Wages Over the Course of Structural Transformation: Evidence from India

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This paper uses labor force survey data from India for 2000 and 2012 to examine how wages behave over the course of structural transformation. We find that wage employment between 2000 and 2012 displays the patterns one would expect for an economy undergoing structural transformation, with employment shares shifting from agriculture to industry and services, and from rural to urban areas and larger cities within urban areas. These shifts, as well as a shift to nonroutine occupations and routine manual occupations outside of agriculture, are associated with an improvement in average wages. Finally, simple Mincerian wage regressions confirm that jobs in larger firms and big cities are associated with significantly higher wages—even more so for women. Overall, our results are consistent with the notion that policies that encourage the expansion of the formal sector and employment in larger firms are crucial for development.

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I. Introduction

There is a large empirical literature on structural transformation that documents and analyzes the shift of output and employment across sectors. (See Asian Development Bank [ADB] 2013 for a comprehensive survey and analysis for Asia and the Pacific.) By and large, the shift takes place from lower to higher productivity sectors and locations over the course of development. This is what McMillan, Rodrik, and Verduzco-Gallo (2014) find for Asia, for example, in contrast to Africa and Latin America. On average, labor productivity in the region increased 3.87% from 1990 to 2005, of which 3.31% of the growth was registered by "within" sector improvements in labor productivity and 0.57% by shifts in employment shares from lower to higher productivity sectors (called "structural change" by the authors). In the case of India, the labor productivity growth figures

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are 4.23% for the overall economy and 3.24% and 0.99% for the within and structural change components, respectively. In contrast, labor productivity growth in Africa and Latin America has been associated with negative contributions from the structural change component (in addition to being relatively low compared with Asia).

What is rarer in the literature is an examination of how wages behave over the course of structural transformation and its various component processes. An exception is analysis of the significant wage gaps that exist between agriculture and other sectors. Several studies, including recent ones such as Alvarez (2017) and Herrendorf and Schoellman (2017), examine these gaps and attempt to determine whether they can be explained by barriers to mobility across sectors or whether unobserved worker characteristics (e.g., innate capabilities that enable some individuals to benefit more from schooling) lead to a systematic sorting of workers, with the more capable finding employment outside of agriculture.

In this paper, we take a step back and use labor force survey data from India to examine how wages behave over the course of structural transformation, especially in terms of its less studied aspects. Specifically, we first examine how wages and employment have evolved not only across production sectors, but also in terms of shifts across occupation groups and from rural to urban areas, distinguishing the latter in terms of whether urban areas take the form of large cities (population of 1 million or more in the first year of our analysis) or smaller cities and towns. We then use a standard decomposition that describes how important such shifts have been in driving average wages in the economy. We also examine employment shifts and wages across firms with fewer than 10 workers and those with 10 or more workers. We call the former small firms and treat them as synonymous with operations in the informal sector; the remaining firms are called large. In keeping with practice in Indian manufacturing where firms with 10 or more workers (and those using power in the production process) must be registered under the Factories Act, we treat these large firms as belonging to the formal sector.[1] Finally, we use simple Mincerian wage regressions to examine the relationship between wages and the more novel elements of structural transformation we examine—i.e., employment in larger firms and cities—while controlling for individual characteristics, sector, and occupation.

Our work adds to the standard macro analysis of structural transformation in two ways. First, rather than examine the evolution of productivity over the course of structural transformation, we consider the evolution of wages. Though intimately related, arguably it is wages that are more directly linked to individual welfare than productivity. Second, we extend the usual analysis of shifts in the sector of employment to also consider the role of shifts in occupation and rural–urban location, and to a more limited extent the role of small firms versus larger firms, in

[1]Unfortunately, and as explained later, data gaps prevent us from understanding the role large firms have actually played in driving average wages in India from 2000 to 2012.

driving average wages. In doing so, we are able to consider the role of occupational changes and urban agglomerations—factors that the recent literature on growth and development has been paying much attention to. As Duernecker and Herrendorf (2017) note, occupations play an important role in the behavior of key labor market outcomes such as worker mobility and job polarization. They are also not affected by a "relabeling" of employment as certain types of work get outsourced from manufacturing firms to arm's-length service providers. Similarly, cities are often viewed as engines of growth. As Henderson (2014) notes, this is because the reallocation of employment from agriculture into industry, in particular, takes place most effectively in cities given agglomeration economies. These additional dimensions we analyze are closely tied to the idea that structural transformation involves the capability to produce more diversified and complex products. The latter requires the emergence of more capable and sophisticated firms, a proxy for which would be the expansion of employment in firms in the formal sector and/or firms with employment above some threshold level (e.g., 10 or more workers), and a shift in occupations—specifically, a growth in occupations that involve more analytical work.

We examine the case of India not only because it is interesting in and of itself, but also because it has broader relevance given that India's labor force survey allows one to examine aspects of employment that are typically not possible, such as employment in firms and cities of different sizes. Starting from 2000, labor force surveys from India (the employment–unemployment surveys conducted by the National Sample Survey Office, henceforth NSS-EUS) enable us to identify whether wage workers are employed in small (informal) or large (formal) enterprises, and whether urban wage workers are employed in urban centers with a population of 1 million or more. As far as we are aware, this is not possible with other labor force surveys in the region.

Our paper mainly focuses on the earnings of wage and salaried workers because information on earnings of self-employed workers is not readily available in labor force surveys. However, we extend our analysis to self-employed workers by imputing their earnings based on the earnings of wage and salaried workers with similar characteristics.

Our main findings are as follows. First, we find that employment in India over the 12 years from 2000 to 2012 displays the patterns one would expect for an economy undergoing structural transformation. That is, the employment shares of wage workers shift from agriculture to industry and services, and from rural to urban areas. Based on the previous literature, these shifts are in the direction of the higher productivity group—for example, see Hasan et al. (2017) on labor productivity across informal and formal sector firms in Indian apparel.

Second, and more importantly, we find that such shifts in employment have been associated with an improvement in average wages. In particular, we use the decomposition of changes in aggregate labor productivity into within sector and structural change (or between sector) components—as in ADB (2013) and McMillan, Rodrik, and Verduzco-Gallo (2014)—to decompose changes in average national wages into analogous components. We find that structural change in some dimensions can account for as much as a quarter to almost a third of the increase in average wages.

Finally, simple Mincerian wage regressions confirm that—when controlling for individual demographics, educational attainment, and even industry of employment and occupational status—a job in a firm with 10 or more workers (and thus a formal sector firm for all practical purposes) and in a large city is associated with higher wages. Significantly, the "premium" to being male is lower in larger firms and cities, suggesting that gender biases diminish along the path of structural transformation. More generally, we find that returns to education are higher in larger firms and in urban areas.

Overall, our results are consistent with the idea that policies that encourage expansion of the formal sector and employment in larger firms are crucial for development. Whether this expansion needs to occur through the formalization or expansion of small firms, or whether policy needs to encourage investment by larger firms in the first place, is not something we can comment on. Our results are also consistent with the idea that urban agglomerations have a key role in providing better paying jobs—regardless of the sector of economic activity—especially for females.

This paper is structured as follows. Section II explains how it fits with the literature on structural transformation and labor market outcomes. Section III describes the wage decomposition framework and the Mincerian wage equation used in our analysis. Section IV explains how variables are constructed using India's labor force survey data. Section V gives the results, describing employment and wages in India over the course of its structural transformation. Section VI contains the conclusions.

II. Literature Review

This paper is motivated by at least two strands of the development literature: (i) structural transformation and (ii) labor market outcomes. ADB (2013) provides a comprehensive discussion of structural transformation, covering both conceptual and empirical issues. Structural transformation involves the transformation of the productive structure of an economy and involves a variety of interrelated processes. These include (i) changes in the structure of production and employment of an economy—the starkest manifestation of which involves a reduction in the shares of output and employment from agriculture and a corresponding increase in output and employment shares in industry and services; (ii) the production of more diversified and complex products, which, in turn, may be captured by two related processes: (a) the emergence of more "capable and sophisticated" firms, a crude proxy for which, would be the expansion of employment in firms in the formal sector and/or firms with employment above some threshold level (e.g., 10 or more workers); and (b) a shift in occupations (e.g., growth in occupations that involve more cognitive or analytical work); and (iii) the process of urbanization, which involves a growing share of population, employment, and production in urban areas.

While the various processes listed above involve an increase in productivity, how these affect workers is less well documented. The widespread concern about the quality of jobs and the widespread use of terms such as "good jobs" is a testimony to the idea that even as countries develop and experience structural transformation, workers may not be benefiting (at least in a commensurate manner). Notwithstanding the fact that labor productivity and wages are related, the relationship between the two is far from watertight. Wage growth depends not only on how much labor productivity grows, but also on how workers' share in output evolves. This is partly determined by the nature of technological change, but other factors also matter, such as the extent of competition in product markets, workers' bargaining power, the relative mobility of capital versus labor, and even social norms. Moreover, general equilibrium considerations also kick in as overall supply and demand conditions in labor markets influence wages over and above sectoral labor productivity. For early expositions of this point, see the works of Lewis (1954) and Harris and Todaro (1970).

This is where the large literature on labor market outcomes comes in. There are many different types of studies, including those which examine the relationship between different types of regulations (especially labor regulations) on outcomes such as wages; studies that examine employment and wage relationships across sectors and types of firms (including formal and informal firms); and, more recently, studies that examine the relationship between urban agglomerations and employment and wages.

Focusing on the last, cities are widely believed to be engines of economic growth and good jobs. In this context, the urbanization process under way in India (and Asia more generally) is good news. However, the link between urbanization and economic dynamism is not assured and a number of urban experts have raised concerns about the nature of urbanization underway in the developing world. For example, Gollin, Jedwab, and Vollrath (2016) bring up the case of two cities, Shanghai and Lagos. Both are large cities in countries with similar urbanization rates. However, it is highly unlikely that their potential to deliver on better economic outcomes for their residents is the same. Similar concerns are raised by Henderson (2014). In a nutshell, the concern that the urbanization underway in the region may not lead to significantly better jobs is driven by the possibility that underinvestment in infrastructure, weak spatial planning, and poor land-use policies lead the forces of congestion to overwhelm the standard benefits of agglomeration (i.e., thicker local labor markets, better input–output linkages, and the potential for knowledge spillovers).

One strand of the literature on structural transformation that focuses directly on wages seeks to understand why wages in agriculture—the largest single employer in most Asian economies—tend to be far lower than wages in other sectors. Alvarez (2017) and Herrendorf and Schoellman (2017) are two recent contributions in this line of the literature. Using labor force survey data from around the developing world, including panel survey data for Brazil by Alvarez (2017) that allows him to track entry and exit by workers across sectors, the papers find more support for the role of unobserved worker characteristics, such as innate capabilities that enable some individuals to benefit more from schooling, to drive a large part of the wage gaps. This is contrary, however, to studies that ascribe an important role to barriers to reallocation of resources across sectors (see, for example, McMillan, Rodrik, and Verduzco-Gallo 2014).

III. Framework for Analysis

Much of our analysis relies on reporting average wages for groupings that are economically meaningful. In particular, in addition to reporting wages across production sectors, we document average wages across occupational groups; locations (rural areas, smaller cities and towns, and large cities); and small (informal) and larger (formal) firms. We also decompose wage growth to understand how much of it is driven by shifts in employment from lower-wage to higher-wage groupings. Finally, we run standard Mincerian regressions to check whether some of the more important average wage differentials we work with in our decompositions remain after controlling for observable characteristics of workers (age, gender, and educational attainment).

The decomposition of wage growth parallels the work on decomposing the components of labor productivity growth (see, for example, ADB 2013; and McMillan, Rodrik, and Verduzco-Gallo 2014) and is computed as follows:

$$\Delta W_t = \sum_i \left(\Delta E_t^i\right) W_{t-1}^i + \sum_i \left(\Delta W_t^i\right) E_{t-1}^i \tag{1}$$

where ΔW_t is the change in average wages; E_t^i is the share of workers in a given sector, region, or occupation of type i in year t; and W_t^i is the average wage of workers in that sector, region, or occupation type. The first term captures the growth of wages caused by the movement of workers from one grouping to another, which we call structural change, while the second term captures the growth of wages caused by rising wages within a group.

As for the Mincerian wage regressions, these simply involve estimating the following equation for worker i:

$$\ln(\text{wage}_i) = \beta_1 age_i + \beta_2 age_i^{\,2} + \beta_3 sex_i + \beta_4 education_i + \sum \beta_j state_j + \sum \beta_k \boldsymbol{X_i} + \varepsilon \tag{2}$$

where $\boldsymbol{X_i}$ refers to variables of interest and controls such as firm size, rural–urban, big cities, sector dummies, and occupation dummies. We introduce education in terms of years of schooling.

IV. Data and Variable Construction

Our main source of data is the NSS-EUS. We use two rounds of the surveys, the 55th (1999–2000, henceforth 2000) and 68th (2011–2012, henceforth 2012). Like standard labor force surveys, they provide us information on individual demographics (gender and age), wages, educational attainment, and sector of employment and occupation. As they are based on nationally representative surveys of households, they capture information on workers in both the formal and informal sectors; they also capture wage and salaried workers as well as self-employed workers.

Earnings data are collected only from wage and salaried workers. For this reason, we limit much of our analysis to wage workers. Unfortunately, information on wages is missing for 35% of the sample of wage workers in 2000 and for 29% in 2012. Thus, average wages have to be computed on the basis of information provided by 65% of wage workers in 2000 and 71% of wage workers in 2012. Fortunately, the pattern of missing wage information across groups appears to be somewhat random, with sufficiently large sample sizes of nonmissing wage observations across sectors, occupations, and educational categories with which to compute what should be reliable estimates of average wages.[2] For the wage decomposition analysis, average wages are based on the sample with wage responses, while employment shares are based on the full sample of wage workers.

Significantly, India's labor force surveys also provide us information on the size of firms that workers are employed in (i.e., whether the firms have 1–5, 5–9, 10–19, or 20 or more workers) and also whether urban respondents to the survey reside in a big city or not (i.e., cities with a population of 1 million or more in 2001). Unfortunately, a large number of nonresponses to the question on firm size, especially in the 2000 labor force survey, limits our ability to draw reliable conclusions on the role of firm size in our wage decompositions. In particular, while in 2012, 8% of wage workers' firm size is reported as unknown, it is 24% in 2000.[3] Thus, we exclude firm size from our analysis of wage decompositions. However, in

[2] Appendix Table A1 shows the number of sample observations for all wage workers (i.e., those with and without wage information) and for wage workers with wage data across industry, occupation, and location groups. The sample sizes are 1,000 or more in almost all cases. Further, the distribution of sample observations is fairly similar within any group. For example, in 2012, 17.3% of all sample wage employees belong to agriculture (10,726 observations out of 61,912) versus 16.5% of all sample wage employees with nonmissing wages (7,193 observations out of 43,691). The equivalent shares in 2000 are 42% and 38.5%, respectively.

[3] It is difficult to ascertain any specific pattern to the nonresponses. The share of unknowns and bad codes is substantial in both urban and rural areas in 2000; about 22% of urban workers and 26% of rural workers have no meaningful response to the firm size question. Unknowns and bad codes are also spread out across sectors: 19% of manufacturing workers; 34% of workers at public utilities; 16% of wholesale and retail trade workers; and 23% of workers in transport, storage, and communication services.

our analysis of Mincerian wage regressions, we use the firm size variable as these regressions are conducted only for 2012.

We ensure that our wage decompositions (equation [1]) are based on defining big cities consistently across the two rounds of the labor force surveys. We do this by taking the list of big cities in the 68th round and checking whether each one had a population of at least 1 million in the 1991 census. This is because big cities in the 55th round were identified on the basis of the 1991 population census. Cities with a population of 1 million or more in 1991 were retained as big cities in the 68th round. Implicitly, we assume that all big cities in the 55th round would also be classified as big in the 68th round.[4]

We use the data on earnings of wage and salaried workers over the reference period (7 days) and information on the number of half days worked over the week to compute daily wage rates. Since it is likely that workers reporting 6 or 7 days of work a week are actually working 5 or 6 days (e.g., those employed in the central government or the corporate sector and getting Saturdays and Sundays off), we top code days worked per week at 5 days. Fewer than 4% of workers in each year report working fewer than 4 days a week.

Like many other labor force surveys, India's does not collect information on the earnings of the self-employed. To extend the analysis to self-employed workers, we impute their earnings by predicting wages for them based on the empirical relationship between the wages of wage workers and individual characteristics observed in the labor force surveys, and a correction for selection of workers into self-employment based on Heckman's two-step procedure in line with a similar exercise by Das et al. (2015). For the selection equation, we let z_i be the probability that worker i is a wage worker, and $z_i = 1$ if

$$z_i^* = w_i\delta + u_i > 0$$

where δ is the set of identification factors including age, sex, marital status, and household size; w_i is the coefficient of δ; and u_i is the error term. If $z_i^* \leq 0$, then worker i is self-employed. We estimated a Mincerian wage equation for wage workers as follows:

$$\ln(\text{wage}) = \beta_1 X + \rho\sigma_u\lambda(w_i\delta)$$

where X is a vector of worker characteristics that include dummies of age, gender, education, location, marital status, and industry. ρ is the correlation between unobserved determinants of propensity to be a wage worker and unobserved determinants of wages, σ_u is the standard deviation of u_i, and λ is the inverse Mills ratio evaluated at $w_i\delta$. Finally, the wages of self-employed workers are estimated

[4]For the wage decompositions, the following cities in the 68th round were reclassified as towns and small cities in order to make the classification consistent across the 55th and 68th rounds: Agra, Faridabad, Meerut, Nashik, Patna, and Pimprichinchwad. However, for the Mincerian wage regressions, as these only involve data from the 68th round, the original classification of big cities in the 68th round was retained.

as the predicted wages of self-employed workers based on the coefficients of this regression. In both 2000 and 2012, 49% of workers were self-employed. Outside of agriculture, the shares are 43% and 39% for 2000 and 2012, respectively. Appendix Tables A2.1 and A2.2 compare the means of worker characteristics between self-employed and wage workers in 2000 and 2012, respectively, and provide *t* statistics on the difference between means of these two groups of workers. The imputed wages of self-employed workers are on average lower than the actual wages of wage workers (Appendix Table A2.3).

We adjust wages for temporal and spatial cost-of-living differences using the national Consumer Price Index and state and urban–rural cost-of-living adjustments based on official poverty lines, as reported in Saxena (2001) and Government of India (2013). Wages beyond 3 standard deviations from the mean are considered outliers and are dropped (less than 1% of the sample).

Since the surveys provide information on levels of education attained, we convert these into years of education by assuming the following correspondence between levels of education and years of education: 0 years for those who are illiterate, 1 year for those with preprimary education, 5 years for those with a primary education, 8 years for a middle school education, 10 years for a secondary education, 12 years for a senior secondary education, 14 years for those who finished a diploma course, 16 years for college graduates, and 19 years for those who completed postgraduate studies.

We work primarily with economic sectors based on the Groningen Growth and Development Centre 10-sector Database (Timmer, de Vries, and de Vries 2015), but we also experiment with a simple breakdown between tradable and nontradable sectors. For the latter classification, we follow Mano and Castillo (2015), who use the World Input–Output Database to calculate the ratio of exports to gross value added across countries for each industry and year, and then compute the average exports-to-gross-value-added ratio during the period 1995–2011. They classify an industry as tradable if the average exports-to-gross-value-added ratio is greater than 10%.

We also classify occupations in terms of whether they involve primarily routine or nonroutine work, and manual or analytical work, based on the work of Autor, Levy, and Murnane (2003) and Reijnders and de Vries (2018), and as described in ADB (2018). Prominent examples of routine manual workers include production workers, while routine analytical workers include clerical workers. Nonroutine manual workers include drivers and personal service workers. Nonroutine analytical workers include legislators, managers, engineering professionals, health professionals, teaching professionals, other professionals, and sales workers.

We use the occupation codes reported in the survey for this purpose. In 2012, 0.4% of wage workers did not have an occupation code, while 1% of wage workers did not have an occupation code in 2000. We drop these observations for decompositions involving occupations (and for the Mincerian regressions).

We work with the following states and union territories: Andhra Pradesh, Assam, Bihar, Chandigarh, Delhi, Goa, Gujarat, Haryana, Himachal Pradesh, Karnataka, Kerala, Madhya Pradesh, Maharashtra, Odisha, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, and West Bengal.

V. Results

A. Employment and Wages by Groups: A Snapshot

Table 1 provides a snapshot of employment shares of wage and salaried workers, average real wages (correcting for temporal changes in prices as well as both temporal and spatial variations in prices), and average years of education across various groups. In terms of employment shares across production sectors, we see a large reduction from 2000 to 2012 in agricultural wage employment (18 percentage points), a large increase in construction (10 percentage points), and a moderate increase in manufacturing (3 percentage points).[5] As for average wages, agriculture experiences one of the highest rates of growth at 4.2% annually. (This dips to 4% annually when spatial price differentials in addition to temporal changes in prices are taken into account.) Business services, which are one of the highest paying sectors on average, experience the lowest growth in wages: 1% annually when correcting only for temporal price changes and 1.8% annually when spatial price differentials are also taken into account.

There are few surprises as far as educational attainment is concerned. Workers in agriculture tend to be the least educated (at most 3 years of education on average), while those in business services and public administration, defense, education, and health services are the best educated.

Turning to locational groupings, the rural share of wage workers declined to two-thirds by 2012, while the employment share of big cities increased by 3 percentage points between 2000 and 2012. The share of smaller cities and towns also increased by 3 percentage points. Not surprisingly, the most educated are to be found in bigger cities. Such cities have considerably higher wages on average.

Firms with 10 or more workers (and outside agriculture) pay better and also have better educated workers. Regarding changes in their prevalence between 2000 and 2012, given the large share of nonresponses on firm size by wage employees—especially in the 2000 labor force survey, it is difficult to draw conclusions. But taken at face value, the share of wage employment in large firms increased slightly between 2000 and 2012.

Turning to the distinction between tradables and nontradables, we see that the main differences arise from the inclusion of agriculture in the former. Without

[5]Appendix Table A3 provides employment shares across the various groups of interest for the self-employed and all workers (i.e., wage and salaried workers plus the self-employed). For ease of reference, the share of wage employees is also provided in the table.

Table 1. **Summary Statistics for Wage and Salaried Employees**

	Employment Shares (%)		Wages, Temporal (₹)		Wages, Temporal + Spatial (₹)		Years of Schooling	
Sectors	**2000**	**2012**	**2000**	**2012**	**2000**	**2012**	**2000**	**2012**
Agriculture	55	37	96	158	94	151	2	3
Mining	1	1	310	504	307	512	4	6
Manufacturing	11	14	275	355	285	390	7	7
Utilities	1	1	529	651	546	733	8	9
Construction	8	18	176	247	181	249	3	4
Trade services	6	7	225	318	233	349	7	8
Transport services	5	7	352	548	363	605	8	9
Business services	2	3	654	739	675	834	13	13
Public administration and defense, education, health and social work	10	9	561	764	572	817	12	13
Personal services	3	3	146	242	150	266	3	6
Urban–Rural	**2000**	**2012**	**2000**	**2012**	**2000**	**2012**	**2000**	**2012**
Rural	73	67	145	232	145	223	3	4
Urban—towns and small cities	19	22	355	490	361	548	7	9
Urban—big cities	8	11	430	582	459	688	9	10
Firm size (without agriculture)	**2000**	**2012**	**2000**	**2012**	**2000**	**2012**	**2000**	**2012**
Large firms[a]	42	43	474	588	489	648	9	10
Small firms[a]	58	57	222	304	228	317	6	6
Tradables (with agriculture)	**2000**	**2012**	**2000**	**2012**	**2000**	**2012**	**2000**	**2012**
Tradable	74	62	159	263	161	275	3	5
Nontradable	26	38	352	436	361	464	8	7
Tradables (without agriculture)	**2000**	**2012**	**2000**	**2012**	**2000**	**2012**	**2000**	**2012**
Tradable	41	39	318	426	328	468	7	8
Nontradable	59	61	352	436	361	464	8	7
Occupation categories	**2000**	**2012**	**2000**	**2012**	**2000**	**2012**	**2000**	**2012**
Routine manual	23	32	219	280	225	295	5	5
Nonroutine manual	8	11	274	369	282	399	5	7
Routine analytic	4	4	507	680	525	748	13	13
Nonroutine analytic	10	15	581	789	594	864	13	13
Agriculture	55	38	94	158	92	150	2	3

[a] A large firm is defined as a firm with 10 or more workers. In 2012, 8% of wage workers reported that their firm size was unknown, while 24% of wage workers in 2000 did not know the size of their firm.

Notes: Employment shares and average years of schooling are based on the full sample of wage workers, while average wages are based on the sample of wage workers with wage data. Wages are expressed as the average daily wage in constant 2012 rupees. Temporal uses the Consumer Price Index to adjust for changes in prices over time. For Temporal + Spatial, differences in spatial prices are taken into account, in addition to changes in prices over time. A big city is defined as a city with a population of 1 million or more as per the 1991 census. This sample is limited to states included in the wage decomposition analysis and Mincerian wage regressions.

Source: Authors' calculations using data from National Sample Survey Office. 2000. "National Sample Survey 1999–2000 (55th round): Schedule 10–Employment and Unemployment Survey." Government of India, Ministry of Statistics and Program Implementation; and National Sample Survey Office. 2012. "National Sample Survey 2011–2012 (68th round): Schedule 1.0–Employment and Unemployment Survey." Government of India, Ministry of Statistics and Program Implementation.

agriculture, the two groups are quite similar in terms of average wages and educational attainment.

Finally, for occupational groupings, we see a large (9 percentage points) increase in routine manual occupations. This group includes the second-least-educated group on average, ahead of only agriculture. As we shall see below, this seems to be driven by an exit of wage workers from agriculture to routine manual work in industry and services.

Given the growing interest in urbanization issues in developing countries (see, for example, Hasan, Jiang, and Kundu 2018), Table 2 provides a snapshot of the employment shares of wage and salaried workers across rural areas, small cities and towns, and big cities in both 2000 and 2012. Not surprisingly, agriculture contributes marginally to wage and salaried employment in towns and small cities, and hardly at all in big cities. However, even within rural areas, the share of agricultural wage employment declined (from 73% to 54%). What is interesting is how important manufacturing is in India's big cities—accounting for almost 30% of wage employment. Additionally, the role of public administration, defense, and social services declines during the review period, as does that of personal services.

Interestingly, there is a sharp contrast in the structure of occupational change across rural areas and big cities. Rural areas see a large increase in routine manual work. This seems to be driven by an almost commensurate decline in agricultural occupations and growth in construction employment. In contrast, big cities see a drop of 6 percentage points in the share of routine manual work and an increase of 8 percentage points in nonroutine analytic work. Thus, unlike the case of developed countries, where a decline in routine manual work is attributed to the growing use of robotics and computers (the so-called fourth industrial revolution), India's pattern is consistent with the idea of "overlapping industrial revolutions" (ADB 2018), where some parts of a developing country are going through first or second industrial revolution processes (thanks to the advent of electricity and the internal combustion engine), while other parts are experiencing more recent technological revolutions.

B. Wage Decompositions

Table 3a summarizes the decomposition of average wages of wage and salaried workers into within and structural change (or between) components for various groupings of interest. When adjusting only for temporal changes in prices using the Consumer Price Index (first three data columns), the average real wage growth is between 3.9% and 4.2% per annum.[6] It is slightly higher when we adjust

[6]There is a slight difference in the average wage growth across decompositions due to differences in the number of observations across decompositions. As noted earlier, a small number of workers do not report their occupations. Additionally, 0.3% of wage workers in 2012 do not report the sector of employment. These observations get dropped in the decompositions involving occupation or sector.

Table 2. **Employment Statistics for Wage and Salaried Employees by City Size**

Year: 2000

	Employment Share (%)			**Wages, Temporal (₹)**			**Wages, Temporal + Spatial (₹)**		
Sectors	**Rural**	**Towns and Small Cities**	**Big Cities**	**Rural**	**Towns and Small Cities**	**Big Cities**	**Rural**	**Towns and Small Cities**	**Big Cities**
Agriculture	73	9	1	99	127	211	98	131	184
Mining	1	2	0	244	503	908	248	485	964
Manufacturing	7	21	29	192	325	362	195	332	389
Utilities	1	2	1	477	671	576	504	658	589
Construction	6	12	8	168	191	259	174	195	275
Trade services	2	14	16	175	228	299	181	231	317
Transport services	3	10	12	290	406	519	296	410	557
Business services	1	3	6	538	712	770	549	712	816
Public[a]	6	21	20	528	631	678	542	628	715
Personal services	2	5	8	135	140	178	146	137	188
Total	100	100	100	168	386	434	170	388	461
	Employment Share (%)			**Wages, Temporal (₹)**			**Wages, Temporal + Spatial (₹)**		
Occupation Categories	**Rural**	**Towns and Small Cities**	**Big Cities**	**Rural**	**Towns and Small Cities**	**Big Cities**	**Rural**	**Towns and Small Cities**	**Big Cities**
Routine manual	17	42	39	185	253	286	190	255	306
Nonroutine manual	5	17	23	263	296	292	270	297	317
Routine analytic	2	8	10	444	552	595	453	553	634
Nonroutine analytic	5	24	27	534	645	679	549	645	714
Agriculture	72	9	1	96	138	181	96	142	193
Total	100	100	100	167	386	434	169	388	461
	Employment Share (%)			**Wages, Temporal (₹)**			**Wages, Temporal + Spatial (₹)**		
Tradable	**Rural**	**Towns and Small Cities**	**Big Cities**	**Rural**	**Towns and Small Cities**	**Big Cities**	**Rural**	**Towns and Small Cities**	**Big Cities**
Tradable	84	46	47	122	344	428	122	348	459
Nontradable	16	54	53	331	418	438	341	418	462
Total	100	100	100	168	386	434	170	387	461

Continued.

wages for both temporal and spatial differences in the cost of living (between 4.2% and 4.5% per annum). Nevertheless, the qualitative patterns are quite similar. As in the case of labor productivity decompositions analyzed by other studies, we find the within term to be the main driver of growth in economy-wide average wages. Nevertheless, for all the groups we consider, structural change contributes

Table 2. *Continued.*

Year: 2012

Sectors	Employment Share (%) Rural	Employment Share (%) Towns and Small Cities	Employment Share (%) Big Cities	Wages, Temporal (₹) Rural	Wages, Temporal (₹) Towns and Small Cities	Wages, Temporal (₹) Big Cities	Wages, Temporal + Spatial (₹) Rural	Wages, Temporal + Spatial (₹) Towns and Small Cities	Wages, Temporal + Spatial (₹) Big Cities
Agriculture	54	5	0	167	212	393	161	232	465
Mining	1	2	0	493	828	1,323	447	882	1,648
Manufacturing	9	22	28	283	399	461	280	451	553
Utilities	1	3	1	698	846	817	712	970	951
Construction	20	15	9	237	285	352	229	316	419
Trade services	3	13	14	273	288	400	274	318	474
Transport services	4	11	15	392	568	880	384	627	1,047
Business services	1	7	10	633	808	840	646	900	1,004
Public[a]	6	17	16	719	847	898	683	943	1,055
Personal services	1	4	7	204	205	271	197	231	319
Total	100	100	100	337	517	605	326	576	719

Occupation Categories	Employment Share (%) Rural	Employment Share (%) Towns and Small Cities	Employment Share (%) Big Cities	Wages, Temporal (₹) Rural	Wages, Temporal (₹) Towns and Small Cities	Wages, Temporal (₹) Big Cities	Wages, Temporal + Spatial (₹) Rural	Wages, Temporal + Spatial (₹) Towns and Small Cities	Wages, Temporal + Spatial (₹) Big Cities
Routine manual	30	40	33	258	330	369	251	367	441
Nonroutine manual	7	18	23	365	409	414	358	456	492
Routine analytic	2	7	8	642	754	792	615	838	942
Nonroutine analytic	7	29	35	727	822	960	698	916	1,136
Agriculture	55	6	1	171	202	246	164	221	284
Total	100	100	100	338	517	606	327	576	720

Tradable	Employment Share (%) Rural	Employment Share (%) Towns and Small Cities	Employment Share (%) Big Cities	Wages, Temporal (₹) Rural	Wages, Temporal (₹) Towns and Small Cities	Wages, Temporal (₹) Big Cities	Wages, Temporal + Spatial (₹) Rural	Wages, Temporal + Spatial (₹) Towns and Small Cities	Wages, Temporal + Spatial (₹) Big Cities
Tradable	69	47	49	244	473	577	239	527	692
Nontradable	31	53	51	420	548	632	404	611	745
Total	100	100	100	337	517	605	326	576	719

[a]Public refers to public administration and defense, education, health, and social work.

Notes: Employment shares are based on the full sample of wage workers, while average wages are based on the sample of wage workers with wage data. Wages are expressed as the average daily wage in constant 2012 rupees. Temporal uses the Consumer Price Index to adjust for changes in prices over time. For Temporal + Spatial, differences in spatial prices are taken into account, in addition to changes in prices over time. A big city is defined as a city with a population of 1 million or more as per the 1991 census. This sample is limited to states included in the wage decomposition analysis and Mincerian wage regressions.

Source: Authors' calculations using data from National Sample Survey Office. 2000. "National Sample Survey 1999–2000 (55th round): Schedule 10–Employment and Unemployment Survey." Government of India, Ministry of Statistics and Program Implementation; and National Sample Survey Office. 2012. "National Sample Survey 2011–2012 (68th round): Schedule 1.0–Employment and Unemployment Survey." Government of India, Ministry of Statistics and Program Implementation.

Table 3. **Wage Decomposition Results**

(a) Wage workers only

Configuration	Temporal: Structural Change (%)	Temporal: Within (%)	Temporal: Economy-wide Wage Growth (%)	Temporal + Spatial: Structural Change (%)	Temporal + Spatial: Within (%)	Temporal + Spatial: Economy-wide Wage Growth (%)
Sector (10 sectors)	1.0	3.1	4.0	1.0	3.3	4.4
Occupations (5 categories)	1.3	2.9	4.2	1.4	3.2	4.5
Urban–Rural	0.5	3.4	3.9	0.5	3.7	4.2
Rural, big cities, towns and small cities	0.5	3.4	3.9	0.6	3.7	4.2
Urban–Rural × Sector (2 × 10)	1.0	3.0	4.0	1.0	3.3	4.4
Sector × Occupation (10 × 5)	1.2	2.9	4.1	1.2	3.2	4.5
Urban–Rural × Sector × Occupation (2 × 10 × 5)	1.2	2.9	4.1	1.2	3.2	4.5

(b) Wage workers and self-employed workers

Configuration	Temporal: Structural Change (%)	Temporal: Within (%)	Temporal: Economy-wide Wage Growth (%)	Temporal + Spatial: Structural Change (%)	Temporal + Spatial: Within (%)	Temporal + Spatial: Economy-wide Wage Growth (%)
Sector (10 sectors)	0.7	2.3	3.0	0.8	2.5	3.3
Occupations (5 categories)	0.7	2.3	3.1	0.8	2.5	3.3
Urban–Rural	0.3	2.7	3.0	0.3	2.9	3.3
Rural, big cities, other urban areas	0.3	2.7	3.0	0.4	2.9	3.3
Urban–Rural × Sector (2 × 10)	0.7	2.3	3.0	0.8	2.5	3.3
Sector × Occupation (10 × 5)	0.8	2.2	3.0	0.9	2.4	3.3
Urban–Rural × Sector × Occupation (2 × 10 × 5)	0.8	2.2	3.0	0.9	2.4	3.3

Notes: Temporal uses the Consumer Price Index to adjust for changes in prices over time. For Temporal + Spatial, differences in spatial prices are taken into account, in addition to changes in prices over time. A big city is defined as a city with a population of 1 million or more as per the 1991 census. This sample is limited to states included in the wage decomposition analysis and Mincerian wage regressions. There is a slight difference in the average economy-wide wage growth across decompositions due to differences in the number of observations across configurations (0.3% of wage workers in 2012 have no sector data, 0.4% in 2012, and 1% in 2000 have no occupation data). These observations get dropped in the decompositions involving occupation or sector.

Source: Authors' calculations using data from National Sample Survey Office. 2000. "National Sample Survey 1999–2000 (55th round): Schedule 10–Employment and Unemployment Survey." Government of India, Ministry of Statistics and Program Implementation; National Sample Survey Office. 2012. "National Sample Survey 2011–2012 (68th round): Schedule 1.0–Employment and Unemployment Survey." Government of India, Ministry of Statistics and Program Implementation.

positively to growth in average wages. The contribution of structural change is around 23%–25% in the sectorwise decomposition (row 1) and around 31% in the occupationwise decomposition (row 2). The contribution of structural change is around 12%–13% when we decompose wages in terms of just urban and rural areas, and 13%–14% when we further distinguish urban areas between those comprising big cities and other cities and towns (rows 3 and 4). The table also considers what happens when we consider a more disaggregated grouping based on combining the sector, occupation, and location groups. Interestingly, the largest such grouping (row 7)—involving a total of 100 groups formed over 10 sectors, 5 occupations, and 2 locations—reveals that structural change drives 27%–29% of total wage growth, which is similar to when just occupation groups are considered.

Table 3b carries out the wage decomposition by including the self-employed and their predicted wages. Economy-wide average wage growth is now lower (due to the lower predicted wages of the self-employed). But, the decompositions yield similar results in terms of the relative importance of the structural change and within group terms. For example, the contribution of structural change remains at 23%–24% in the sector-wise decomposition (row 1), and it remains close at 9%–12% when we decompose wages in terms of urban and rural areas and when we further distinguish urban areas between those comprising big cities and other cities and towns (rows 3 and 4).

Thus far, our results indicate that India's economy has undergone structural transformation in a fairly standard manner. Employment is exiting agriculture, rural areas, and less remunerative occupations for better-paying production sectors and occupations, and for urban areas, especially big cities. Although not shown, employment also appears to be moving from smaller (informal) firms to larger (formal) firms, subject to the data caveat noted earlier (i.e., that the missing observations for the firm size variable are randomly distributed in both 2000 and 2012). All of these shifts have helped raise average wages in the economy.

C. Wages across Locations and Firm Type

We now turn to the issue of whether the higher real wages of larger firms and cities, especially larger cities, holds even when controlling for individual demographics and educational attainment. Tables 4a–4d present the results of the Mincerian wage regressions using data only for 2012, the year for which our information on firm size of workers is fairly complete.[7] We drop the agriculture sector from this analysis since firm size is not a well-defined concept for farms. To avoid the possibility that the coefficients on wage determinants are largely driven

[7]We do not adjust for population weights. Also, we divide age by 10 and age^2 by 100 to improve the readability of their coefficients.

Table 4. **Mincerian Wage Regressions**

(a) Base

	Base	**Sector and Occupation Dummies**				
Variables	**(1) log wage**	**(2) log wage**	**(3) log wage**	**(4) log wage**	**(5) log wage**	**(6) log wage**
Age/10	0.5138***	0.4257***	0.4187***	0.4308***	0.4272***	0.4236***
	(0.0181)	(0.0171)	(0.0167)	(0.0170)	(0.0170)	(0.0166)
$Age^2/100$	–0.0446***	–0.0376***	–0.0375***	–0.0381***	–0.0379***	–0.0381***
	(0.0023)	(0.0021)	(0.0021)	(0.0021)	(0.0021)	(0.0021)
Sex (Male = 1)	0.2644***	0.3245***	0.3393***	0.3256***	0.3339***	0.3451***
	(0.0108)	(0.0108)	(0.0106)	(0.0107)	(0.0107)	(0.0105)
Years of schooling	0.0735***	0.0479***	0.0435***	0.0472***	0.0465***	0.0424***
	(0.0006)	(0.0008)	(0.0008)	(0.0008)	(0.0008)	(0.0008)
Large firm = 1			0.2625***			0.2488***
			(0.0073)			(0.0073)
Big city = 1				0.2077***		0.1493***
				(0.0119)		(0.0121)
Urban = 1					0.1201***	0.0745***
					(0.0071)	(0.0072)
Constant	3.7331***	4.4820***	4.3028***	4.4716***	4.4074***	4.2584***
	(0.0370)	(0.0437)	(0.0431)	(0.0434)	(0.0437)	(0.0430)
Sector dummies	No	Yes	Yes	Yes	Yes	Yes
Occupation dummies	No	Yes	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	30,519	30,519	30,519	30,519	30,519	30,519
R-squared	0.4175	0.4873	0.5080	0.4924	0.4921	0.5136

Continued.

Table 4. *Continued.*

(b) Firm size

	Large Firms					**Small Firms**				
	Base	**Sector + Occupation Dummies**				**Base**	**Sector + Occupation Dummies**			
Variables	**(1) log wage**	**(2) log wage**	**(3) log wage**	**(4) log wage**	**(5) log wage**	**(6) log wage**	**(7) log wage**	**(8) log wage**	**(9) log wage**	**(10) log wage**
Age/10	0.5171***	0.4245***	0.4314***	0.4255***	0.4302***	0.4856***	0.3910***	0.3933***	0.3919***	0.3937***
	(0.0319)	(0.0300)	(0.0299)	(0.0299)	(0.0298)	(0.0205)	(0.0193)	(0.0192)	(0.0192)	(0.0192)
$Age^2/100$	−0.0389***	−0.0322***	−0.0329***	−0.0325***	−0.0329***	−0.0469***	−0.0392***	−0.0393***	−0.0393***	−0.0394***
	(0.0040)	(0.0038)	(0.0037)	(0.0037)	(0.0037)	(0.0026)	(0.0024)	(0.0024)	(0.0024)	(0.0024)
Sex (Male = 1)	0.1779***	0.2374***	0.2397***	0.2500***	0.2498***	0.3145***	0.4240***	0.4214***	0.4268***	0.4234***
	(0.0172)	(0.0168)	(0.0168)	(0.0168)	(0.0168)	(0.0130)	(0.0132)	(0.0131)	(0.0132)	(0.0132)
Years of schooling	0.0811***	0.0541***	0.0537***	0.0524***	0.0524***	0.0573***	0.0302***	0.0299***	0.0298***	0.0297***
	(0.0009)	(0.0013)	(0.0013)	(0.0013)	(0.0013)	(0.0008)	(0.0010)	(0.0010)	(0.0010)	(0.0010)
Big city = 1			0.1416***		0.0996***			0.1795***		0.1648***
			(0.0167)		(0.0172)			(0.0162)		(0.0167)
Urban = 1				0.1269***	0.1082***				0.0530***	0.0328***
				(0.0116)	(0.0120)				(0.0085)	(0.0087)
Constant	3.7746***	4.4686***	4.4511***	4.3876***	4.3872***	3.8319***	4.1125***	4.1081***	4.0901***	4.0946***
	(0.0642)	(0.0674)	(0.0672)	(0.0675)	(0.0674)	(0.0427)	(0.0673)	(0.0671)	(0.0673)	(0.0671)
Sector dummies	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Occupation dummies	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,001	12,001	12,001	12,001	12,001	18,518	18,518	18,518	18,518	18,518
R-squared	0.4690	0.5367	0.5395	0.5413	0.5426	0.3340	0.4226	0.4264	0.4238	0.4268

Continued.

Table 4. *Continued.*

(c) Urban versus rural

	Urban					Rural				
	Base	Sector + Occupation Dummies				Base	Sector + Occupation Dummies			
Variables	**(1) log wage**	**(2) log wage**	**(3) log wage**	**(4) log wage**	**(5) log wage**	**(6) log wage**	**(7) log wage**	**(8) log wage**	**(9) log wage**	**(10) log wage**
Age/10	0.5903***	0.5152***	0.5229***	0.5046***	0.5113***	0.4342***	0.3167***	0.3167***	0.3136***	0.3136***
	(0.0261)	(0.0245)	(0.0243)	(0.0238)	(0.0237)	(0.0247)	(0.0232)	(0.0232)	(0.0230)	(0.0230)
$Age^2/100$	−0.0541***	−0.0480***	−0.0486***	−0.0476***	−0.0481***	−0.0351***	−0.0261***	−0.0261***	−0.0261***	−0.0261***
	(0.0033)	(0.0031)	(0.0030)	(0.0030)	(0.0030)	(0.0031)	(0.0029)	(0.0029)	(0.0029)	(0.0029)
Sex (Male = 1)	0.2270***	0.2498***	0.2483***	0.2689***	0.2673***	0.3171***	0.4528***	0.4528***	0.4541***	0.4541***
	(0.0148)	(0.0150)	(0.0149)	(0.0146)	(0.0145)	(0.0155)	(0.0153)	(0.0153)	(0.0152)	(0.0152)
Years of schooling	0.0789***	0.0558***	0.0554***	0.0497***	0.0495***	0.0651***	0.0326***	0.0326***	0.0310***	0.0310***
	(0.0008)	(0.0011)	(0.0011)	(0.0011)	(0.0011)	(0.0008)	(0.0011)	(0.0011)	(0.0011)	(0.0011)
Big city = 1			0.1629***		0.1370***			–		–
			(0.0131)		(0.0128)					
Large firm = 1				0.3155***	0.3081***				0.1684***	0.1684***
				(0.0103)	(0.0102)				(0.0105)	(0.0105)
Constant	3.5904***	4.4650***	4.4471***	4.2496***	4.2396***	3.8711***	4.4526***	4.4526***	4.3455***	4.3455***
	(0.0528)	(0.0611)	(0.0609)	(0.0598)	(0.0596)	(0.0514)	(0.0610)	(0.0610)	(0.0608)	(0.0608)
Sector dummies	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
Occupation dummies	No	Yes	Yes	Yes	Yes	No	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	15,880	15,880	15,880	15,880	15,880	14,639	14,639	14,639	14,639	14,639
R-squared	0.4340	0.5064	0.5112	0.5342	0.5376	0.3872	0.4714	0.4714	0.4805	0.4805

Continued.

Table 4. *Continued.*

(d) Big cities versus towns and small cities

	Big Cities			Towns and Small Cities		
	Base	Sector + Occupation		Base	Sector + Occupation	
Variables	**(1) log wage**	**(2) log wage**	**(3) log wage**	**(4) log wage**	**(5) log wage**	**(6) log wage**
Age/10	0.4594***	0.4247***	0.4338***	0.6324***	0.5395***	0.5232***
	(0.0527)	(0.0494)	(0.0480)	(0.0297)	(0.0277)	(0.0270)
$Age^2/100$	−0.0401***	−0.0375***	−0.0394***	−0.0584***	−0.0504***	−0.0494***
	(0.0067)	(0.0063)	(0.0061)	(0.0037)	(0.0034)	(0.0034)
Sex (Male = 1)	0.1971***	0.1935***	0.2160***	0.2328***	0.2661***	0.2829***
	(0.0319)	(0.0321)	(0.0313)	(0.0165)	(0.0167)	(0.0163)
Years of schooling	0.0841***	0.0593***	0.0530***	0.0767***	0.0533***	0.0475***
	(0.0018)	(0.0022)	(0.0022)	(0.0009)	(0.0012)	(0.0012)
Large firm = 1			0.2894***			0.3127***
			(0.0211)			(0.0117)
Constant	3.8504***	4.3288***	4.1234***	3.5100***	4.4271***	4.2275***
	(0.1059)	(0.3918)	(0.3814)	(0.0602)	(0.0672)	(0.0657)
Sector dummies	No	Yes	Yes	No	Yes	Yes
Occupation dummies	No	Yes	Yes	No	Yes	Yes
State dummies	Yes	Yes	Yes	Yes	Yes	Yes
Observations	3,278	3,278	3,278	12,602	12,602	12,602
R-squared	0.5039	0.5684	0.5919	0.4233	0.5019	0.5289

Notes: This sample excludes public administration and defense. Standard errors are in parentheses. *** = $p < 0.01$, ** = $p < 0.05$, * = $p < 0.1$.
Source: Authors' calculations using data from National Sample Survey Office. 2000. "National Sample Survey 1999–2000 (55th round): Schedule 10–Employment and Unemployment Survey." Government of India, Ministry of Statistics and Program Implementation; and National Sample Survey Office. 2012. "National Sample Survey 2011–2012 (68th round): Schedule 1.0–Employment and Unemployment Survey." Government of India, Ministry of Statistics and Program Implementation.

by government workers, we remove workers belonging to the industry division of public administration and defense in all the analysis.

The main results are as follows. First, even after controlling for age, gender, and educational attainment, employment in a large firm is associated with a wage premium of around 26%. (It is slightly lower at 25% if dummies for urban areas and big cities are included.) Interestingly, employment in a big city is associated with higher wages as well, but the premium to being in a big city falls dramatically in models that also include the dummy for employment in large firms. For example, comparing the coefficients in columns 4 and 6 in Table 4a, the wage premium to being in a large city falls from around 21% to 15%.

Given the apparent importance of working in a large firm, Table 4b splits the sample into two by separating workers in large firms from those in small firms. This reveals that returns to an extra year of education are a little higher in larger firms than in smaller firms. For example, while the estimated coefficient on years of education is 0.05 in large firms, it is 0.03 in small firms (columns 2–5). Perhaps more significantly, the premium to being male—or put differently, the gender bias against females—is dramatically lower in larger firms. For example, column 5 reveals that the male dummy takes on a value of 0.25 for large firms, which is much less than the 0.42 estimated for small firms. On the other hand, the big city premium is higher for small firms than in large firms. Table 4c splits the overall sample between rural and urban areas. The returns to an extra year of education and working in a large firm are both larger in urban areas, while the wage premium to being male is less. Table 4d splits the urban sample into big cities and towns and small cities. The returns to an extra year of education and working in a large firm are similar. However, the apparent disadvantage of being female is clearly less in larger cities.

We conduct a series of robustness checks to see whether the main results of our Mincerian wage regressions remain. The robustness checks confirm that they do. First, we introduce district dummies. These control for any unobservable differences across districts that might influence wages. Controlling for unobserved characteristics at the district level yields wage premiums that are very close to our main results and slightly improved goodness-of-fit (R-squares of up to 0.54).[8] The wage premium to working in a large firm is around 24%. Between large firms and small firms, the returns to an extra year of education and the gender bias against females remain the same as in the main results. The big city premium is slightly higher in small firms than in large firms. The main results are also preserved when splitting the sample between urban and rural areas, and when splitting the urban sample into big cities and towns and small cities.

Second, we address the possibility that state-owned enterprises are driving our main results—such as lower biases against female workers in large firms. We

[8] The results of our robustness checks are available upon demand.

exclude state-owned enterprises from the analysis by dropping from the sample workers employed in government or public sector enterprises. In this robustness check, the wage premium to working in a large firm is slightly lower at 22%, but still close to the 26% that we have shown in the main results. The returns to education in large firms remain at 5% per year of schooling. The returns are 2% in small firms. The gender bias against females is still lower in large firms than in smaller firms, although the gap between large firms and smaller firms with respect to this gender bias is down to 8 percentage points. The returns to education and working in a large firm both remain higher in urban areas than in rural areas. The wage premium to being male increases to 34% in urban areas, but it remains lower than the 41% wage premium in rural areas. Within urban areas, the wage premium to being male rises to 38% in towns and small cities, while it remains close to our main results for big cities. Thus, even after dropping all government workers, the gender bias against females remains lowest in big cities, in contrast to rural areas, towns, and small cities. Finally, we restricted the wage regressions to the manufacturing sector only. The wage premiums in the manufacturing sector reflect the main results as well.

VI. Conclusions

This paper uses labor force survey data from India to examine how wages behave over the course of structural transformation, especially in terms of its less studied aspects. Focusing on wage and salaried employment, we find first that employment in India over the 12 years between 2000 and 2012 displays the patterns one would expect for an economy undergoing structural transformation. During the review period, wage employment shares shift from agriculture to industry and services; from rural to urban areas, and to larger cities within urban areas; and from agricultural occupations toward occupations involving both more routine manual work and more nonroutine analytic work. The last of these shifts is consistent with the idea of developing countries undergoing overlapping industrial revolutions (ADB 2018).

Second, we find that such shifts in employment have been associated with an improvement in average wages. Finally, simple Mincerian wage regressions confirm that—when controlling for demographics, educational attainment, and even industry of employment and occupational status—a job in a larger firm and bigger city is associated with significantly higher wages. The premium to being male is lower in larger firms and cities, suggesting that gender biases diminish along the path of structural transformation. More generally, returns to education are higher in larger firms and in urban areas.

Overall, we take our results to emphasize the importance of policies that encourage the expansion of the formal sector and employment in larger firms.

Whether this needs to occur through the formalization or expansion of small firms, or whether policy needs to encourage investment in larger firms in the first place, is not something we can comment on. Less directly, our results are consistent with the idea that urban agglomerations have a key role in providing better-paying jobs—regardless of the sector of economic activity—especially for females.

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Appendix 1

Table A1. **Sample Sizes (Unweighted): All Wage Workers and Wage Workers with Wage Data**

	All Wage Workers	**Wage Workers with Wage Data**	**All Wage Workers**	**Wage Workers with Wage Data**
	2000		**2012**	
Sectors				
Agriculture	50,732	29,962	10,726	7,193
Mining	1,486	1,044	741	596
Manufacturing	15,618	10,724	9,179	6,536
Utilities	1,337	955	1,010	771
Construction	9,750	6,238	13,355	9,523
Trade services	9,391	6,370	5,533	3,167
Transport services	7,589	5,256	5,966	3,973
Business services	2,776	1,923	2,595	1,791
Public administration and defense, education, health, and social work	17,634	12,322	10,552	8,786
Personal services	4,481	3,026	2,089	1,355
Missing			166	
Total	120,794	77,820	61,912	43,691
Urban–Rural				
Rural	70,171	42,895	34,330	23,436
Urban—towns and small cities	38,010	26,063	22,449	16,586
Urban—big cities	12,613	8,862	5,133	3,669
Total	120,794	77,820	61,912	43,691

Continued.

Table A1. *Continued.*

	All Wage Workers	Wage Workers with Wage Data	All Wage Workers	Wage Workers with Wage Data
	2000		2012	
Firm size (without agriculture)				
Large firms[a]	23,501	16,415	17,988	14,140
Small firms[a]	30,890	20,538	26,408	19,311
Missing	15,671	10,905	6,790	3,047
Total	70,062	47,858	51,186	36,498
Occupation categories				
Routine manual	31,660	21,179	23,127	16,478
Nonroutine manual	12,914	8,864	9,511	6,630
Routine analytic	5,976	4,211	3,144	2,564
Nonroutine analytic	19,113	13,322	14,322	10,149
Agriculture	49,931	29,518	11,541	7,774
Missing	1,200	726	267	96
Total	120,794	77,820	61,912	43,691

[a]A large firm is defined as a firm with 10 or more workers. In 2012, 8% of wage workers reported that their firm size was unknown, while 24% of wage workers in 2000 did not know the size of their firm.
Note: This sample is limited to states included in the wage decomposition analysis and Mincerian wage regressions.
Source: Authors' calculations using data from National Sample Survey Office. 2000. "National Sample Survey 1999–2000 (55th round): Schedule 10–Employment and Unemployment Survey." Government of India, Ministry of Statistics and Program Implementation; and National Sample Survey Office. 2012. "National Sample Survey 2011–2012 (68th round): Schedule 1.0–Employment and Unemployment Survey." Government of India, Ministry of Statistics and Program Implementation.

Appendix 2

Table A2.1. **Comparison of Means between Wage Workers and Self-Employed Workers, 2000**

	Wage Workers		Self-Employed			
Variable	**Mean**	**std. dev.**	**Mean**	**std. dev.**	***t* statistic**	***p* value**
Age	34.7597	12.4752	37.0746	14.4777	−42.9798	0.0000
Gender (Male = 1)	0.7498	0.4331	0.7622	0.4258	−7.2666	0.0000
Household size	2.3040	1.3087	2.7645	1.6218	−78.2823	0.0000
Education (share of workers in each category)						
Not literate	0.3865	0.4869	0.3639	0.4811	11.7675	0.0000
Literate without formal schooling (EGS, NFEC, AEC)	0.0022	0.0465	0.0020	0.0451	0.7551	0.4502
Literate without formal schooling (TLC)	0.0017	0.0416	0.0020	0.0446	−1.5421	0.1231

Continued.

Table A2.1. *Continued.*

Variable	Wage Workers Mean	Wage Workers std. dev.	Self-Employed Mean	Self-Employed std. dev.	*t* statistic	*p* value
Literate without formal schooling (others)	0.0071	0.0842	0.0082	0.0904	−3.1365	0.0017
Literate: below primary	0.0959	0.2945	0.1037	0.3049	−6.5506	0.0000
Literate: primary	0.1083	0.3108	0.1283	0.3344	−15.5614	0.0000
Literate: middle	0.1313	0.3377	0.1619	0.3684	−21.7602	0.0000
Literate: secondary	0.1062	0.3081	0.1139	0.3177	−6.2170	0.0000
Literate: higher secondary	0.0569	0.2316	0.0558	0.2296	1.1399	0.2543
Literate: graduate and above in agriculture	0.0036	0.0600	0.0025	0.0498	5.1901	0.0000
Literate: graduate and above in engineering or technology	0.0058	0.0756	0.0018	0.0427	16.3251	0.0000
Literate: graduate and above in medicine	0.0024	0.0490	0.0025	0.0501	−0.5507	0.5818
Literate: graduate and above in other subjects	0.0921	0.2892	0.0534	0.2248	37.8954	0.0000
Marital status (share of workers in each category)						
Never married	0.2166	0.4119	0.1880	0.3907	17.9544	0.0000
Currently married	0.7296	0.4442	0.7629	0.4253	−19.3431	0.0000
Widowed	0.0457	0.2089	0.0443	0.2058	1.7191	0.0856
Divorced or separated	0.0081	0.0897	0.0047	0.0687	10.6790	0.0000

AEC = Adult Education Centre, EGS = Education Guarantee Scheme, NFEC = Non-Formal Education Course, TLC = Total Literacy Campaign.
Note: This sample is limited to states included in the wage decomposition analysis and Mincerian wage regressions.
Source: Authors' calculations using data from National Sample Survey Office. 2000. "National Sample Survey 1999–2000 (55th round): Schedule 10–Employment and Unemployment Survey." Government of India, Ministry of Statistics and Program Implementation; and National Sample Survey Office. 2012. "National Sample Survey 2011–2012 (68th round): Schedule 1.0–Employment and Unemployment Survey." Government of India, Ministry of Statistics and Program Implementation.

Table A2.2. **Comparison of Means between Wage Workers and Self-Employed Workers, 2012**

Variable	Wage Workers Mean	Wage Workers std. dev.	Self-Employed Mean	Self-Employed std. dev.	*t* statistic	*p* value
Age	36.7707	12.1132	39.8818	13.7260	−43.2183	0.0000
Gender	0.7873	0.4092	0.7860	0.4101	0.5737	0.5662
Household size	4.8128	2.3155	5.7097	2.9165	−61.0940	0.0000
Education (share of workers in each category)						
Not literate	0.2238	0.4168	0.2304	0.4211	−2.8407	0.0045
Literate without formal schooling (EGS, NFEC, AEC)	0.0015	0.0385	0.0022	0.0464	−2.8278	0.0047
Literate without formal schooling (TLC)	0.0003	0.0180	0.0005	0.0219	−1.4150	0.1571
Literate without formal schooling (others)	0.0015	0.0387	0.0020	0.0443	−2.0126	0.0442

Continued.

Table A2.2. *Continued.*

Variable	Wage Workers Mean	Wage Workers std. dev.	Self-Employed Mean	Self-Employed std. dev.	*t* statistic	*p* value
Literate: below primary	0.0887	0.2844	0.0943	0.2922	−3.4717	0.0005
Literate: primary	0.1234	0.3289	0.1317	0.3382	−4.5178	0.0000
Literate: middle	0.1596	0.3662	0.1853	0.3885	−12.2806	0.0000
Literate: secondary	0.1228	0.3282	0.1579	0.3646	−18.2118	0.0000
Literate: higher secondary	0.0804	0.2719	0.0947	0.2928	−9.1415	0.0000
Literate: diploma or certificate course	0.0280	0.1649	0.0110	0.1041	22.5028	0.0000
Literate: graduate	0.1144	0.3183	0.0716	0.2579	26.7958	0.0000
Literate: postgraduate and above	0.0557	0.2294	0.0185	0.1348	36.1190	0.0000
Marital status (share of workers in each category)						
Never married	0.1969	0.3977	0.1402	0.3472	27.5144	0.0000
Currently married	0.7467	0.4349	0.8134	0.3896	−29.2546	0.0000
Widowed	0.0487	0.2152	0.0426	0.2020	5.2277	0.0000
Divorced or separated	0.0077	0.0875	0.0037	0.0610	9.6243	0.0000

AEC = Adult Education Centre, EGS = Education Guarantee Scheme, NFEC = Non-Formal Education Course, TLC = Total Literacy Campaign.

Note: This sample is limited to states included in the wage decomposition analysis and Mincerian wage regressions.

Source: Authors' calculations using data from National Sample Survey Office. 2000. "National Sample Survey 1999–2000 (55th round): Schedule 10–Employment and Unemployment Survey." Government of India, Ministry of Statistics and Program Implementation; and National Sample Survey Office. 2012. "National Sample Survey 2011–2012 (68th round): Schedule 1.0–Employment and Unemployment Survey." Government of India, Ministry of Statistics and Program Implementation.

Table A2.3. **Daily Wage of Wage Workers and Imputed Daily Wage of Self-Employed Workers in Current Rupees**

	Wage Workers	Self-Employed Workers	Wage Workers	Self-Employed Workers
	2000		2012	
Mean	101.2	66.3	349.0	197.2
25th percentile	35.0	39.9	140.0	128.5
Median	55.0	54.8	210.0	165.6
75th percentile	100.0	77.5	342.8	223.5

Note: This sample is limited to states included in the wage decomposition analysis and Mincerian wage regressions.

Source: Authors' calculations using data from National Sample Survey Office. 2000. "National Sample Survey 1999–2000 (55th round): Schedule 10–Employment and Unemployment Survey." Government of India, Ministry of Statistics and Program Implementation; and National Sample Survey Office. 2012. "National Sample Survey 2011–2012 (68th round): Schedule 1.0–Employment and Unemployment Survey." Government of India, Ministry of Statistics and Program Implementation.

Appendix 3

Table A3. **Employment Shares of Wage Workers, Self-Employed Workers, and All Workers** (%)

	Wage Workers		Self-Employed Workers		Wage Workers and Self-Employed Workers	
	2000	**2012**	**2000**	**2012**	**2000**	**2012**
Sectors						
Agriculture	55	37	65	57	60	47
Mining	1	1	0	0	1	1
Manufacturing	11	14	11	10	11	12
Utilities	1	1	0	0	0	1
Construction	8	18	2	4	5	11
Trade services	6	7	15	17	10	12
Transport services	5	7	3	5	4	6
Business services	2	3	1	2	1	3
Public administration and defense, education, health, and social work	10	9	1	2	5	6
Personal services	3	3	3	3	3	3
Urban–Rural						
Rural	73	67	82	78	78	72
Urban—towns and small cities	19	22	14	16	16	19
Urban—big cities	8	11	4	6	6	8
Firm size (without agriculture)						
Large firms[a]	42	43	2	3	23	27
Small firms[a]	58	57	98	98	77	73
Tradables (with agriculture)						
Tradable	74	62	80	75	77	68
Nontradable	26	38	20	25	23	32
Tradables (without agriculture)						
Tradable	41	39	44	41	42	40
Nontradable	59	61	56	59	58	60
Occupation categories						
Routine manual	23	32	14	13	19	23
Nonroutine manual	8	11	5	6	7	9
Routine analytic	4	4	0	0	2	2
Nonroutine analytic	10	15	17	23	14	19
Agriculture	55	38	64	57	59	47

[a]A large firm is defined as a firm with 10 or more workers. In 2012, 8% of wage workers reported that their firm size was unknown, while 24% of wage workers in 2000 did not know the size of their firm.

Notes: Employment shares are based on the full sample of workers (with or without wage data). A big city is defined as a city with a population of 1 million or more as per the 1991 census. This sample is limited to states included in the wage decomposition analysis and Mincerian wage regressions.

Source: Authors' calculations using data from National Sample Survey Office. 2000. "National Sample Survey 1999–2000 (55th round): Schedule 10–Employment and Unemployment Survey." Government of India, Ministry of Statistics and Program Implementation; and National Sample Survey Office. 2012. "National Sample Survey 2011–2012 (68th round): Schedule 1.0–Employment and Unemployment Survey." Government of India, Ministry of Statistics and Program Implementation.