548	1548	1548	1548
Unemployment, rounds 60–68				
Log rel. unemp	0.021***	− 0.020***	0.002	− 0.004*
(s.e.)	(0.003)	(0.002)	(0.002)	(0.002)
Log rel. wage	− 0.001	0.010**	0.055***	0.156***
(s.e.)	(0.004)	(0.004)	(0.009)	(0.019)
Constant	0.261***	0.537***	0.239***	0.534***
(s.e.)	(0.008)	(0.007)	(0.003)	(0.004)
R2/R2 within	0.029	0.031	0.042	0.190
No. regions	566	566	566	566
No. observations	2016	2016	2016	2016
Specifications with lagged relative non-employment				
Non-employment, rounds 62–68				
Log rel. non-emp	0.145***	− 0.118***	− 0.035***	− 0.045***
(s.e.)	(0.012)	(0.011)	(0.011)	(0.016)
Log rel. wage	0.001	0.003	0.040***	0.103***
(s.e.)	(0.004)	(0.004)	(0.008)	(0.012)
Constant	0.257***	0.545***	0.232***	0.535***
(s.e.)	(0.007)	(0.007)	(0.003)	(0.004)
R2/R2 within	0.073	0.062	0.030	0.113
No. regions	566	566	566	566
No. observations	1660	1660	1660	1660
Non-employment, rounds 60–68				
Log rel. non-emp	0.132***	− 0.116***	− 0.042***	− 0.069***
(s.e.)	(0.011)	(0.012)	(0.013)	(0.016)
Log rel. wage	0.006	0.008**	0.067***	0.164***
(s.e.)	(0.004)	(0.004)	(0.011)	(0.018)
Constant	0.256***	0.544***	0.228***	0.525***
(s.e.)	(0.007)	(0.007)	(0.004)	(0.005)
R2/R2 within	0.064	0.055	0.068	0.205
No. regions	567	567	567	567
No. observations	2194	2194	2194	2194

Table 10 (continued)

Regressions are estimated by pooled ordinary least squares (OLS) and fixed effects (FE). (1) denotes "Others" and (2) denotes the disadvantaged groups as defined by the EUS-NSSO data ("ST", "SC", "OBC"). Standard errors clustered at the district level appear in parentheses. All regressions include year fixed effects. ***, ** and * denote significance at the 1%, 5% and 10% level, respectively. Data Source: Indian EUS-NSSO

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