

# Urbanization, Structural Transformation and Rural-Urban Disparities in China and India\*

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## Abstract

Over the past three decades India and China have experienced rapid economic growth along with a rapid structural transformation of the economy away from agriculture towards manufacturing and services. Underneath the overall similarity in aggregate takeoffs however is one significant difference: rural and urban disparities have evolved very differently in the two countries: rural-urban wage gaps have been declining in India while they have widened in China during this period. We formalize a two-sector model with differential sectoral income elasticities. In the model, both structural transformation and urbanization respond endogenously to sectoral and aggregate productivity shocks. While the structural transformation effect tends to widen the urban-rural wage gap, the urbanization effect due to migration tends to reduce it. We show that the model can quantitatively account for both the wage convergence in India as well as the wage divergence in China.

**JEL Classification:** J6, R2

**Keywords:** Rural urban disparity, urbanization, structural transformation

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# 1 Introduction

The process of structural transformation wherein countries transform from being rural and agrarian to becoming more urbanized and non-agriculture is a ubiquitous feature of the development process. The process is however potentially extremely disruptive given the required reallocation of people and resources across time, sectors and activities. While there has been a lot of work on understanding the flow of productive resources across sectors during these episodes, their effects on the relative fortunes of the people at the center of this transformation is somewhat less analyzed. Put differently, the work on structural transformation has mostly focused on the adjustment of quantities. Their effects on prices of goods and wages in different sectors and locations hasn't typically been a focus of attention. In this paper we fill this gap in the context of the experiences of China and India since the 1980s, a period in which they have been undergoing a rapid structural transformation. Given that upwards of 1.5 billion people still reside in rural China and India combined (which is almost a fifth of the world population), the scale of the disruption and reallocation unleashed by this process is potentially massive with attendant implications for overall inequality in the two countries.

The paper introduces two main innovations. First, we explicitly inject locations into the analysis of structural transformation by distinguishing between rural and urban locations. This is in contrast to the standard approach which typically conflates agricultural activities with rural locations on the one hand, and non-agricultural activities with urban locations on the other. As we show empirically and quantitatively, this conflation can be misleading both as a physical description as well as for understanding the consequences of the process for the relative fortunes of people living in these locations. Second, the paper focuses not just on quantity movements but also on prices during this process by examining the changes in wages by sector and location as well as the relative sectoral prices of goods.

Our data analysis reveals some interesting contrasts between China and India during this period. While both countries have exhibited similar patterns of structural transformation accompanied by rising urbanization, the movements in wages have been very different. Between 1988 and 2008 the mean wage gap between rural and urban workers in China has widened by 10 percentage points with the median gap widening by an even larger 31 percentage points. In contrast, the mean urban-rural wage gap in India between 1983 and 2010 has declined by 35 percentage points while the corresponding median wage gap has contracted by a massive 66 percentage points. Somewhat puzzlingly, we find that individual worker attributes account for only a small fraction of the movements in wages. Interestingly, the contrasting wage movements in the two countries have occurred in the backdrop of similar qualitative movements in the inter-sectoral wage gaps as well as in the relative sectoral prices of goods. This evidence suggests to us that the conflation of sectors and locations is not an innocuous abstraction.

To explain the contrasting trends in the urban-rural wage gaps in the two countries, the paper

formalizes a two-sector, two-location overlapping generations model of structural transformation. Our model generates structural transformation due to non-homothetic preferences and growth in agricultural productivity. This is a familiar channel in the literature. The key new part is that we also allow individuals to choose, through migration, their location of residence and work during their adult working years. Consequently, the model generates structural transformation and urbanization as a joint endogenous response to sectoral productivity shocks.

Locations in our model are distinguished by two features: sectoral productivities and amenities. Crucially, we allow both of these distinguishing features of locations to be affected by aggregate migration flows. In our baseline environment, we assume that urban locations provide some extra amenities which raise utility of urban residents. However, these amenities are also subject to negative congestion externalities which depend on the magnitude of migrants into urban locations. In an extension of the model, we also introduce agglomeration economies in production that depend positively on the magnitude of urban labor force growth.

Productivity shocks in the model have two effects on wages in urban and rural areas. On the one hand, the non-homotheticity induces a differential demand effect with demand for agricultural goods declining in relative terms. This lowers the relative wage in agriculture. With rural areas being predominantly agricultural, this tends to make the urban-rural wage gap larger. On the other hand, the productivity shock also induces migration of workers from rural to urban locations. The magnitude of the rural-to-urban migration depends both on the size of the wage gap as well as the induced congestion effects of migration on urban amenities. The direct effect of the migration-induced increase in the relative supply of urban labor is a lowering of the urban-rural wage gap. However, in the presence of agglomeration economies on production, the increase in the urban labor force also raises urban productivity. This tends to widen the urban-rural wage gap. The end effect on the location wage gap depends on the relative strengths of these effects which, in turn, depends on the relative strengths of the productivity shocks in the two sectors.

We calibrate the model to China and India separately and examine its quantitative predictions for both structural transformation and wage gaps by feeding in the actually observed changes in sectoral productivity during the sample period. For India the productivity shocks account for both the structural transformation and the movements in the wage gaps. For China too the model accounts for both the structural transformation and wage divergence though the quantitative magnitude of the wage divergence is somewhat muted. In addition, the model also generates the rise in the relative price of agricultural that is a feature of the data in both China and India during this period. This is an important result because standard models of structural transformation with non-homotheticities typically predict the opposite. Overall, we view the results as being supportive of the model and key mechanisms formalized in it.

Counterfactual experiments on the model suggest that a key factor behind the widening wage gap in China is the restriction on migration within the country. We find that lowering the implied

migration restrictions in China to the corresponding levels in India would generate a sharp 41 percentage point contraction in the wage gap along with an additional 12 percentage point decline of the rural share of the workforce between 1988 and 2008. Our model also suggests that had agricultural and non-agricultural productivities in India grown at the significantly faster rates observed in China, India would have seen the urban-rural wage gap decline by an additional 5.3 percentage points while the urban share of the labor force would have grown to a significantly higher 48 percent by 2010 rather than the 30 percent in the data.

We should note that our mechanism for generating structural change relies on lower income elasticity of demand for agricultural goods due to non-homotheticity in preferences. This is a *demand-side* effect generated by changing incomes. There is also a *supply-side* mechanism that has been proposed in the literature (dating back to Baumol (1967)) which relies on differential sectoral productivity growth. In particular, Ngai and Pissarides (2007) use a multi-sector model to show that as long as the elasticity of substitution between final goods is less than unity, over time factors would move to the sector with the lowest productivity growth. In both China and India this mechanism leads to a counterfactual implication since productivity growth in non-agriculture was faster than in agriculture. Hence, the Ngai and Pissarides (2007) mechanism would imply that factors should have migrated to the agricultural sector over time while the data shows the opposite. One could get around this by assuming that the elasticity of substitution between final goods is greater than unity. However, given the lack of precise estimates on this elasticity, it seems heroic to put the entire onus of the explanation on the configuration of a poorly measured parameter. Consequently, we shut down this channel by assuming that the elasticity of substitution between final goods is unity. This also implies that the reasons for structural transformation in the model are the non-homotheticity in preferences.<sup>1,2</sup>

Our focus on rural-urban gaps probably is closest in spirit to the work of Young (2012) who has examined the rural-urban consumption expenditure gaps in 65 countries. Like us, he finds that only a small fraction of the rural-urban inequality can be accounted for by individual characteristics, such as education differences. He attributes the remaining gaps to competitive sorting of workers to rural and urban areas based on their unobserved skills.<sup>3</sup> Our work is also related to an empirical literature studying rural-urban gaps in different countries (see, for instance, Nguyen, Albrecht, Vroman, and

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<sup>1</sup>See Laitner (2000), Kongsamut, Rebelo, and Xie (2001) and Gollin, Parente, and Rogerson (2002) for a formalization of the non-homothetic preference mechanism. Our work is also related to the factor deepening channel for structural transformation formalized in Acemoglu and Guerrieri (2008). An overview of this literature can be found in Herrendorf, Rogerson, and Valentinyi (2013a).

<sup>2</sup>Another supply-side channel is the skill acquisition cost mechanism proposed by Caselli and Coleman (2001) in their study of regional convergence between the North and South of the USA. In their model a fall in the cost of acquiring skills to work in the non-agricultural sector induces a fall in farm labor supply and leads to an increase in farm wages and relative prices.

<sup>3</sup>Young's explanation based on selection is complementary to Lagakos and Waugh (2012). Our finding of unexplained changes in rural-urban wage gaps over time also finds an echo in the work of Gollin, Lagakos, and Waugh (2012) who find large and unexplained differences in value-added per worker in agriculture relative to non-agriculture in developing countries.

Westbrook (2007) for Vietnam, Wu and Perloff (2005) and Qu and Zhao (2008) for China and others). These papers generally employ household survey data and relate changes in urban-rural inequality to individual and household characteristics.

Our modeling of congestion and production externalities in urban locations borrows from the literature on economic geography. However, we abstract from the sources of these externalities and instead simply assume that they depend on the size of the local population. This simplification allows us to focus on the effect of these externalities of migration on the locational distribution of production. An extensive discussion on the microfoundations of these externalities can be found in the works of ? and ?. Our modeling approach is similar in spirit to the work of ?.

It is worthwhile elaborating on the reasons for our focus on the distinction between rural and urban locations over and beyond the standard distinction between agriculture and non-agricultural sectors. Our interest in locations stems from the fact that moving resources across space is often costly and subject to additional policy imposed frictions. This distinction is fairly well appreciated in the context of international economics where the fact that resource mobility across countries is costly is taken as a natural description of the environment. Mobility of factors within a country though are rarely seamless. Language, culture, distance are all impediments to frictionless mobility of factors across locations. In addition, policy imposed restrictions such as the Houko system in China which effectively disincentivize movement of rural workers to urban areas are additional factors that make locations an important feature of economic allocations and outcomes. Put differently, if all resources could be freely reallocated across locations to reflect their sectoral comparative advantage, then an exclusive focus on sectoral dynamics would be enough. However, in the absence of such costless reallocation, locations become an important additional factor in understanding the effect of aggregate shocks on the fortunes of workers within an economy.<sup>4</sup>

The rest of the paper is organized as follows: the next section presents the data and the main results on changes in the rural-urban gaps as well as the analysis of the extent to which these changes were due to changes in individual characteristics of workers. Section 3 presents our model and examines the role of aggregate shocks in explaining the patterns. The last section contains concluding thoughts.

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<sup>4</sup>The presence of frictions in locational reallocation of factors shows up both in the data and in the policy initiatives within countries. Thus, in both India and China one finds evidence of rural workers moving from agriculture into non-agriculture within rural areas. Put differently, a non-trivial share of the structural transformation in these economies occurs through inter-sectoral movement of workers from agriculture to non-agriculture within the same location. Consequently, one finds a significant share of rural workers engaged in non-agricultural work even though non-agricultural productivity and wages are significantly higher in urban areas. On the policy front, India has initiated one of the largest public works programs globally called the National Rural Employment Guarantee Scheme (NREGA). The program guarantees 100 days work to every rural worker. The policy is clearly a response to a perceived concern that the market mechanism was not effective in generating sufficient urban, non-agricultural employment for workers switching out of agricultural work in rural areas.

## 2 Empirical results

Our primary data source for China is the Chinese Household Income Project (CHIP). We use five rounds of the CHIP (1988, 1992, 1995, 2002 and 2008). Since our interest is in determining the trends in wages and determinants of wages such as education and occupation, we choose to restrict the sample to individuals in the working age group 16-65 who are identified as working and who report working at least 1900 hours per year. These restrictions leave us with 47,000 to 83,000 individuals per survey round. The data for India comes from successive rounds of the Employment & Unemployment surveys of the National Sample Survey (NSS) of households in India. The survey rounds that we include in the study are 1983, 1993-94, 1999-2000, 2004-05, and 2009-10.<sup>5</sup> We restrict the sample to individuals in the working age group 16-65, who are working full time (defined as those who worked at least 2.5 days in the week prior to being sampled), who are not enrolled in any educational institution, and for whom we have both education and occupation information. We further restrict the sample to individuals who belong to male-led households.<sup>6</sup> These restrictions leave us with, on average, 140,000 to 180,000 individuals per survey round. Details on our data are provided in Appendix A.1.

Our primary focus is on real wages. For China, we use annual wage income which are deflated using province-level CPI deflators that differ for rural and urban sectors. For India we measure wages as the daily wage/salaried income received for the work done by respondents during the previous week (relative to the survey week), if the reported occupation during that week is the same as worker's usual occupation (one year reference).<sup>7</sup> Wages can be paid in cash or kind, where the latter are evaluated at current retail prices. We convert wages into real terms using state-level poverty lines that differ for rural and urban sectors.<sup>8</sup> We express all wages in 1983 rural Maharashtra poverty lines.

We start by computing the wage gaps between urban and rural workers in China and India.<sup>9</sup> Panel (a) of Figure 1 shows the mean and median gaps for China while Panel (b) shows the corresponding

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<sup>5</sup>There is also a survey round for 1987-88, but we did include it in our analysis as the number of observations for wages in this round falls dramatically relative to the other rounds. This decline is mainly accounted for by the drop in the rural wage observations.

<sup>6</sup>This avoids households with special conditions since male-led households are the norm in India.

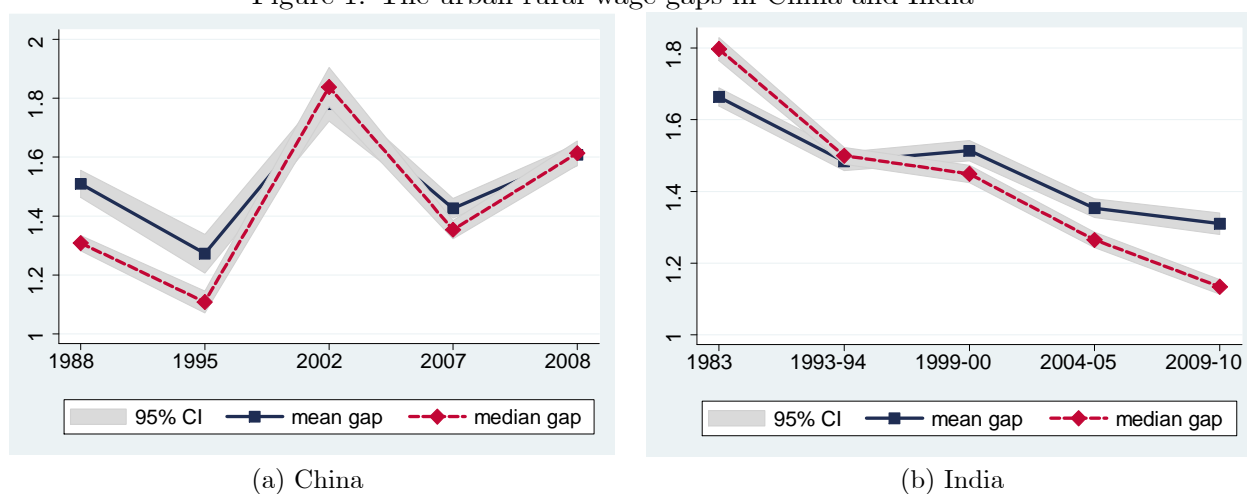
<sup>7</sup>This allows us to reduce the effects of seasonal changes in employment and occupations on wages.

<sup>8</sup>In 2004-05 the Planning Commission of India changed the methodology for estimation of poverty lines. Among other changes, they switched from anchoring the poverty lines to a calorie intake norm towards consumer expenditures more generally. This led to a change in the consumption basket underlying poverty line calculations. To retain comparability across rounds we convert the 2009-10 poverty lines obtained from the Planning Commission under the new methodology to the old basket using a 2004-05 adjustment factor. That factor was obtained from the poverty lines under the old and new methodologies available for the 2004-05 survey year. As a test, we used the same adjustment factor to obtain the implied "old" poverty lines for the 1993-94 survey round for which the two sets of poverty lines are also available from the Planning Commission. We find that the actual old poverty lines and the implied "old" poverty lines are very similar, giving us confidence that our adjustment is valid.

<sup>9</sup>The wage gaps are obtained from a regression of (log) wages on age, age squared and a rural dummy. The reported wage gaps are exponents of -1 times the coefficient on the rural dummy. Mean gaps are obtained from the OLS regressions, while median gaps are obtained from the Recentered Influence Function (RIF) regressions (see Firpo, Fortin, and Lemieux (2009) for more details on the latter).

gaps for India. The panels present a striking contrast: both the mean and the median urban-rural wage gaps widened in China between 1988 and 2008 while they narrowed in India between 1983 and 2010. Specifically, in China, the mean urban-rural wage gap has increased from 51% in 1988 to 61% in 2008 – a 10 percentage points rise. On contrary, in India, the mean urban-rural gap has shrunk from 66% in 1983 to 31% in 2010 – a 35 percentage points decline. The changes in median wages were even more pronounced in both countries. For instance, the median urban wage premium has increased in China from 31% in 1988 to 61% in 2008 – a 31 percentage points rise; which it has declined in India from 80% to 13% – a stunning 66 percentage points fall. Thus, we observe divergence in urban and rural wages in China, but a convergence in India over the past 30 years.

Figure 1: The urban-rural wage gaps in China and India



Notes: Panel (a) shows the mean and median urban-rural wage gaps for China, while Panel (b) shows the same wage gaps for India. These are obtained from a regression of (log) wages on a rural dummy and age controls.

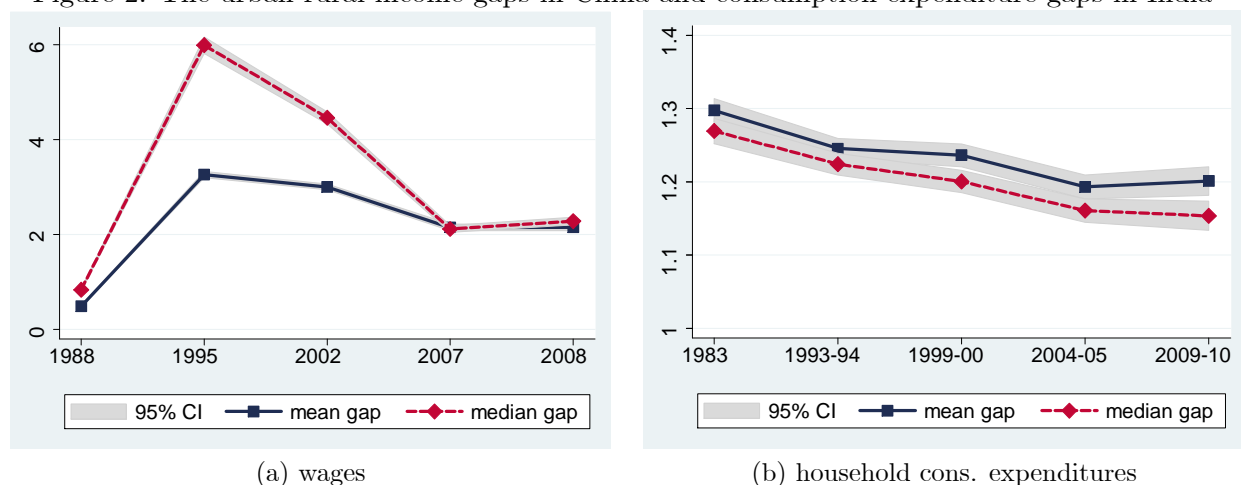
To understand whether the divergence pattern in China and convergence pattern in India documented above were specific to wages or applied more broadly, we consider other sources and proxies for income in the two countries. This is particularly important for rural households a significant proportion of whom tend to be self-employed and therefore do not report any wage income. Thus, we consider family income in China and household consumption expenditures in India. Both variables are in real per capita terms.<sup>10</sup> Family income is obtained as the sum of wage income and XXX. In India we use household consumption expenditure to proxy for family income, which is a function of both wage income (reported in the NSS dataset), and self-employment income (not reported in the the NSS data). Thus, by studying the dynamics of consumption expenditures gaps between urban and rural areas we can get an idea of how overall income gaps have evolved over time.

Panel (a) of figure 2 reports the mean and median gaps in (per capita) annual family income of urban and rural households in China using CHIP dataset, while panel (b) shows the mean and

<sup>10</sup>Family income in China is annual income, while consumption expenditures in India are monthly expenditures.

median urban-rural gaps in per capita monthly consumption expenditures in India using NSS data. These figures confirm our findings for wages. In China, urban family income has diverged from rural family income over time, very much like wage income, but with income gap rising sharper than wage gap. In contrast, in India, consumption expenditures in urban and rural families have been converging over time, although the convergence is more muted than that observed for wages. This is not surprising, given that the consumption expenditure gaps are smaller to start with; and that consumption habits tend to adjust slowly over time.

Figure 2: The urban-rural income gaps in China and consumption expenditure gaps in India



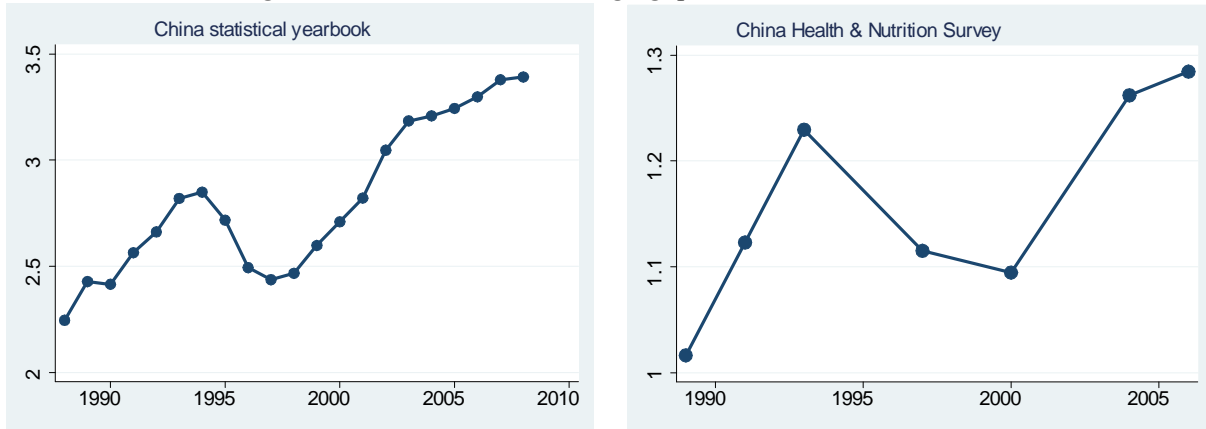
Notes: Panel (a) shows the urban-rural per capita family income gaps in China using CHIP data, while panel (b) shows the urban-rural per capita consumption expenditure gaps for India using NSS data. The income gaps are obtained as -1 times the exponents of coefficients on the rural dummy from OLS and RIF regressions of (log) income on a rural dummy. The consumption gaps are obtained in the same way, except the regressions also include the household size to account for possible scale effects in household consumption.

We should note that while the NSS data for India is a nationally representative sample, the CHIP data for China is not nationally representative as it contains data for households from nine provinces. To examine the robustness of the wage patterns documented in Figure 1, Figure 3 plots the urban-rural wage gaps computed from two other sources: China statistical yearbook (panel (a)), and China Health and Nutrition Survey (panel (b)). Panel (a) shows the ratio of urban average income to rural average income in China since 1988, while panel (b) constructs the ratio of mean urban to rural wages over 1989-2006 period. Like the CHIP dataset, the China Health and Nutrition Survey dataset contains individual- and household-level survey data. However, it is significantly smaller than CHIP. Both plots reveal the same pattern of widening income and wage gaps between urban and rural Chinese workers over the past three decades.

One concern about the aggregate pattern of widening wage gaps in China and contracting gaps in India is that they may be driven by some outlier provinces or states. To check the robustness of the patterns, Panel (a) of Figure 4 plots scatter of the urban-rural wage gaps across provinces



Figure 3: The urban-rural wage gaps in China: robustness



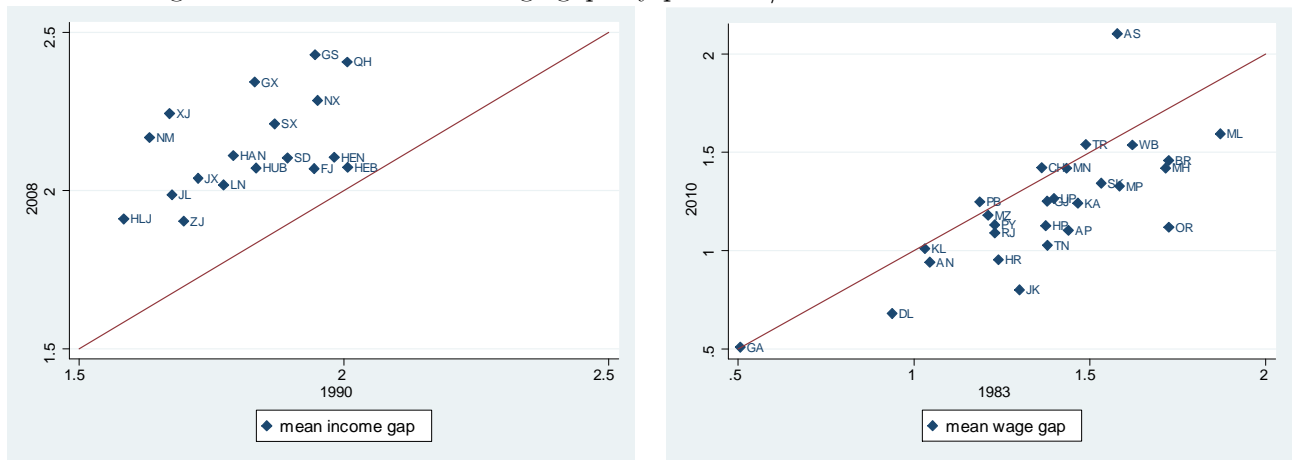
(a) mean income gap

(b) mean wage gap

Notes: Panel (a) shows the ratio of mean income in urban areas to mean income in rural areas in China using Statistical Yearbook data; Panel (b) reports the ratio of mean wages in urban and rural areas in China Health and Nutrition Survey.

in China for 1990 and 2008, while Panel (b) plots the scatter of wage gaps for states in India for 1983 and 2010. The key feature to note is most of the points for China lie above the 45 degree line indicating larger gaps in 2008 relative to 1990. The corresponding scatter of points for Indian states lie primarily below the 45 degree line indicating a narrowing of the wage gap between urban and rural workers between 1983 and 2010. Thus, wage divergence in China and wage convergence in India seem to be taking place across-the-board.

Figure 4: The urban-rural wage gaps by province/state in China and India



(a) China

(b) India

Notes: Panel (a) shows the urban-rural wage gaps for provinces in China for 1990 and 2008. Panel (b) shows the urban-rural wage gaps for India for 1983 and 2009-10 NSS rounds.

Two important reasons for our focus on urban-rural wage gaps as opposed to just inter-sectoral wage gaps can be seen from Table 1. First, in both China and India, the structural transformation

has been accompanied by a progressive increase in the share of the rural labor force engaged in non-agricultural activities. Thus,  $\frac{L_{RA}}{L_R}$  fell from 0.79 to 0.66 in China while it fell from 0.78 to 0.66 in India during the period under study. In effect, the share of the rural labor force engaged in non-agricultural activities in these two countries rose from just under 1/4 to around 1/3. Clearly, movement of factors from agriculture to non-agriculture is not isomorphic with movement of factors from rural to urban areas. Second, while the inter-sectoral wage gaps declined in both rural and urban location in both countries, a key difference between the China and India was that the urban-rural wage gap increased within each sector in China while they declined in India. Hence, one of the main differences between the two countries was the behavior of urban-rural wage gaps. The inter-sectoral gaps moved fairly similarly.

Table 1: Employment shares and wage gaps

	China		India	
	1988	2008	1983	2010
<i>employment shares:</i>				
$L_U$	0.26	0.35	0.22	0.30
$L_{RA}/L_R$	0.79	0.66	0.78	0.66
$L_{UA}/L_U$	0.05	0.03	0.11	0.07
<i>wage gaps:</i>				
within $A$	2.052	2.509	0.934	1.027
	(0.102)	(0.393)	(0.018)	(0.042)
within $N$	1.408	1.600	1.082	0.994
	(0.022)	(0.019)	(0.012)	(0.014)
$R$ between	1.300	1.195	1.962	1.679
	(0.051)	(0.102)	(0.022)	(0.019)
$U$ between	0.970	0.748	2.259	1.709
	(0.030)	(0.088)	(0.050)	(0.069)
overall mean	1.510	1.608	1.664	1.310
	(0.023)	(0.019)	(0.013)	(0.015)

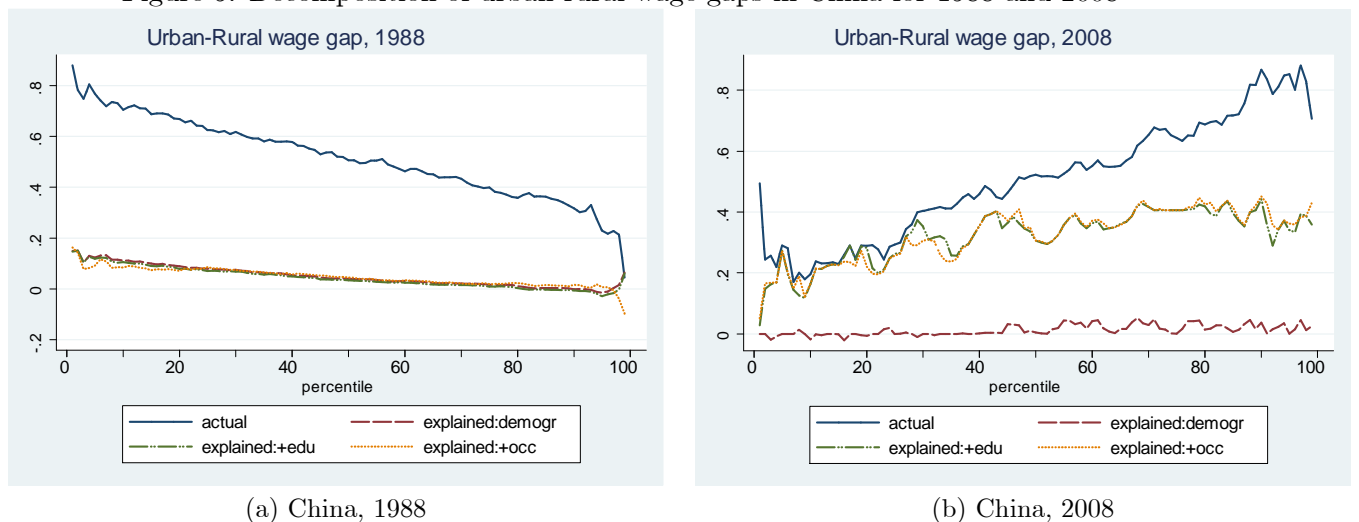
What explains the observed patterns in the urban-rural wage gaps in the two countries? The standard explanations focus on measured attributes in wages such as demographics, education, occupation, etc.. How much of the wage convergence/divergence documented above is driven by a convergence/divergence of measured covariates? We examine this using a procedure developed by DiNardo, Fortin, and Lemieux (1996) (DFL from hereon) to decompose the difference in the observed wage distributions of urban and rural labor within a sample round into two components – the part that is explained by differences in attributes and the part that is explained by differences in the wage structure of the two groups. To obtain the explained part, for each set of attributes we construct a counterfactual density for urban workers by assigning them the rural distribution of the attributes.<sup>11</sup>

<sup>11</sup>The DFL method involves first constructing a counterfactual wage density function for urban individuals by giving them the attributes of rural households. This is done by a suitable reweighting of the estimated wage density function of urban households. We choose to do the reweighting this way to avoid a common support problem, i.e., there may not be enough rural workers at the top end of the distribution to mimic the urban distribution. The counterfactual urban wage density is then compared with the actual urban wage density to assess the contribution of the measured attributes to the observed wage gap.

We consider several sets of attributes. First, we evaluate the role of individual demographic characteristics such as age, age squared, gender and geographic location. Second, we add education to the set of attributes and obtain the incremental contribution of education to the observed wage convergence. Lastly, we evaluate the role played by differences in the occupation distribution for the urban-rural wage gaps.

Figure 5 presents our findings for China for 1988 (panel (a)) and 2008 (panel (b)). The solid line shows the actual urban-rural (log) wage gaps for the entire wage distribution, while the broken lines show the gaps explained by differences in attributes of the two groups, where we introduced the attributes sequentially. The plot for 1988 says that observed gaps in attributes explained very little of the actual wage gap in that year. In 2008 by contrast, measured attributes, especially education, explain almost 60 percent of the actual median gap with the explanatory power becoming smaller at the higher income percentiles. The two graphs combined suggest that a significant part of the overall movement in the wage gaps was unaccounted for by measured covariates of wages.

Figure 5: Decomposition of urban-rural wage gaps in China for 1988 and 2008

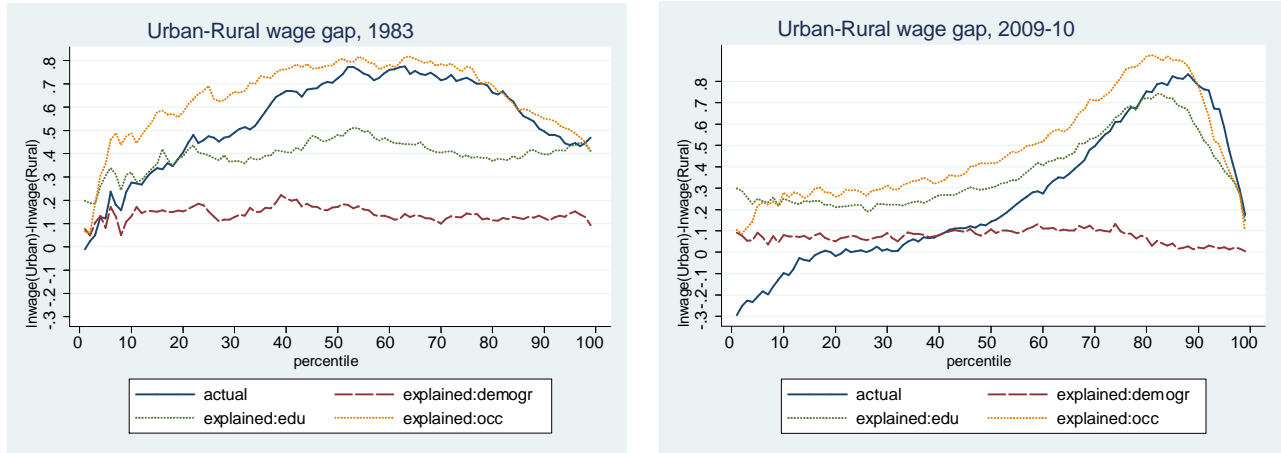


Notes: Each panel shows the actual log wage gap between urban and rural workers for each percentile, and the counterfactual percentile log wage gaps when urban workers are sequentially given rural attributes. Three sets of attributes are considered: demographic (denoted by "demogr"), demographics plus education ("edu"), and all of the above plus occupations ("occ"). The left panel shows the decomposition for 1988 while the right panel is for 2008.

Figure 6 plots the same graphs for India for 1988 (panel (a)) and 2009-2010 (panel (b)). Like in China, demographic characteristics explain a small fraction of the urban-rural wage gap. In 1983 differences in education account for almost the entire wage gap at the bottom of the distribution, while differences in occupation explain the wage gap for the upper 50 percent of the distribution. Put differently, education and occupation choices can jointly account for almost the entire wage gap distribution in India in 1983. In 2009-10 however, differences in education attainments between

urban and rural workers explain a large fraction of the gap at the top end of the distribution (70th percentile and above). However, for those below the 70th percentile, covariates such as demographic characteristics, education and occupation choices systematically *over-predict* the actual wage gaps. This is particularly stark for the bottom 15 percent where the actual wage gap is negative while the demographic characteristics, education endowments and differences in occupations predict that the urban-rural gap should be positive 30 percent.

Figure 6: Decomposition of urban-rural wage gaps in India for 1983 and 2009-10



(a) India, 1983

(b) India, 2010

Notes: Each panel shows the actual log wage gap between urban and rural workers for each percentile, and the counterfactual percentile log wage gaps when urban workers are sequentially given rural attributes. Three sets of attributes are considered: demographic (denoted by "demogr"), demographics plus education ("edu"), and all of the above plus occupations ("occ"). The left panel shows the decomposition for 1988 while the right panel is for 2008.

These results suggest that a large part of the observed convergence in wage differences cannot be explained by standard covariates of wages. Hence, the wage structure of urban and rural workers and changes therein during the sample period play an important role in our data.

### 3 The Role of Aggregate Shocks

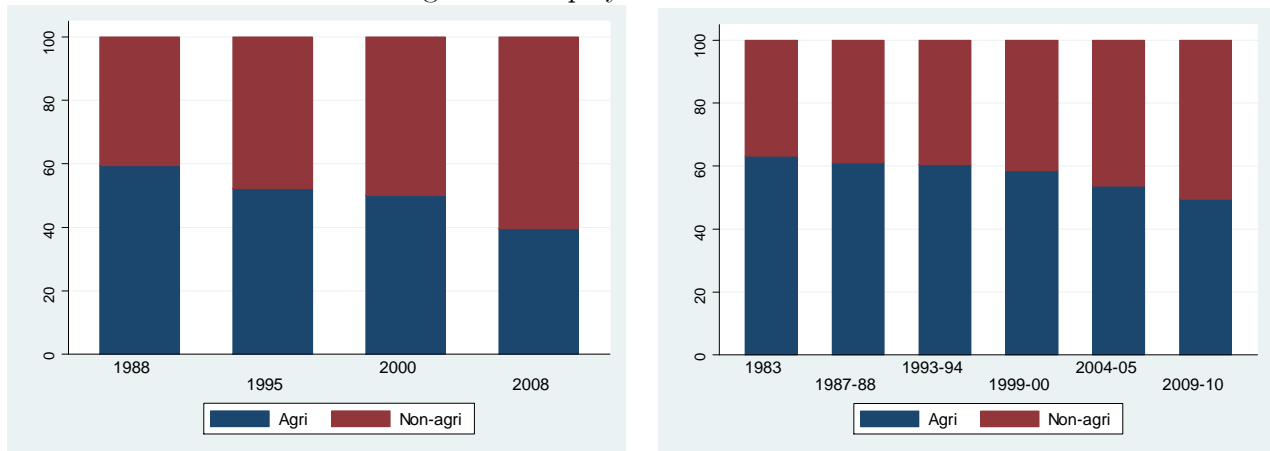
The previous results suggest that a large part of the movement in the wage gap between rural and urban workers in China and India cannot be accounted for by convergence in the individual characteristics of the two groups. What then explains the trends? One possibility is that aggregate developments during this period may have played a role. Specifically, the period since the 1980s was marked by a sharp increase in the aggregate growth rate, structural transformation and rapid urbanization of the economy in both countries. Could these aggregate changes have contributed to the observed trends in rural-urban gaps in China and India? In this section we examine this possibility by exploring their effects through the lens of a structural model.

### 3.1 Key aggregate facts

Before presenting the model it is useful to summarize some key aggregate developments in China and India over the last three decades. Our key aggregate facts relate to the structural composition of employment and output, sectoral productivities, the urban share of the labor force, and relative prices. We want the model to be consistent with these facts.

The ongoing process of structural transformation of China and India can be seen through Figures 7 and 8. Figure 7 shows employment shares in agriculture and non-agriculture for China (panel (a)) and India (panel (b)). Figure 8 shows the distribution of output across the agriculture and non-agriculture in the two economies. As is easy to see, agriculture has been releasing workers in both countries, and its share of output has also been declining over time in both. The non-agricultural sector, on the other hand, has expanded both as a share of employment and as a share of output in both India and China. These are the textbook features of structural transformation.

Figure 7: Employment distribution



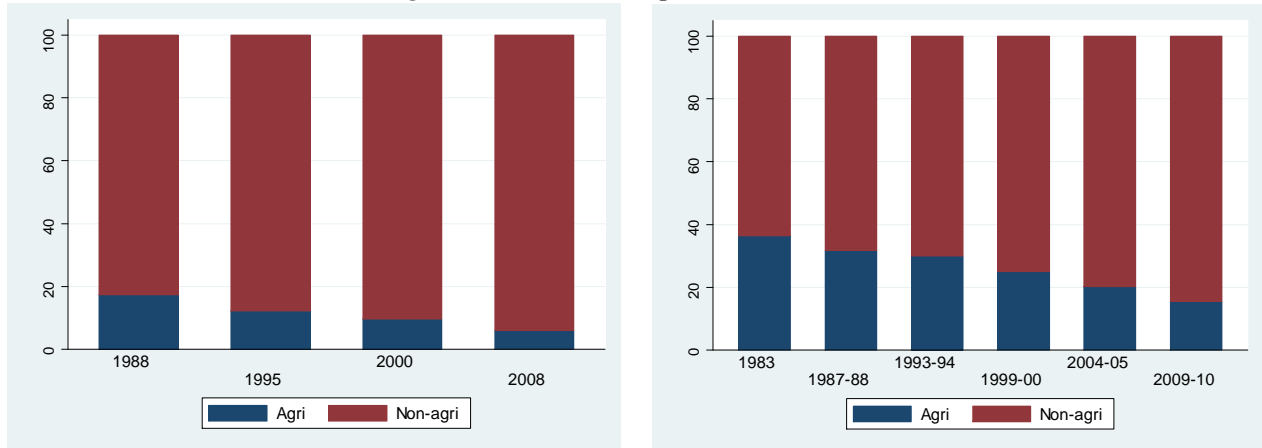
(a) China: employment shares

(b) India: employment shares

Notes: Panel (a) of this Figure presents the distribution of workforce across agricultural and non-agricultural sectors for China while panel (b) presents the employment distribution across the two sectors for India.

The third key aggregate fact of interest is the behavior of sectoral labor productivities that were underlying the process of structural transformation. Figure 9 presents labor productivity in agriculture and non-agriculture in China and India. In both countries labor productivity in both agriculture and non-agriculture was increasing during this period, with non-agricultural productivity expanding at a much faster pace. The patterns in the two economies were remarkably similar, although the labor productivity growth was much faster in China than in India. Thus, the labor productivity in agriculture increased by 67 percent in India between 1983 and 2010, and by 163 percent between 1990 and 2008 in China. The non-agricultural labor productivity rose by 200

Figure 8: Sectoral output distribution



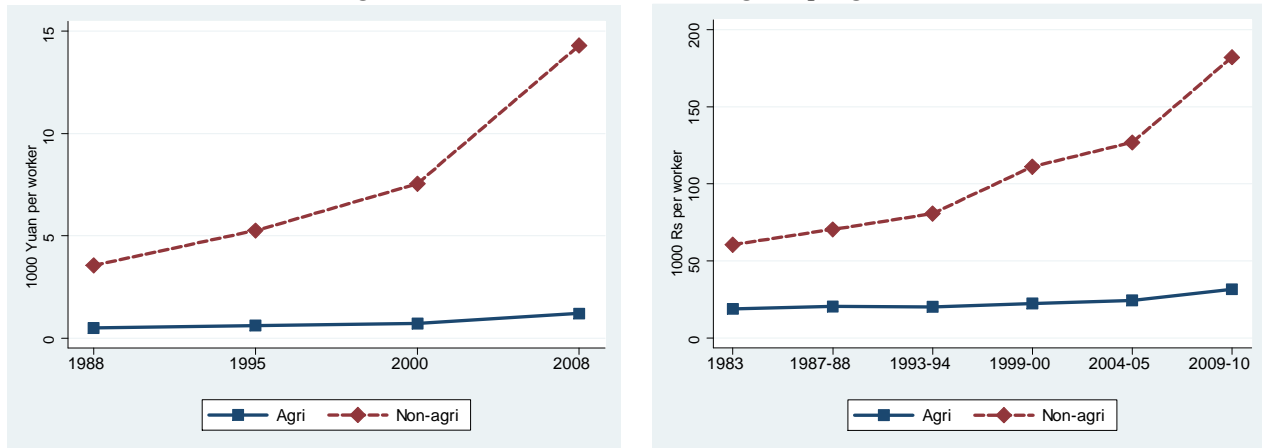
(a) China: output shares

(b) India: output shares

Notes: Panel (a) of this Figure presents the distribution of output across agricultural and non-agricultural sectors in China. China.China.China. Panel (b) presents same distribution for India.

percent in India and 338 percent in China during the same periods.<sup>12</sup>

Figure 9: Sector-biased technological progress



(a) China

(b) India

Notes: Panel (a) shows sectoral labor productivity during the 1990-2008 period for China, while panel (b) shows the same for India for the 1983-2010 period.

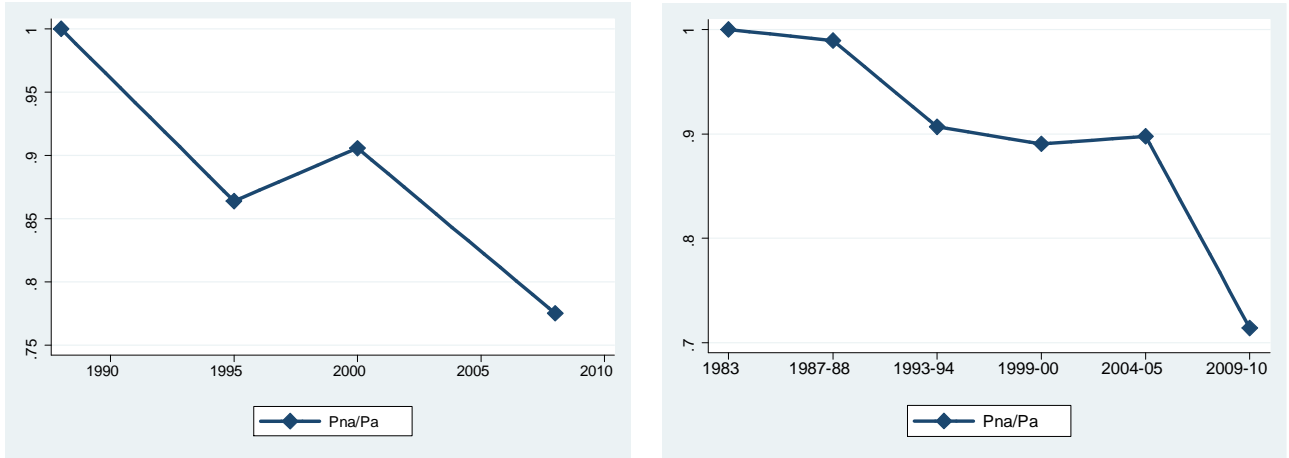
Lastly, Figure 10 presents the evolution of the relative price of non-agricultural goods (relative to agricultural good) in China and India since the 1980s. The movement in this relative price is remarkably similar in the two countries. The relative price of non-agriculture declined by 23 percent in China and 29 percent in India.<sup>13</sup> It is worth noting that the world relative price of agriculture

<sup>12</sup>When reporting growth rates of labor productivity we used 1990 as the starting year for China instead of 1988 because of discontinuity in the sectoral employment data for China in 1989. We suspect that the definition of employed must have been changed in that year.

<sup>13</sup>These numbers were obtained using nominal and real output series from the National Accounts Statistics provided by the Ministry of Statistics and Programme Implementation (MOSPI) of Government of India and the National Statistical Yearbook in China.

was actually falling during most of the period since the 1980s, in contrast to the rising relative price of agriculture in China and India.

Figure 10: Relative price of non-agriculture



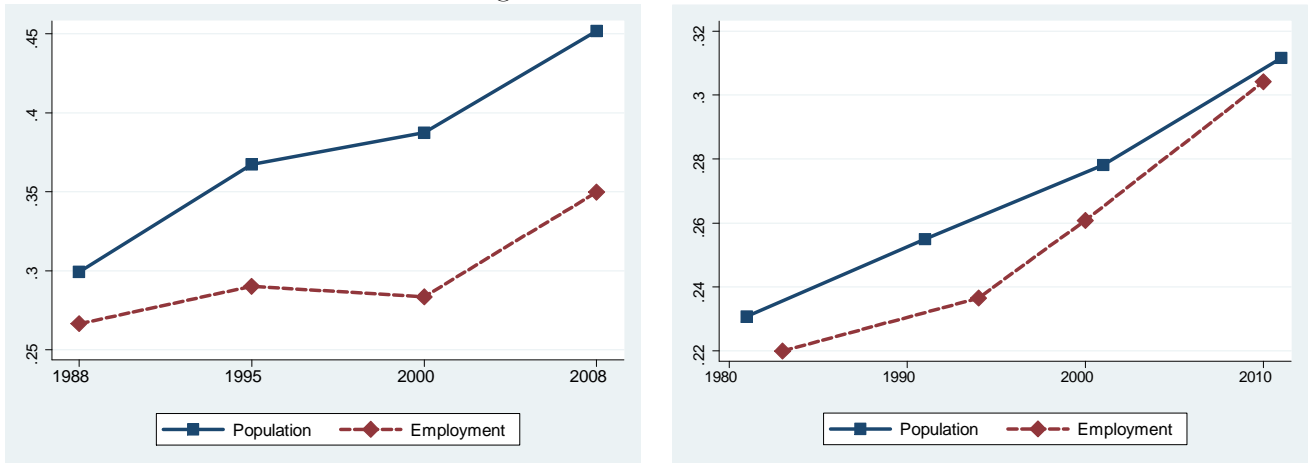
(a) China

(b) India

Notes: This figure shows the price of non-agricultural output relative to agricultural output.

The final key aggregate fact relates to urbanization. Figure 11 shows the urban share of both population and employment in China (panel (a)) and India (panel (b)) during their sample periods of 1988-2008 and 1983-2010, respectively. Just as in patterns on relative prices and structural transformation, the urbanization patterns are qualitatively very similar with the urban share of employment rising from 26 to 35 percent in China and 22 to 30 percent in India.

Figure 11: Urban share



(a) China

(b) India

Notes: This figure shows the urban share of population and employment.

Our main takeaway from these aggregate facts in China and India is the patterns of structural transformation, sectoral productivity growth, urbanization and relative price movements were all very similar qualitatively. However, there were quantitative differences in the changes, especially in

sectoral productivity growth and the size of the structural transformation.

### 3.2 A Structural Explanation

We formalize a simple model with two sectors (agriculture and non-agriculture) and two locations (rural and urban). The goal of the exercise is to structurally identify the minimal features that can generate three key facts characterizing the Indian economy during 1983-2010 and the Chinese economy during 1988-2008 period, as outlined above: (i) a structural transformation; (ii) rising urbanization; (iii) changing urban-rural wage gaps; and (iv) an improvement in the agricultural terms of trade. We then quantitatively examine the relative contributions of the identified factors to the observed wage convergence in India and wage divergence in China.

Consider an economy with two locations: rural and urban. Each location produces two goods – an agricultural good and a non-agricultural good. Under our formalization, locations are defined by two key distinguishing characteristics: (a) their productivities in producing the two goods; and (b) the amenities they provide for their residents. We elaborate on these below.

We assume that goods markets are integrated in this economy so that the price of each good is equalized across locations. However, labor mobility across locations is costly. Hence, factor markets are segmented across locations at any point in time implying that factor prices can also differ across locations. We assume throughout that there is no uncertainty in this economy so that we shall focus on equilibria with perfect foresight.

### 3.3 Technology

The location-specific technologies for producing the two goods are

$$Y_t^{jA} = A_t^j \left( L_t^{jA} \right)^{\alpha^j}, \quad j = R, U \quad (3.1)$$

$$Y_t^{jN} = N_t^j \left( L_t^{jN} \right)^{\beta^j}, \quad j = R, U \quad (3.2)$$

where  $\alpha^j \in (0, 1)$  and  $\beta^j \in (0, 1)$ . Throughout the paper we shall use  $R$  to denote rural and  $U$  to denote urban.  $L^{jA}$  denotes total employment of labor in the agricultural sector in location  $j = R, U$ . Similarly,  $L^{jN}$  denotes total employment of labor in the non-agricultural sector in location  $j = R, U$ . Note that underlying these decreasing returns to labor technologies is a fixed factor like land.  $A^j$  and  $N^j$  denote the total factor productivity in location  $j = R, U$  in the agricultural and non-agricultural sectors, respectively. Note, that we allow the sectoral productivities to be different across location. Indeed, this is a key aspect distinguishing locations in the model.

Competitive firms in each location and sector hire labor to maximize profits. Consequently,

$$w_t^{jA} = \alpha^j \frac{Y_t^{jA}}{L_t^{jA}}, \quad j = R, U \quad (3.3)$$



$$w^{jN} = \beta^j \frac{p_t Y_t^{jN}}{L_t^{jN}}, \quad j = R, U \quad (3.4)$$

where  $w^{jA}$  denotes the real wage in location  $j$  in the agricultural sector while  $w^{jN}$  is the real wage in location  $j$  in sector  $N$ .  $p$  is the relative price of the non-agricultural good in terms of the agricultural good, which we treat as the numeraire good throughout. Clearly, profits of firms then are

$$\Pi_t^{jA} = (1 - \alpha^j) Y_t^{jA} \quad (3.5)$$

$$\Pi_t^{jN} = (1 - \beta^j) p_t Y_t^{jN} \quad (3.6)$$

These are the returns to the fixed factor.

### 3.4 Households

Each location is inhabited by overlapping generations of two-period lived individuals. In the first period of life each individual chooses the location where she wants to live next period. Changing locations however is costly. Young individuals who choose to change their location have to pay  $\tau$  units of the agricultural good as a relocation cost. These relocation costs can be financed through borrowing in domestic capital markets. In the second period of life individuals work in the location they chose when young, have children, consume and then die. Each worker in location  $j = R, U$  at date  $t$  has 1 kid so that population is constant in this economy over time.<sup>14</sup>

In the second period of their lives, individuals have an endowment of one unit of time which they supply inelastically to the labor market in their location of residence. Labor time supplied to the agricultural sector is productive directly. Labor time supplied to the  $N$ -sector however requires some sectoral training which entails a cost  $\tau^j$  units of the agricultural good per unit of labor time. Note that we are allowing the labor training costs to be location specific, since  $j = R, U$ .

Individuals derive utility from consumption only when old. Hence, utility of an individual born at date  $t$  in location  $i$  and who chooses to work and consume in location  $j$  at date  $t + 1$  is

$$V_t^{ij} = u \left( c_{t+1}^{ij} \right) \varepsilon_{t+1}^j, \quad u' > 0, \quad u'' < 0$$

where

$$c_t^{ij} = \left( c_t^{ijA} - \bar{a} \right)^\theta \left( c_t^{ijN} + \bar{n} \right)^{1-\theta}, \quad i = R, U, \quad j = R, U$$

$c_t^{ij}$  denotes consumption of an individual born in location  $i$  and consuming in location  $j$ .  $\bar{a}$  de-

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<sup>14</sup>Our formalization of the migration decision as a dynamic choice is aimed at capturing long-term migration. We could potentially allow within-period, short-term migration as well by having workers change locations after observing the locational productivities for the period and paying for the migration cost out of their current period wage earnings. This would not change the theoretical logic of the model. We choose to abstract from this margin since a large part of these short-term flows tend to reverse themselves within a year as opposed to the long term migration flows that contribute to the growing urbanization of the economy.

notes the minimum consumption level of the agricultural good and  $\bar{s}$  is the minimum level of the non-agricultural good that is produced at home. This is a standard method of introducing non-homotheticity into the model which makes the income elasticity of demand for the agricultural good less than the corresponding income elasticity of the non-agricultural good.

$\varepsilon^j$  is a term reflecting amenities available in location  $j = R, U$ .  $\varepsilon^j$  reflects the level of amenities in that location and is exogenous to the individual, and is identical for all individuals. This amenity term is the second feature that distinguishes locations in the model (the first being the locational productivity in producing the two goods). We shall assume that the location amenities factor for location  $j$  is given by

$$\varepsilon_t^j = \bar{\varepsilon}^j e\left(M_t^j, L_t^{jj}\right), \quad j = R, U \quad (3.7)$$

where  $M_t^j$  denotes the number of migrant workers in location  $j$  at date  $t$  and  $L_t^{jj}$  denotes the total number of workers in location  $j$  at date  $t$  who were also born in location  $j$ . The function  $e(\cdot, \cdot)$  captures externalities that could arise from new migrants into the location as well as the size of the location. We shall specialize this function as

$$e\left(M_t^j, L_t^{jj}\right) = \left(1 + \frac{M_t^j}{L_t^{jj}}\right)^\phi, \quad \phi < 0, \quad j = R, U$$

$\phi < 0$  implies that there are negative externalities associated with population growth due to migration into a location. Note that  $e$  reduces to unity when migration ceases. This reflects the idea that the negative externalities associated with city growth reflect transitions where population growth exceeds the ability of the location to absorb the new immigrants. In a stationary state, migration ends and the city augments its infrastructure to reflect its new size.

In the following we shall specialize the utility function to the CRRA form:

$$u(c) = \frac{c^{1-\frac{1}{\sigma}}}{1-\frac{1}{\sigma}}, \quad \sigma > 1$$

where  $\sigma$  denotes the intertemporal elasticity of substitution which we shall assume throughout to be greater than one.

The budget constraints facing individuals in the two periods of their lives are

$$\tau_t I_t^i = b_{t+1}^i, \quad i = R, U \quad (3.8)$$

$$c_{t+1}^{ijA} + p_{t+1} c_{t+1}^{ijN} + R_{t+1} b_{t+1}^i I_t^{ij} + \frac{T_{t+1}}{L_{t+1}} = w_{t+1}^{jA} l_{t+1}^{jA} + \left(w_{t+1}^{jN} - \tau_t^j\right) l_{t+1}^{jN} + \frac{\sum_{j=R,U} \left(\Pi_{t+1}^{jA} + \Pi_{t+1}^{jN}\right)}{L_{t+1}}, \quad i, j = R, U \quad (3.9)$$

where  $R_{t+1}$  denotes the gross interest factor on loans contracted in period  $t$ .  $I_t^{ij}$  is an indicator function that takes a value of one if a young individual at time  $t$  in location  $i$  decides to migrate

to location  $j$ .  $I_t^{ij} = 0$  otherwise.  $L_{t+1} = L_{t+1}^R + L_{t+1}^U$  denotes the total population of old at time  $t+1$ . The last term on the right hand side of equation (3.9) reflects the fact that all firms are owned equally by the old who receive dividends from firms in proportion to their ownership.  $\frac{T}{L}$  denotes the common per capita lump sum tax that is imposed by the government on all households.

The first-order-condition dictating the optimal consumption mix of the two goods is given by

$$p_t = \left( \frac{1-\theta}{\theta} \right) \left( \frac{c_t^{ijA} - \bar{a}}{c_t^{ijN} + \bar{n}} \right), \quad i = R, U, \quad j = R, U \quad (3.10)$$

Combining equation (3.10) with the budget constraint (3.9) yields the optimal consumption plans of the old in location  $j$  at date  $t$  as:

$$c_t^{ijA} = \theta \left[ \hat{y}_t^{ij} + \left( \frac{1-\theta}{\theta} \right) \bar{a} + p_t \bar{n} \right], \quad j = R, U \quad (3.11)$$

$$p_t c_t^{ijN} = (1-\theta) \left[ \hat{y}_t^{ij} - \bar{a} - \left( \frac{\theta}{1-\theta} \right) p_t \bar{n} \right], \quad j = R, U \quad (3.12)$$

where  $\hat{y}_t^{ij} = w_t^{jA} l_t^{ijA} + (w_t^{jN} - \tau_t^j) l_t^{ijN} - R_t b_t^i I_{t-1}^i - \frac{T_t}{L_t} + \frac{\sum_{j=R,U} (\Pi_t^{jA} + \Pi_t^{jN})}{L_t}$  denotes the disposable income of a worker in location  $j$  at time  $t$  who was born in location  $i$  at date  $t-1$ .

The optimal labor supply decision of a worker in location  $j = R, U$  at date  $t$  dictates that

$$w_t^{jA} = w_t^{jN} - \tau_t^j, \quad j = R, U \quad (3.13)$$

This condition reflects the fact that the worker can freely allocate their labor time to either the agricultural sector or to the non-agricultural sector in their location at cost  $\tau^j$  per unit of labor supplied to the non-agricultural sector.

Before proceeding further, it is worth noting that since all individuals supply their one unit of labor time inelastically to the market, and since all individuals in a location  $i$  face the same sectoral wages in that location,  $w_t^{jA}$  and  $w_t^{jN}$ , the sectoral labor allocation by all individuals in the same location must be identical, i.e.,  $l_t^{ijk} = l_t^{jjk} = l_t^{jk}$  for all  $t$  and for all  $i, j = R, U$  and  $k = A, N$ .

### 3.4.1 Location decision

The young at date  $t$  get to choose where they want to work next period. If they choose to change locations then they have to pay a fixed cost  $\tau$ . The location decision of the young at date  $t$  is dictated by a comparison of lifetime utility at each location. To illustrate the mechanics of this decision we use the notation  $V_t^{ij}$  to denote the lifetime utility of a worker born at date  $t$  in location  $i$  and working in location  $j$  when old. The optimal consumption plans given in equations (3.11) and (3.12) above

imply that

$$V_t^{ij} = u \left( \frac{\Gamma}{p_{t+1}^{1-\theta}} \left\{ \hat{y}_{t+1}^{ij} - \bar{a} + p_{t+1} \bar{n} \right\} \right) \varepsilon_{t+1}^j, \quad i, j = R, U$$

where  $\Gamma \equiv \theta^\theta (1 - \theta)^{1-\theta}$ . This expression shows that there are there four types of workers at any date depending on where the worker was born and where they chose to locate as workers. Using equation (3.13) and the fact that each worker has one unit of labor time when old, the disposable income of the four types of workers are

$$\hat{y}_{t+1}^{RR} = w_{t+1}^{RA} - \frac{T_{t+1}}{L_{t+1}} + \frac{\sum_{j=R,U} \left( \Pi_{t+1}^{jA} + \Pi_{t+1}^{jN} \right)}{L_{t+1}} \quad (3.14)$$

$$\hat{y}_{t+1}^{RU} = w_{t+1}^{UA} - R_{t+1} \tau_t - \frac{T_{t+1}}{L_{t+1}} + \frac{\sum_{j=R,U} \left( \Pi_{t+1}^{jA} + \Pi_{t+1}^{jN} \right)}{L_{t+1}} \quad (3.15)$$

$$\hat{y}_{t+1}^{UR} = w_{t+1}^{RA} - R_{t+1} \tau_t - \frac{T_{t+1}}{L_{t+1}} + \frac{\sum_{j=R,U} \left( \Pi_{t+1}^{jA} + \Pi_{t+1}^{jN} \right)}{L_{t+1}} \quad (3.16)$$

$$\hat{y}_{t+1}^{UU} = w_{t+1}^{UA} - \frac{T_{t+1}}{L_{t+1}} + \frac{\sum_{j=R,U} \left( \Pi_{t+1}^{jA} + \Pi_{t+1}^{jN} \right)}{L_{t+1}} \quad (3.17)$$

Since all young individuals can switch location, and there is perfect foresight, for individuals to be indifferent between changing locations or staying on where they were born, their lifetime welfare must be independent of their location choice when young. This implies that

$$V_t^{RR} = V_t^{RU}; \quad V_t^{UR} = V_t^{UU}$$

Given the positive cost of migration and no individual specific amenity effects, in this environment we will either have rural born individuals moving to the urban location or urban individuals moving to the rural location but not simultaneous movement in both directions. To see this note that the rural young will migrate to urban areas only if  $V_t^{RU} \geq V_t^{RR}$  while the urban young workers will migrate to rural areas if  $V_t^{UR} \geq V_t^{UU}$ . For simultaneous migration in both directions we must then have

$$\frac{V_t^{RU}}{V_t^{RR}} \geq 1 \geq \frac{V_t^{UU}}{V_t^{UR}}$$

It is easy to check that with  $\tau > 0$  this is generically contradictory. Hence, migration flows will occur in only one direction. Without loss of generality, in the remainder of the paper we shall restrict attention to parameter ranges such that  $\frac{V_t^{RU}}{V_t^{RR}} \geq 1 \geq \frac{V_t^{UR}}{V_t^{UU}}$  which implies that only individuals born in rural areas would have an incentive to change locations.

A rural young would be indifferent between switching and not switching locations if and only if

$V_t^{RR} = V_t^{RU}$ . This gives the indifference condition

$$w_{t+1}^{UA} - R_{t+1}\tau_t - w_{t+1}^{RA} = \left[ \left( \frac{\varepsilon_{t+1}^R}{\varepsilon_{t+1}^U} \right)^{\frac{\sigma}{\sigma-1}} - 1 \right] (\hat{y}_{t+1}^{RR} - \bar{a} + p_{t+1}\bar{n}). \quad (3.18)$$

This condition must be satisfied at all dates in our economy. In other words, a rural young would be indifferent between staying in the rural location or moving to the urban location if the wage increase that the location switch will generate for her tomorrow net of the moving cost she incurs is exactly equal to the foregone relative utility from staying on in the rural location. Note that when the amenities of the two locations are identical so that  $\varepsilon_{t+1}^R = \varepsilon_{t+1}^U$ , the indifference condition reduces to  $w_{t+1}^{UA} - R_{t+1}\tau_t = w_{t+1}^{RA}$ .<sup>15</sup>

### 3.5 Government

A key feature of the model is that the young have to decide on their location decision when they have no source of income. Consequently, this has to be financed through borrowing. We assume that there is a government agency that imposes a lump sum tax  $T$  on households and uses these proceeds along with the repayments of past loans by current workers to finance new loans to the young in any period. The budget constraint of the government is

$$T_t + \mu_{t-1}L_{t-1}^R R_t b_t = \mu_t L_t^R b_{t+1}$$

where  $\mu_t$  denotes the measure of rural young that choose to change location at date  $t$ . From equation (3.8) it is clear that  $b_t = \tau_t$  for all  $t$  since borrowing is needed only to finance the location switching cost. Hence, the budget constraint can be written as

$$T_t + \mu_{t-1}L_{t-1}^R R_t \tau_{t-1} = \mu_t L_t^R \tau_t \quad (3.19)$$

The government can either choose the interest rate  $R_t$  or adjust the lump sum tax  $T_t$  to ensure that equation (3.19) holds at every  $t$  for all values of the other variables. We shall assume that the credit agency lends to the young at a constant interest factor so that  $R_t = R$  for all  $t$ .<sup>16</sup> In this case

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<sup>15</sup>We assume that the initial old generation at date  $t = 0$  can freely choose their location so that  $w_0^{UA} - w_0^{RA} = \left[ \left( \frac{\varepsilon_0^R}{\varepsilon_0^U} \right)^{\frac{\sigma}{\sigma-1}} - 1 \right] (\hat{y}_0^{RR} - \bar{a} + p_0\bar{n})$ .

<sup>16</sup>Alternatively, the government could finance the switching cost by setting  $T_t = 0$  for all  $t$  but for the funding agency to adjust the interest rate every period to ensure that  $\mu_{t-1}L_{t-1}^R R_t \tau_{t-1} = \mu_t L_t^R \tau_t$ . This amounts to the migrant workers being charged an interest rate that is just sufficient to finance location switches by young rural individuals at every date. In this case the interest rate would become endogenous and be given by  $R_t = \frac{\mu_t L_t^R \tau_t}{\mu_{t-1} L_{t-1}^R \tau_{t-1}}$ . In this scenario, the initial period switches at  $t = 0$  would be financed through a one-time lump sum tax  $T_0 = \mu_0 L_0^R \tau_0$ .

$T_t$  becomes endogenous and is given by

$$T_t = \mu_t L_t^R \tau_t - \mu_{t-1} L_{t-1}^R R \tau_{t-1}.$$

### 3.6 Aggregation

To complete the description of this economy, we now aggregate the individual variables to represent aggregate variables. First, the population dynamics of the two locations and the economy as a whole are given by

$$L_t^R = (1 - \mu_{t-1}) L_{t-1}^R \quad (3.20)$$

$$L_t^U = L_{t-1}^U + \mu_{t-1} L_{t-1}^R \quad (3.21)$$

$$L_t = L_t^R + L_t^U \quad (3.22)$$

The total sectoral allocation of labor in each location is given by

$$L_t^{Uk} = l_t^{UUk} L_{t-1}^U + l_t^{RUk} \mu_{t-1} L_{t-1}^R, \quad k = A, N$$

$$L_t^{Rk} = l_t^{Rk} (1 - \mu_{t-1}) L_{t-1}^R, \quad k = A, N$$

Next, we use the individual consumption plans to derive aggregate values of consumption of the two goods. At every date there are three types of workers in this economy – those that were born and work in rural areas; those that were born and work in urban areas; and those that were born in rural areas but changed locations to work in urban areas. Hence,

$$C_t^{Uk} = c_t^{UUk} L_{t-1}^U + c_t^{RUk} \mu_{t-1} L_{t-1}^R, \quad k = A, N$$

$$C_t^{Rk} = c_t^{Rk} (1 - \mu_{t-1}) L_{t-1}^R, \quad k = A, N$$

give the total consumption of each good in the two locations. Clearly, aggregate consumption of the two goods are  $C_t^k = C_t^{Uk} + C_t^{Rk}$  where  $k = A, N$ .

Using the optimal consumption plans given by equations (3.11) and (3.12) and combining them with the firms' and the funding agencies budget constraints, we can write the aggregate consumption demand of the two goods as

$$C_t^A = \theta [Y_t^A + p_t Y_t^N - \tau_t^R L_t^{RN} - \tau_t^U L_t^{UN} - \tau_t \mu_t L_t^R] + [(1 - \theta) \bar{a} + \theta p_t \bar{n}] L_t \quad (3.23)$$

$$p_t C_t^N = (1 - \theta) [Y_t^A + p_t Y_t^N - \tau_t^R L_t^{RN} - \tau_t^U L_t^{UN} - \tau_t \mu_t L_t^R] - [(1 - \theta) \bar{a} + \theta p_t \bar{n}] L_t \quad (3.24)$$

### 3.7 Equilibrium

To describe the equilibrium for this economy we first note that at every date all equilibrium allocations must be consistent with market clearing in each sector, i.e.,

$$C_t^A + \tau_t^R L_t^{RN} + \tau_t^U L_t^{UN} + \tau_t \mu_t L_t^R = Y_t^A \quad (3.25)$$

$$C_t^N = Y_t^N \quad (3.26)$$

Define the price and quantity vectors,  $\Psi$  and  $\Omega$  respectively, as

$$\begin{aligned} \Psi_t &= \{p_t, w_t^{UA}, w_t^{UN}, w_t^{RA}, w_t^{RN}\} \\ \Omega_t &= \{c_t^{UUA}, c_t^{UUN}, c_t^{RUA}, c_t^{RUN}, c_t^{RA}, c_t^{RN}, l_t^{UUA}, l_t^{UUN}, l_t^{RUA}, l_t^{RUN}, l_t^{RA}, l_t^{RN}, \mu_t\} \end{aligned}$$

**DEFINITION:** *The perfect foresight competitive equilibrium for this economy is a time path of the vectors  $(\Psi_t, \Omega_t)$  such that all young and old individuals, and firms satisfy their optimality conditions, budget constraints are satisfied and all markets clear at all dates for a given path of the productivity vector  $\{A_t^R, A_t^U, N_t^R, N_t^U\}$ .*

#### 3.7.1 Characterizing the equilibrium

To describe the equilibrium of this model in greater detail and characterize its properties, substitute the aggregate solution for  $C^A$  into the market clearing conditions given by equation (3.25) to get

$$\begin{aligned} &\theta [Y_t^A + p_t Y_t^N - \tau_t^R L_t^{RN} - \tau_t^U L_t^{UN} - \tau_t \mu_t L_t^R] + [(1 - \theta) \bar{a} + \theta p_t \bar{n}] L_t \\ &= Y_t^A - \tau_t^R L_t^{RN} - \tau_t^U L_t^{UN} - \tau_t \mu_t L_t^R \end{aligned}$$

This expression can be rewritten as

$$p_t = \left( \frac{1 - \theta}{\theta} \right) \left[ \frac{Y_t^A - \bar{a} L_t - \tau_t^R L_t^{RN} - \tau_t^U L_t^{UN} - \tau_t \mu_t L_t^R}{Y_t^N + \bar{n} L_t} \right] \quad (3.27)$$

In addition, the optimality condition for sectoral labor allocations given by equation (3.13) implies that  $w_t^{RA} + \tau_t^R = w_t^{RN}$  and  $w_t^{UA} + \tau_t^U = w_t^{UN}$ . These imply two independent conditions that must hold at all times:

$$p_t = \frac{\alpha^R A_t^R (L_t^{RA})^{\alpha^R - 1} + \tau_t^R}{\beta^R N_t^R (L_t^{RN})^{\beta^R - 1}} \quad (3.28)$$

$$\frac{\alpha^R A_t^R (L_t^{RA})^{\alpha^R - 1} + \tau_t^R}{\beta^R N_t^R (L_t^{RN})^{\beta^R - 1}} = \frac{\alpha^U A_t^U (L_t^{UA})^{\alpha^U - 1} + \tau_t^U}{\beta^U N_t^U (L_t^{UN})^{\beta^U - 1}} \quad (3.29)$$

The indifference condition for the location decision dictates that

$$w_t^{UA} - R\tau_{t-1} - w_t^{RA} = \left[ \left( \frac{\varepsilon_t^R}{\varepsilon_t^U} \right)^{\frac{\sigma}{\sigma-1}} - 1 \right] (\hat{y}_t^{RR} - \bar{a} + p_t \bar{n})$$

which, using the firms' optimal labor demand conditions, gives

$$\alpha^U A_t^U (L_t^{UA})^{\alpha^U - 1} - R\tau_{t-1} - \alpha^R A_t^R (L_t^{RA})^{\alpha^R - 1} = \left[ \left( \frac{\varepsilon_t^R}{\varepsilon_t^U} \right)^{\frac{\sigma}{\sigma-1}} - 1 \right] (\hat{y}_t^{RR} - \bar{a} + p_t \bar{n}) \quad (3.30)$$

Since the labor adding up constraint in each location at any date  $t$  implies that

$$L_t^j = L_t^{jA} + L_t^{jN}, \quad j = R, U$$

it is easy to verify that equations (3.27), (3.28), (3.29) and (3.30) define a system of four equations in four unknowns –  $L_t^{RA}, L_t^{UA}, p_t$  and  $\mu_t$  – as functions of the state vector  $\mathbf{S}_t = \{A_t^j, N_t^j, L_t^j, \tau_t^j, \tau_t\}$ . All the other variables of the model can then be determined recursively once the solution for these four variables are obtained from this system. Note that the choice of  $\mu_t$  induces a new distribution of rural and urban workers at time  $t + 1$  given by  $L_{t+1}^R$  and  $L_{t+1}^U$ .

## 4 A Special Case

In order to build intuition regarding the model, we now specialize our environment to facilitate analytical progress. Specifically, we make five assumptions:

*Assumption 1.*  $\alpha^R = \alpha^U = \beta^R = \beta^U = \beta$ .

*Assumption 2.*  $\tau_t^R = \tau_t^U = 0$ .

*Assumption 3.*  $\tau_t = 0$ .

*Assumption 4.*  $\frac{A_t^R}{A_t^U} \geq \frac{N_t^R}{N_t^U}$ .

*Assumption 5.*  $\varepsilon_t^U = \varepsilon_t^R$  for all  $t$ .

Assumption 1 implies that production technologies differ across locations and sectors solely due to differences in total factor productivities and nothing else. Assumption 2 sets the training costs of switching to the non-agricultural sector to zero, i.e., there are no training costs. Assumption 3 makes mobility across location costless. Assumption 2 and 3 jointly convert our environment into a model with no frictions in labor allocations, either across sectors or across locations. Assumption 4 implies that rural locations are relatively more productive in producing the agricultural good while urban locations are relatively more productive in producing the non-agricultural good. Assumption 5 says that there are no amenity differences between urban and rural locations. Recalling equation (3.7), this amounts to assuming that  $\phi = 0$  and  $\bar{\varepsilon}^j = \bar{\varepsilon}$  for all  $j$ . This assumption implies that the migration



indifference condition for the rural young reduces to  $w_t^{UA} - R\tau_{t-1} = w_t^{RA}$ . This greatly simplifies the analytical illustration of the effects of productivity shocks in this economy.

In the following it shall also be useful to follow the notation:

$$k^A = \frac{L^{UA}}{L^{RA}}, \quad k^N = \frac{L^{UN}}{L^{RN}}, \quad k = \frac{L^U}{L^R}, \quad s^A = \frac{L^{RA}}{L^R} \quad (4.31)$$

Noting that  $\frac{L^{UA}}{L^{RA}} \frac{L^{RA}}{L^R} + \frac{L^{UN}}{L^{RN}} \frac{L^{RN}}{L^R} = \frac{L^U}{L^R}$ , it is easy to verify that one can use the definitions in (4.31) to get

$$s^A = \frac{k - k^N}{k^A - k^N} \quad (4.32)$$

Of particular interest to us is the variable  $k = \frac{L^U}{L^R}$ . It represents the degree of *urbanization* of the economy since it gives the distribution of a given workforce between urban and rural locations.

Under our notational convention in (4.31) and Assumptions 1 and 2, the optimality condition given by equation (3.29) reduces to

$$k_t^N = \gamma_t k_t^A, \quad \gamma_t \equiv \left( \frac{A_t^R/A_t^U}{N_t^R/N_t^U} \right)^{\frac{1}{1-\beta}} \quad (4.33)$$

Moreover, under Assumption 4 above,  $\gamma_t \geq 1$  for all  $t$ . Hence, the non-agricultural sector employs relatively more urban labor while the agricultural sector is more intensive in rural labor.

Next, we can rewrite use the indifference condition for switching locations, equation (3.30), as

$$k_t^A = \left[ \frac{A_t^U}{A_t^R} - \frac{R_t \tau_{t-1}}{\beta A_t^R} \left\{ \frac{(\gamma_t k_t^A - k_t) L_t}{(\gamma_t - 1)(1 + k_t)} \right\}^{1-\beta} \right]^{\frac{1}{1-\beta}} \quad (4.34)$$

This equation gives the solution for  $k_{t+1}^A$  as a function of  $L_{t+1}$ ,  $k_{t+1}$  and  $\gamma_{t+1}$ , all of which are part of the state space at date  $t + 1$ . Under Assumptions 1 and 2, the expression for  $k_{t+1}^A$  reduces to

$$k_t^A = \left( \frac{A_t^U}{A_t^R} \right)^{\frac{1}{1-\beta}}$$

Since  $k^N = \gamma k^A$  and  $s^A = \frac{k - k^N}{k^A - k^N}$ , the expression for  $k^A$  above also implies that  $k_t^N = \left( \frac{N_t^U}{N_t^R} \right)^{\frac{1}{1-\beta}}$  and

$$s_t^A = \frac{k_t - \left( \frac{N_t^U}{N_t^R} \right)^{\frac{1}{1-\beta}}}{\left( \frac{A_t^U}{A_t^R} \right)^{\frac{1}{1-\beta}} - \left( \frac{N_t^U}{N_t^R} \right)^{\frac{1}{1-\beta}}}. \quad \text{Clearly, given an initial urbanization level } k_t \text{ and the sectoral productiv-$$

ities  $A_t^j$  and  $N_t^j$ , the allocation of rural and urban labor to the two sectors is fully determined.

While aggregate population and sectoral productivities both follow exogenous processes, the urbanization of the economy given by the urban to rural labor ratio  $k_{t+1} = \frac{L_{t+1}^U}{L_{t+1}^R}$  evolves endogenously

over time. Using equations (3.20) and (3.21), the evolution equation for  $k$  can be written as

$$k_{t+1} = \frac{k_t + \mu_t}{1 - \mu_t} \quad (4.35)$$

which can be rewritten as

$$\mu_t = \frac{k_{t+1} - k_t}{1 + k_{t+1}} \quad (4.36)$$

Hence, at every date  $t$ , once the productivity realizations for the period are known, all labor and sectoral allocations are known. The locational allocations of labor for next period in turn are fully determined once next period's productivity realizations (or, more generally, their expectations) are formed.

Substituting all of these relations in equations (3.27) and (3.28), equating the two, and rearranging the result gives:

$$\left( \frac{k_t - \gamma_t k_t^A}{k_t^A - k_t} \right)^{\beta-1} = \left( \frac{1 - \theta}{\theta} \right) \left[ \frac{\left( \frac{k_t - \gamma_t k_t^A}{(1 - \gamma_t) k_t^A} \right)^\beta (1 + k_t^A) - \frac{\bar{a}}{A_t^R} (1 + k_t)^\beta L_t^{1-\beta}}{\left( \frac{k_t^A - k_t}{(1 - \gamma_t) k_t^A} \right)^\beta (1 + \gamma_t k_t^A) + \frac{\bar{n}}{N_t^R} (1 + k_t)^\beta L_t^{1-\beta}} \right] \quad (4.37)$$

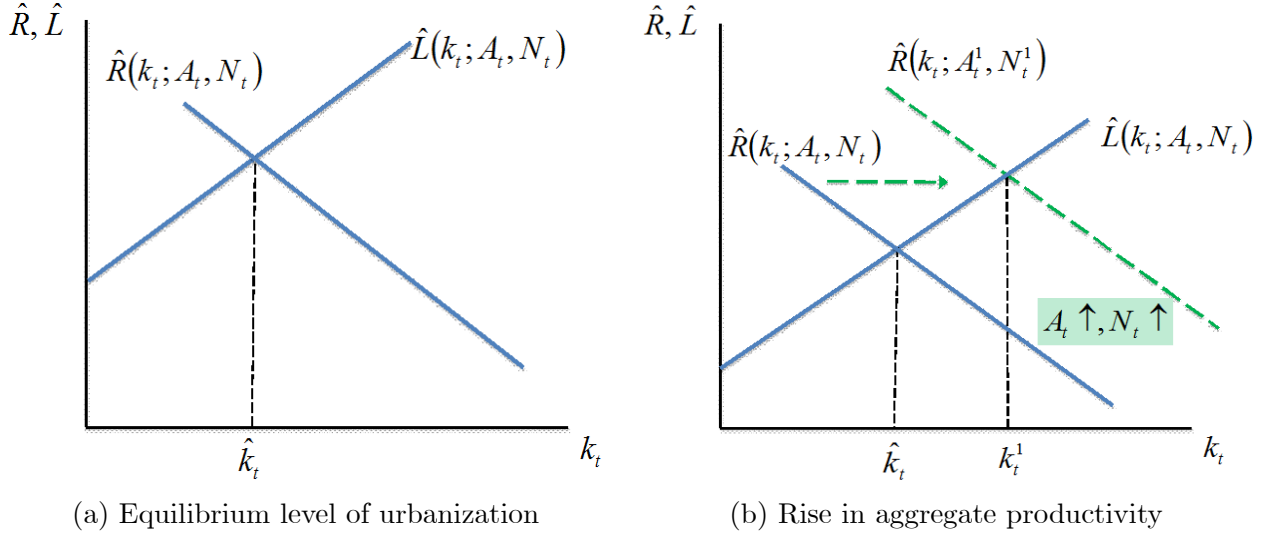
Since  $k_t^A = \left( \frac{A_t^U}{A_t^R} \right)^{\frac{1}{1-\beta}}$  is solely a function of agricultural productivities in urban and rural locations, equation (4.37) determines the solution for  $k_t$  as a function of sectoral productivities and aggregate labor supply at each date  $t$ . Consequently, along any perfect foresight equilibrium path, at date  $t$  one can compute the equilibrium degree of urbanization  $k_{t+1}$  from equation (4.37) by updating it one period. This solution then implies that  $\mu_t$ , the equilibrium measure of young individuals in rural locations who switch locations at date  $t$ , can be determined from equation (4.36).<sup>17</sup>

To characterize the equilibrium and examine the effects of various shocks on the economy, it is useful to represent equation (4.37) graphically. Let  $\hat{L}_t$  and  $\hat{R}_t$  be the left and right hand sides of equation (4.37). Panel (a) of Figure 12 shows that  $\hat{L}_t$  is rising in  $k_t$  while  $\hat{R}_t$  is declining in  $k_t$ . The equilibrium degree of urbanization at each date  $t$  is denoted by  $\hat{k}_t$ . For unchanging productivities  $A^j$  and  $N^j$ , the equilibrium  $k_t$  will also be constant over time, i.e., the solution will describe the steady state level of urbanization.

In terms of adjustment dynamics, along paths with a constant population and stationary productivities, the transition to steady state occurs with a maximum lag of one year. Given any initial  $k_0$ , the solution for  $k_1$  from equation (4.37) determines the equilibrium  $\mu_0$ . From  $t = 1$  onwards, there are no further changes in the population distribution between rural and urban locations and the economy remains completely stationary.

<sup>17</sup>Note that our assumption of zero population growth implies that  $L_t$  constant and independent of time.

Figure 12: Equilibrium  $k$  and productivity shocks



## 4.1 Productivity Shocks

There are four different productivity parameters in the model:  $A^R, A^U, N^R, N^U$ . This allows us to examine the effects of aggregate productivity shocks, sectoral productivity shocks as well as locational productivity shocks.

### 4.1.1 Aggregate productivity growth

We first consider aggregate productivity shocks that raise the productivity levels of  $A^R, A^U, N^R, N^U$  equiproportionately at each date. More specifically, suppose the productivity processes are given by

$$A_{t+1}^j = (1 + g) A_t^j, \quad j = R, U \quad (4.38)$$

$$N_{t+1}^j = (1 + g) N_t^j, \quad j = R, U \quad (4.39)$$

where  $g > 0$  gives the rate of balanced aggregate productivity growth. Hence,  $\frac{A_t^U}{A_t^R}, \frac{N_t^U}{N_t^R}, \frac{N_t^U}{A_t^U}$  and  $\frac{N_t^R}{N_t^U}$  all remain unchanged even though the levels of all the productivity parameters rise permanently at each  $t$ . In terms of equation (4.37), only the right hand side is affected as  $\frac{\bar{a}}{A_t^R} (1 + k_t)^\beta L_t^{1-\beta}$  and  $\frac{\bar{n}}{N_t^R} (1 + k_t)^\beta L_t^{1-\beta}$  both decline along such productivity paths. As a result, for every level of  $k_t$  the right hand side rises. In terms of Figure 12, panel (b) of the figure shows that at each date  $\hat{R}$  shifts up and to the right in response to this aggregate productivity. Hence, the equilibrium  $\hat{k}_t$  rises. This implies that along paths with aggregate productivity growth urbanization rises secularly over time.

The allocation of labor in each location to the two sectors is given by  $\frac{L_t^{RA}}{L_t^R} = s_t^A$  and  $\frac{L_t^{UA}}{L_t^U} = \frac{k_t^A s_t^A}{k_t}$ . Along paths with aggregate productivity growth,  $k_t^A = \left(\frac{A_t^U}{A_t^R}\right)^{\frac{1}{1-\beta}}$  remains unchanged while  $k_t$  rises.

Moreover, along paths with rising  $k_t$ ,  $s_t^A = \frac{k_t - \left(\frac{N_t^U}{N_t^R}\right)^{\frac{1}{1-\beta}}}{\left(\frac{A_t^U}{A_t^R}\right)^{\frac{1}{1-\beta}} - \left(\frac{N_t^U}{N_t^R}\right)^{\frac{1}{1-\beta}}}$  must decline since  $\left(\frac{A_t^U}{A_t^R}\right)^{\frac{1}{1-\beta}} < \left(\frac{N_t^U}{N_t^R}\right)^{\frac{1}{1-\beta}}$ . Hence, both  $\frac{L_t^{RA}}{L_t^R}$  and  $\frac{L_t^{UA}}{L_t^U}$  decline along paths with rising aggregate productivity. This implies that the employment share of agriculture in both locations falls while that of non-agriculture rises as the economy grows.

The overall share of agricultural employment in this economy is given by  $\frac{L_t^A}{L_t} = \frac{L_t^{UA}}{L_t^U} \frac{L_t^U}{L_t} + \frac{L_t^{RA}}{L_t^R} \frac{L_t^R}{L_t}$  which can be rewritten as

$$\frac{L_t^A}{L_t} = \frac{s_t^A (1 + k_t^A)}{1 + k_t}$$

Since  $k^A$  is constant along paths with aggregate productivity growth while  $s^A$  falls and  $k$  rises, it is clear that  $\frac{L_t^A}{L_t}$  must fall. Hence, the economy undergoes a structural transformation along paths with aggregate growth.

To complete a description of the economy along paths with aggregate productivity growth we need to describe the paths of goods and factor prices. Given that there are no costs of switching locations or sectors it is easy to see that factor prices must be equalized across sectors and locations in this special case, i.e.,

$$w_t^{RA} = w_t^{UA}; w_t^{RA} = w_t^{RN}; w_t^{UA} = w_t^{UN} \quad \text{for all } t$$

The relative price of the non-agricultural good is given by  $p_t = \frac{A_t^R}{N_t^R} \left(\frac{s_t^A}{1-s_t^A}\right)^{\beta-1}$ . As we noted above,  $\frac{A_t^R}{N_t^R}$  remains unchanged along paths with aggregate productivity increases while  $s_t^A$  declines. Hence, along paths with rising aggregate productivity the relative price of non-agriculture,  $p_t$ , must rise, i.e., the agricultural terms of trade worsens.

In the limit as  $t \rightarrow \infty$ , the non-homothetic components in the numerator and denominator of the right hand side of equation (4.37) vanish and the economy settles into balanced growth with a limiting stationary degree of urbanization given by

$$\hat{k} = \frac{\left[\hat{\gamma} (1 + \hat{k}^A) - \theta (\hat{\gamma} - 1)\right] \hat{k}^A}{1 + \{1 + \theta (\hat{\gamma} - 1)\} \hat{k}^A}$$

where  $\hat{\gamma} = \left(\frac{A_0^R/A_0^U}{N_0^R/N_0^U}\right)^{\frac{1}{1-\beta}}$  and  $\hat{k}^A = \left(\frac{A_0^U}{A_0^R}\right)^{\frac{1}{1-\beta}}$ . It is easy to check that  $\hat{k} > 0$ . Furthermore, the associated limiting  $s_t^A$  is given by

$$\hat{s}^A = \frac{\hat{k} - \left(\frac{N_0^U}{N_0^R}\right)^{\frac{1}{1-\beta}}}{\left(\frac{A_0^U}{A_0^R}\right)^{\frac{1}{1-\beta}} - \left(\frac{N_0^U}{N_0^R}\right)^{\frac{1}{1-\beta}}}$$

We collect these results in the following Proposition:

**Proposition 1** *Under Assumptions 1-5 and aggregate productivity growth given by equations (4.38)-(4.39), there is a secular decline in the agricultural employment share of overall labor as well as rural labor and urban labor individually. This structural transformation is accompanied by rising urbanization and a secular fall in the relative price of the agricultural good.*

#### 4.1.2 Sector-biased productivity change

We now examine the impact of productivity changes that are biased towards the non-agricultural sector. In particular, suppose the economy is initially in steady state with constant productivities in all sectors given by  $A_0^R, A_0^U, N_0^R, N_0^U$ . Denote this steady state as date  $t = 0$ . Now suppose that at  $t = 0$  news arrives that the productivity process from  $t = 1$  will be

$$A_t^j = (1 + \varepsilon g) A_0^j \text{ for all } t \geq 1, \quad j = R, U \quad (4.40)$$

$$N_t^j = (1 + g) N_0^j, \quad j = R, U \quad (4.41)$$

where  $\varepsilon < 1$  and  $g > 0$ . The shock permanently raises  $\frac{N_t^j}{A_t^j}$  from  $t \geq 1$  for  $j = R, U$ . Hence, this is a non-agriculture biased productivity change. Since  $\frac{N_t^U}{N_t^R} = \frac{N_0^U}{N_0^R}$  and  $\frac{A_t^U}{A_t^R} = \frac{A_0^U}{A_0^R}$ , it directly follows both  $k_t^A = \left(\frac{A_t^U}{A_t^R}\right)^{\frac{1}{1-\beta}}$  and  $\gamma_t = \left(\frac{A_t^R/A_t^U}{N_t^R/N_t^U}\right)^{\frac{1}{1-\beta}}$  remain unchanged. It is straightforward to verify from equation (4.37) that the degree of urbanization in the new steady state must be greater than the level of urbanization in the initial steady state,  $k_1 > k_0$ . This, in turn, implies that  $s^A, \frac{L^{RA}}{L^R}, \frac{L^{UA}}{L^U}$  and  $\frac{L^A}{L}$  must all decline permanently in response to the shock.

The response of  $p$ , the relative price of the non-agricultural good, is however ambiguous since there are two offsetting effects. On the one hand, the productivity process implies that  $\frac{A^R}{N^R}$  falls. On the other hand,  $s^A$  declines as well. Consequently, the behavior of  $p_t = \frac{A_t^R}{N_t^R} \left(\frac{s_t^A}{1-s_t^A}\right)^{\beta-1}$  is ambiguous and depends on the relative strengths of these two opposing effects. As before, there are no sectoral or locational wage differences in this special case since there are no costs of switching. We collect these results in the following Proposition:

**Proposition 2** *Under Assumptions 1-5 and N-sector-biased productivity growth given by equations (4.40)-(4.41), there is a decline in the agricultural employment share of overall labor as well as rural labor and urban labor individually. This structural transformation is accompanied by an increase in the degree of urbanization. The movement in the relative price of the agricultural good however is ambiguous.*

Qualitatively, the main difference in outcomes between the case of aggregate productivity growth and sector-biased productivity growth then is the impact on the relative goods price. The predictions for structural transformation are identical in the two cases.<sup>18</sup>

<sup>18</sup>A different but related experiment would be an unanticipated, permanent increase in sectoral or aggregate productivity starting from a steady state. Thus, suppose all sectoral productivities are constant over time and the economy is in steady state. Now, suppose  $A^j$  rises permanently by a factor  $\gamma^A$  and  $N^j$  rises by a factor  $\gamma^N$  for  $j = R, U$ . In

## 5 Quantitative Results

We now quantitatively assess the ability of the full model to explain the observed rural-urban wage dynamics along with the aggregate macroeconomic facts. To do so we calibrate the model separately for India and China to match their conditions at the initial dates of our data sample. In particular, for China we use year 1988 as representing its initial steady state, while for India we use year 1983. We then conduct the following experiment. We compute the changes in the sectoral labor productivities in China during 1983-2008, and in India during 1983-2010 period. Keeping all the calibrated parameters unchanged, we feed these changes in sectoral productivities into the model and examine their effects on goods and factor prices, factor allocations and migration.

### 5.1 Calibration for the 1980s

We calibrate the model parameters to match the key moments of wages and employment in the data. More precisely, we choose eleven parameters that minimize the distance between eleven moments in the data in the 1980s and in the model. Specifically, to calibrate the urban and rural share of the employment in India in 1983 we use Census of India and NSS data. The Census is conducted every 10 years on the first year of each decade. Thus, in 1981 the total population of India was 683.3 million people, of which 525.6 million lived in rural areas and 157.7 million lived in urban areas. To obtain labor force numbers we multiply these population figures by the share of working age population in 1983 from the NSS equal to 0.54 in rural areas and 0.59 in urban areas; by the labor force participation rate in 1983 from the NSS equal to 0.66 in rural areas and 0.59 in urban areas; and by the share of employed in the labor force equal to 0.94 in urban areas and 0.96 in rural areas. These calculations give us the urban employment share at 22 percent of total in 1983. In China the urban employment share was 0.26 percent in 1988.

Second, we match the sectoral distribution of the labor force in rural and urban areas. Our third set of targets are the four wage gaps. First, we match the "within" gaps: within-agriculture and within-non-agriculture wage gaps between urban and rural areas. They stood at -7 percent and 8 percent, respectively, in India; and at 105 percent and 41 percent, respectively, in China. "Between" gaps which capture the wage premium in non-agricultural jobs relative to agricultural jobs stood at 96 percent in rural areas and 126 percent in urban areas in India; and 29 percent and -3 percent, respectively, in China.

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this case, the location indifference condition at the initial date will clearly not hold since workers cannot move within that period. Hence, the initial distribution of  $L$  would be exogenously given and rural and urban wages would not be equalized at the initial date. It can be shown that such an unanticipated increase in aggregate productivity would induce a structural transformation with rising employment shares of the non-agricultural sector in both locations. However, the urban-rural wage gap would widen and the price of the non-agricultural good would rise in the period of the shock. Analogously, a permanent unanticipated increase in the productivity of sector-N relative to sector-A (an N-sector biased technological improvement), would have similar effects on the structural transformation but have ambiguous effects on the relative price of good  $N$  and on the wage gap in the period of the shock. The adjustments in the next period to both the shocks would be as described in the propositions above.

We also target the output share of agriculture in total GDP in India in 1983 at 36 percent and 17 percent in China. Lastly, we target three moments characterizing consumption expenditures in the two countries. The first is the share of agriculture in the total consumption of households. In linking the model to the data above we followed the value-added approach to interpreting a sector.<sup>19</sup> Hence, to keep the model internally consistent we define the arguments in the utility functions in value added terms as well. To obtain such value-added equivalents of consumption we follow the literature and compute agricultural consumption in value added terms as the agricultural value added, while non-agricultural consumption is non-agricultural value added minus investment.<sup>20</sup> This gives us the share of agricultural value added in total consumption equal to 47 percent in India and 33 percent in China. Second, to pin down the minimum consumption level of agriculture, we follow Anand and Prasad (2010) who estimated minimum consumption requirement value to be 50 percent of food consumption for a sample of 6 emerging economies, including India. We use the same 50 percent number for China in 1988. Third, we target the home production share in the consumption of non-agricultural goods and services at 30 percent in both countries. This number is implied by the time allocation statistics in the US over our sample period, where US households spent on average 12 hours per week in home production and 40 hours per week in market employment. These numbers are also similar to those reported in China since the mid-2000s.<sup>21</sup>

Our free parameters are technology parameters  $\alpha$  and  $\beta$ , the training costs  $\tau_U$  and  $\tau_R$ , migration cost  $\tau$ , the sectoral productivity levels  $A^U, N^R, N^U$ , the agricultural consumption share  $\theta$ , the minimum agricultural consumption parameter  $\bar{a}$  and the home production of services parameter  $\bar{n}$ . These parameters are calibrated to jointly match the eleven data moments described above. We also need to parameterize the process for externalities in rural and urban locations. In particular,  $\frac{\bar{\varepsilon}^R}{\bar{\varepsilon}^U}$  characterizes the relative level of amenities available in rural and urban locations. Since measuring this ratio is difficult, we assume that rural and urban locations do not differ in terms of amenities they offer to their residents, i.e.  $\frac{\bar{\varepsilon}^R}{\bar{\varepsilon}^U} = 1$ . Parameter  $\phi$  captures the elasticity of available amenities with respect to local population changes, with  $\phi < 0$  implying negative externalities associated with population growth due to migration into a location. We calibrate this parameter to match the sensitivity of urban employment share to sectoral productivity changes. Specifically, we choose the value for parameter  $\phi$ , such that the model correctly reproduces the change in the urban employment share over our sample period in response to sectoral productivity changes. The resulting parameter values are summarized in Table 2.

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<sup>19</sup>See Herrendorf, Rogerson, and Valentinyi (2013b) for a careful discussion of value added and final expenditure approaches to interpreting the data.

<sup>20</sup>See appendix A.2 for data sources.

<sup>21</sup>See Conference Board.

Table 2: Model parameters, 1983

	parameter	China	India
<i>fixed parameters</i>			
Intertemporal elasticity of substitution	$\sigma$	2	2
Relative amenities level b/n R and U locations	$\frac{\bar{\varepsilon}^R}{\bar{\varepsilon}^U}$	1	1
<i>estimated parameters</i>			
Labor weight in A sector	$\alpha$	0.25	0.08
Labor weight in N sector	$\beta$	0.57	0.23
Training cost for U households	$\tau_U$	-0.08	0.23
Training cost for R households	$\tau_R$	0.18	0.19
Migration cost	$\tau$	0.72	0.15
Productivity in rural non-agri	$N^R$	0.83	0.92
Productivity in urban agri	$A^U$	0.18	0.07
Productivity in urban non-agri	$N^U$	1.46	1.10
A consumption share	$\theta$	0.43	0.45
Home production of non-agri goods	$\bar{n}$	0.29	0.41
Minimum agricultural consumption	$\bar{a}$	0.68	0.71
Externalities from migration	$\phi$	-0.33	-0.05

## 5.2 Results

How much of the observed dynamics in urban-rural wages is accounted for by changes in sectoral productivity growth in the two sectors? To answer this question we compute the changes in sectoral labor productivity, the dynamics of which during 1983-2010 period in India and 1988-2008 period in China are presented in Figure 9. In India agricultural labor productivity increased by 67 percent between 1983 and 2010, while non-agricultural labor productivity increased by 200 percent. The corresponding numbers in China between 1990 and 2008 were 163 percent and 338 percent.

We feed the measured sectoral productivity growth in the two countries into the model while keeping all other parameters unchanged. Specifically, we use the following dynamic equation for sectoral productivities in each country:

$$\begin{aligned} A_{t+1}^j &= A_t^j (1 + g_t^A), \quad j = R, U \\ N_{t+1}^j &= N_t^j (1 + g_t^N), \quad j = R, U, \end{aligned}$$

where  $g_t^A$  and  $g_t^N$  are productivity growth rates in agricultural and non-agricultural sectors, respectively. These sectoral productivities are taken as exogenous by households and firms. They are equal to the growth rates in labor productivities measured in the data and reported above, and are assumed to be the same across locations (we relax this assumption in the next section).

The results for China are summarized in Table 3, while for India in Table 4. Several results stand out. First, the changes in productivity lead to positive net migration flows from rural to urban areas in both countries. These results are consistent with Figure 11 which shows that both China and India have become much more urbanized since the 1980s. In particular, in 2010 the urban employment share in India was 0.3, while the corresponding number for China was 0.35. These imply



an 8 percentage points increase in the urban employment share in India between 1983 and 2010, and a 9 percentage points increase in the urban share of employment in China during 1988-2008 period. The model reproduces these urbanization dynamics perfectly.

Second, the share of the workforce employed in agriculture declines in both rural and urban areas in both countries. Thus, the model successfully replicates the patterns of sectoral transformation observed in the data for China and India.

Table 3: Model and data: China, 1988 versus 2008

	1988		2008	
	data	model	data	model
<i>employment shares:</i>				
$L_U$	0.26	0.26	0.35	0.35
$L_{RA}$	0.79	0.79	0.66	0.56
$L_{UA}$	0.05	0.05	0.03	0.03
<i>wage gaps:</i>				
within $A$	2.052	2.035	2.509	1.922
within $N$	1.408	1.433	1.600	1.730
$R$ between	1.300	1.323	1.195	1.089
$U$ between	0.970	0.932	0.748	0.980
overall mean	1.510	1.782	1.608	1.814
<i>aggregates:</i>				
$N/A$ relative price	1.00	1.00	0.779	0.903
$A$ share of $Y$	0.17	0.67	0.06	0.51
$A$ share of $C$	0.33	0.65	0.16	0.49

Table 4: Model and data: India, 1983 versus 2010

	1983		2010	
	data	model	data	model
<i>employment shares:</i>				
$L_U$	0.22	0.22	0.30	0.30
$L_{RA}$	0.78	0.78	0.66	0.59
$L_{UA}$	0.11	0.11	0.07	0.04
<i>wage gaps:</i>				
within $A$	0.934	0.937	1.027	1.204
within $N$	1.082	1.080	0.994	1.211
$R$ between	1.962	1.961	1.679	1.405
$U$ between	2.259	2.260	1.709	1.414
overall mean	1.664	1.642	1.310	1.441
<i>aggregates:</i>				
$N/A$ relative price	1.00	1.00	0.714	0.844
$A$ share of $Y$	0.36	0.71	0.16	0.58
$A$ share of $C$	0.47	0.68	0.23	0.56

Third, gaps between urban and rural wages decline following the shocks in India but increase in China. The direction and size of the decline predicted by the model for India replicates closely the patterns observed in the data. Importantly, the conditional wage gaps show the adjustments similar to those in the data. Specifically, the gap between urban and rural wages within agricultural

activities exhibits an increase, in line with the data. The "between" non-agriculture and agriculture wage gaps decline dramatically by 0.85 in urban areas and 0.56 in rural areas. While the direction of the change is correct, the model overpredicts the size of these declines relative to data. The overall mean wage gap between urban and rural areas falls by 0.20 in response to sectoral productivity growth, which accounts for 57 percent of the decline in urban-rural wage gap in the data for India.

In China, the model also does a good job in capturing the adjustments in conditional wages over time. For instance, the model predicts a fall in the inter-sectoral wage gap in rural areas although the fall exceeds that found in the data. The model also predicts a slight increase in the inter-sectoral wage gap in the urban areas, while we observe a decline in that wage gap in the data. For the "within" wage gaps, the model correctly predicts an increase in the urban-rural wage gap in non-agriculture, but counterfactually generates a convergence between urban and rural wages in agriculture. Overall mean wages between urban and rural areas diverge both in the model and in the data, although the model underpredicts the extent of wage divergence.

Fourth, the model predicts a decline in the relative price of non-agricultural goods in both countries, consistent with the empirical evidence. The model also predicts a fall in the share of agriculture in output and consumption, with the declines being comparable to those found in the data.

Overall, our results suggest that aggregate factors have played an important role in urban-rural dynamics in India and China in the past 20-30 years. Growth of agricultural productivity and an even faster growth of non-agricultural productivity can account for a large share of the sectoral transformation and relative price dynamics in both countries. The same forces also account for majority of wage convergence between urban and rural areas in India and predict some divergence in urban-rural wages in China. Furthermore, these factors induce the within- and between-wage adjustments, consistent with data.

To understand these results, recall that the productivity changes in the model generate two competing effects on prices and allocations. First, an increase in productivity (aggregate or sectoral) leads to a rise in non-agricultural relative price, pushing up wages of non-agricultural workers and away from the wages of agricultural workers. The consequence of this is worker reallocation from agricultural to non-agricultural employment. Since urban locations are predominantly non-agricultural, urban-rural wage gap widens. This is the standard demand-driven explanation of structural transformation. We refer to this as the "demand effect". The second effect arises as a consequence of the first effect as widening urban-rural wage gaps also trigger migration from rural to urban areas. Net migration into urban areas increases labor supply in those areas. This in turn leads to a higher production of non-agricultural goods, moving the sectoral terms of trade against them. This brings wages of urban workers closer to the wages of rural workers, i.e. the urban-rural wage gap declines. We refer to this effect as the "migration effect". Whether the urban-rural wages converge or diverge depends on the relative strengths of these two effects.

Clearly, the migration effect is stronger in India where the estimated migration costs and negative

migration externalities are smaller. In contrast, for China we estimate larger migration costs and higher negative externalities arising from migration. As a result, the migration effect is weaker and urban-rural wage gap rises over time.

### 5.2.1 Agglomeration externalities in production

The baseline model that we developed introduced a negative congestion externality of migration on urban amenities. That formalization ignored a second often discussed externality of migration which is its positive effect on aggregate productivity. This positive production externality is typically proposed as an explanation for the concentration of economic activity in locations as well as the growth of cities. This is clearly an important margin for understanding and explaining the growth of cities, which is a key goal of this paper. Accordingly, we now introduce a positive agglomeration externality in production.

We assume that sectoral urban productivities evolve according to:

$$A_{t+1}^j = A_t^j \left(1 + g_t^{jA}\right), \quad j = R, U \quad (5.42)$$

$$N_{t+1}^j = N_t^j \left(1 + g_t^{jA}\right), \quad j = R, U \quad (5.43)$$

where  $g^{jA}$  and  $g^{jN}$  denote the sectoral total factor productivity growth in location  $j = R, U$ . These sectoral productivities are taken as exogenously given by households and firms. To introduce production externalities in urban areas, we postulate that urban total factor productivity growth gets an additional boost from growth in the urban labor force. Specifically, we assume that

$$1 + g_t^{Uk} = \left(1 + X_t^k\right) \left(1 + g_t^{Rk}\right), \quad k = A, N \quad (5.44)$$

where

$$1 + X_t^k = \left(\frac{L_t^U}{L_{t-1}^U}\right)^{\phi_k}, \quad k = A, N \quad (5.45)$$

Clearly, as long as there is positive migration into urban areas so that  $X^k > 0$ , productivity *growth* in both sectors is going to be higher in urban areas relative to rural locations.<sup>22</sup>

There are two interesting special cases here. First, for  $\phi_A = \phi_N$  the urban production externality is identical across sectors. Second, when  $\phi_A = 0$  the externality only affects the non-agricultural sector while agricultural productivities grow at the same rate in urban and rural locations. Notice that since  $L_t^U = L_{t-1}^U + M_t$ , i.e., the urban population at time  $t$  is the sum of the urban population

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<sup>22</sup>Our formalization that urban productivity growth depends on urban population growth is consistent with an environment where productivity growth depends upon ideas that are carried by individuals. Implicitly, the formulation is a stand-in for environments where faster population growth in a location induces greater exchange of ideas and consequently faster TFP growth.

at  $t - 1$  plus the new migrants at  $t$ , equation (5.45) can be written as

$$1 + X_t^k = \left(1 + \frac{M_t}{L_{t-1}^U}\right)^{\phi_k}, \quad k = A, N$$

Migration from rural to urban areas now have two effects. On the one hand, negative congestion externalities reduce the level of urban amenities according to equation (3.7). This is unchanged from our baseline case. But now, the process of urban migration also raises productivity in urban locations in both sectors relative to their rural counterparts. Thus, productivity growth becomes urban-biased in this case. The parameter  $\phi_k$  is **country-specific** and will now be identified by the relative strengths of these two effects.

Our identification strategy for the parameters of the model are the same as before: we calibrate the parameters of the model to target the same set of moments in the initial period. We then hit the model with the measured average sectoral productivity growths during the sample period. Notice that the average sectoral productivity growths for the country as a whole are given by

$$1 + g_t^k = s_t^{Rk} (1 + g_t^{Rk}) + (1 - s_t^{Rk}) (1 + g_t^{Uk}), \quad k = A, N$$

where  $s^{Rk}$  is the fraction of sector- $k$  labor working in rural locations. Hence, the average gross sectoral growth rate is just the weighted average of the corresponding location-specific sectoral growth rates. We measure both  $g^k$  and  $s^{Rk}$  from the data. We assume that  $\phi_A = \phi_N = \phi$  and calibrate the parameter  $\phi$  to match the net rural-to-urban migration flows during the sample period. This gives a value of  $\phi = 0.42$  in China and  $\phi = 0.055$  in India. These parameter estimates imply a 14% boost to urban productivity in China, and 1.7% boost to urban productivity in India.<sup>23</sup>

The last two columns of Table 5 reports the changes in the relevant variables predicted by the model under agglomeration externalities as well as those under the baseline case where these production externalities are absent. The table makes clear that a more rapid increase in relative urban productivity stalls the wage convergence in both countries. For instance, in India the resulting wage convergence between urban and rural labor is smaller, with the gap declining by 0.18 compared to 0.20 in the case of shocks that are symmetric across locations. In China, urban and rural wages are diverging by 0.24, which is even larger than in the data.

The introduction of agglomeration externalities in urban production has two effects on the economy. On the one hand, the rural-to-urban migration induces greater urban population growth and density. This raises urban productivity in both sectors which increases the relative wages of urban workers. This widens the urban-rural wage gap. On the other hand, a larger urban-rural wage gap creates a greater incentive for migration which, all else equals, drives down the wage gap due to

<sup>23</sup>Note that our specification implies that  $1 + g^{Rk} = \frac{1 + g^k}{1 + (1 - s^{Rk})X^k}$ ,  $k = A, N$  which can be used to infer the location-specific productivities by substituting in the measured values for  $g^k$ ,  $X^k$  and  $s^{Rk}$  from the data.

the increase in relative urban labor supply. In our calibration of the two countries, the first effect dominates and the wage gap expands relative to the case where productivity growth is symmetric across locations.

These results are indicative of the robustness of our baseline model to allowing for positive externalities of migration through agglomeration effects in production. However, they also resonate particularly for China where a number of authors have found evidence of location biased factor allocation. For instance, in China rates of return on capital investment tend to be higher in smaller cities and rural areas, suggesting that urban locations are typically favoured for capital allocation by the government. This raises the productivity of urban workers relative to workers in rural areas (see Jefferson and Singh (1999); Bai, Hsieh, and Qian (2006)). Given that the baseline model was underpredicting the wage divergence in China, the addition of agglomeration effects of migration on urban productivity appears to provide one rationalization for the higher observed wage divergence in the data. It also provides a background rationalization for the evidence in Jefferson and Singh (1999) and Bai, Hsieh, and Qian (2006).

Table 5: Changes under agglomeration production externalities

	Baseline		Agglomeration	
	China	India	China	India
<i>changes in employment shares:</i>				
$L_U$	0.09	0.08	0.063	0.075
$L_{RA}$	-0.23	-0.19	-0.198	-0.187
$L_{UA}$	-0.02	-0.07	-0.019	-0.067
<i>changes in wage gaps:</i>				
within $A$	-0.113	0.267	0.107	0.289
within $N$	0.297	0.131	0.482	0.147
$R$ between	-0.234	-0.556	-0.226	-0.551
$U$ between	0.048	-0.846	0.049	-0.849
overall mean	0.032	-0.201	0.240	-0.177
<i>changes in aggregates:</i>				
$N/A$ relative price	-0.097	-0.156	-0.073	-0.072
$A$ share of $Y$	-0.16	-0.13	-0.162	-0.129
$A$ share of $C$	-0.16	-0.12	-0.155	-0.119

Note: The results under Agglomeration report the results of introducing an urban agglomeration effect on productivity due to migration while keeping overall sectoral productivity growth unchanged as under the baseline case.

### 5.3 Experiments

The model allows us to conduct counterfactual experiments to better understand the differences in the structural transformation process and wage dynamics in India and China. We conduct the following three experiments. First, we are interested in assessing the counterfactual path of urban-rural inequality in India if it grew like China; Second, we ask what would happen to urban-rural inequality in China if migration costs were reduced to India's levels. Third, we assess what effect

the location biased technical change would have on urban-rural inequality in India and China.

### 5.3.1 India growing like China

For this experiment we use the model calibrated to India and feed into it the measured sectoral productivity growth for China, keeping all other parameters unchanged. Specifically, we assume that agricultural labor productivity increased by 163% and non-agricultural labor productivity increased by 338% in India. The results are presented in column (i) of Table 6. The table reports the changes in the relevant indicators as well as the corresponding changes in those variables under the baseline case. With the sectoral productivity growing faster now, the model predicts a larger flow of migrants from rural to urban areas, leading to a larger increase in urban labor share over time – to 0.33 compared to 0.3 in the benchmark model for India. The labor reallocating from agricultural activities is also larger when sectoral productivity growth is equal to China’s. Specifically, agricultural employment share in rural areas would decline from 0.78 to 0.5, while agricultural employment share in urban areas would fall from 0.11 to 0.03. Given the larger migration effect, the urban-rural wage convergence would also be larger, with the overall wage gap contracting from 1.642 in 1983 to 1.388 in 2008. Notice that the effect on relative prices now, however, differs from the benchmark result. The relative price of non-agricultural goods rises when India grows like China. This is because the "demand effect" is also stronger when India’s productivity rises faster.

Table 6: Experiments

	Baseline		Experiment 1	Experiment 2
	China	India	(i)	(ii)
<i>changes in employment shares:</i>				
$L_U$	0.09	0.08	0.105	0.219
$L_{RA}$	-0.23	-0.19	-0.28	-0.17
$L_{UA}$	-0.02	-0.07	-0.08	-0.02
<i>changes in wage gaps:</i>				
within $A$	-0.113	0.267	0.344	-0.584
within $N$	0.297	0.131	0.192	-0.127
$R$ between	-0.234	-0.556	-0.747	-0.24
$U$ between	0.048	-0.846	-1.055	0.043
overall mean	0.032	-0.201	-0.254	-0.41
<i>changes in aggregates:</i>				
$N/A$ relative price	-0.097	-0.156	0.068	-0.163
$A$ share of $Y$	-0.16	-0.13	-0.18	-0.17
$A$ share of $C$	-0.16	-0.12	-0.16	-0.25

Note: Experiment1 applies China’s sectoral productivity growth to India calibration; Experiment2 uses the migration externality parameter estimated for India ( $\kappa = -0.05$ ) in China’s calibration.

### 5.3.2 China migration costs as in India

In this experiment we reduce the migration externalities in China to their levels in India. This is equivalent to reducing the migration cost. The results of this experiment are presented in column

(ii) of Table 6. Not surprisingly, lower costs lead to larger migration flows predicted by the model, with the urban employment share rising to 0.48% in 2008. The migration effect increases in the model, and in fact, the increase is large enough to overturn urban-rural wage divergence in China. With lower migration externalities the urban-rural wage gap declines by 0.41, i.e. the model predicts wage convergence over time. Moreover, all conditional wage gaps decline. This experiment suggests that bringing the migration costs in China down to their levels in India would produce a significant reduction in wage inequality there.

## 6 Conclusion

This paper has studied the experience of China and India over the past thirty years to form a better understanding of the process of structural transformation of countries during the development process. A unique aspect of our work is that we focused on both quantities and prices. In addition, we have examined the process of structural transformation jointly with the process of urbanization. Our data analysis has revealed some interesting contrasts between China and India during this period. While the structural transformation experience of the two economies has been quite similar, the movements in wages have not. Specifically, while urban-rural wage gaps widened in China, they have contracted in India during this period. Interestingly, this has occurred in the backdrop of similar qualitative movements in the inter-sectoral wage gaps as well as in the relative sectoral prices of goods. This evidence suggests to us that the standard practice of equating the agricultural sector with rural locations and non-agriculture with urban locations is not an innocuous abstraction. Indeed, a significant part of the structural transformation from agriculture to non-agriculture occurs *within* rural locations.

To explain the contrasting trends in the two countries, the paper formalized a two-sector, two-location overlapping generations model of structural transformation. Our model generates structural transformation through non-homothetic preferences and growth in agricultural productivity. We have showed that the model, calibrated to China and India, can generate the opposing movements in the urban-rural wage gaps observed in the two economies. An important ancillary result of the model is that it can account for the fact that the relative price of the non-agricultural good declined in both China and India during this period. It is important to note that this data fact is at odds with the rise in this relative price that is implied by standard non-homothetic models of structural transformation.

We believe that our results suggest that the redistributive and allocational implications of structural transformation cannot be adequately analyzed without explicitly taking into account the accompanying migration and urbanization that is generic to this process. Moreover, an analysis of the implications of structural transformation should include an explicit investigation of prices of both factors and goods in order to form a better understanding of the mechanics of the process as well as for devising appropriate analytical structures that best describe them. A larger cross-country study

along these lines would appear to be a fruitful avenue for future work.

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## A Appendix: Not for publication

### A.1 Data

#### A.1.1 India

The National Sample Survey Organization (NSSO), set up by the Government of India, conducts rounds of sample surveys to collect socioeconomic data. Each round is earmarked for particular subject coverage. We use the latest six large quinquennial rounds – 38(Jan-Dec 1983), 43(July 1987-June 1988), 50(July 1993-June 1994), 55(July 1999-June 2000), 61(July 2004-June 2005) and 66(July 2009-June 2010) on Employment and Unemployment (Schedule 10). Rounds 38 and 55 also contain migration particulars of individuals. We complement those rounds with a smaller 64th round(July 2007-June 2008) of the survey since migration information is not available in all other quinquennial survey rounds.

The survey covers the whole country except for a few remote and inaccessible pockets. The NSS follows multi-stage stratified sampling with villages or urban blocks as first stage units (FSU) and households as ultimate stage units. The field work in each round is conducted in several sub-rounds throughout the year so that seasonality is minimized. The sampling frame for the first stage unit is the list of villages (rural sector) or the NSS Urban Frame Survey blocks (urban sector) from the latest available census. The NSSO supplies household level multipliers with the unit record data for each round to help minimize estimation errors on the part of researchers. The coding of the data changes from round to round. We re-coded all changes to make variables uniform and consistent over the time.

In our data work, we only consider individuals that report their 3-digit occupation code and education attainment level. Occupation codes are drawn from the National Classification of Occupation (NCO) – 1968. We use the "usual" occupation code reported by an individual for the usual principal activity over the previous year (relative to the survey year). The dataset does not contain information on the years of schooling for the individuals. Instead it includes information on general education categories given as (i) not literate -01, literate without formal schooling: EGS/ NFEC/ AEC -02, TLC -03, others -04; (ii) literate: below primary -05, primary -06, middle -07, secondary -08, higher secondary -10, diploma/certificate course -11, graduate -12, postgraduate and above -13. We aggregate those into five similarly sized groups as discussed in the main text. We also convert these categories into years of education. The mapping we used is discussed in the main text.

The NSS only reports wages from activities undertaken by an individual over the previous week (relative to the survey week). Household members can undertake more than one activity in the reference week. For each activity we know the "weekly" occupation code, number of days spent

working in that activity, and wage received from it. We identify the main activity for the individual as the one in which he spent maximum number of days in a week. If there are more than one activities with equal days worked, we consider the one with paid employment (wage is not zero or missing). Workers sometimes change the occupation due to seasonality or for other reasons. To minimize the effect of transitory occupations, we only consider wages for which the weekly occupation code coincides with usual occupation (one year reference). We calculate the daily wage by dividing total wage paid in that activity over the past week by days spent in that activity.

Lastly, we identify full time workers in our dataset. We assume that an individual is a full time worker if he is employed (based on daily status code) for at least two and half days combined in all activities during the reference week. We drop observations if total number of days worked in the reference week is more than seven.

### **A.1.2 China**

The Chinese Household Income Project (CHIP) is organized by Chinese and international researchers, with the assistance from National Bureau of Statistics (NBS), to study the distribution of personal income in both rural and urban areas in China. There are five waves available: 1988, 1995, 2002, 2007 and 2008. The last two waves were also part of the RUMiC (Rural-Urban Migrants in China) survey project. All waves contain separately a rural and urban survey, on which we base our definition of rural and urban.

Our sample of full-time workers includes observations with working status as employed or self-employed and total annual hour larger than 1900 hours. The status variable categories vary across years. We recoded it to a consistent 8 categories: Employed, Self-employed, Unemployed, Retired, Homemaker, Disabled, Student/pre-school, and Others. For years with a separate self-employment indicator, we made sure it lines up with status. All years except for 1988 contain hour information. The 1995, 2007, and 2008 waves give hours per week. We first top code the observations larger than 100 to 100 hours, then multiply the hour per week statistics by 50 weeks, assuming two weeks of national holiday in China. In 2002, we divided the annual hour by 50, top code it, and then multiply back 50, to make the numbers consistent with other years. For the 1988 rural survey, we include all employed and self-employed people with non-missing wages. For the 1988 urban survey we dropped temporary workers (about 340 of them) from the sample of employed or self-employed.

## **A.2 Consumption moments: Data and calculations**

### **A.2.1 Consumption value added**

For India we used sectoral value added from GDP by economic activity data from Statement 10 of National Accounts Statistics provided by the Ministry of Statistics and Programme Implementation (MOSPI) of Government of India. Investment is measured as gross capital formation, and was

obtained from Statement 20 of National Accounts Statistics provided by MOSPI. Both value added and investment is in constant 1999-00 prices and can be accessed from [http://mospi.nic.in/Mospi\\_New/site/India\\_Statistics.aspx?status=1&menu\\_id=43](http://mospi.nic.in/Mospi_New/site/India_Statistics.aspx?status=1&menu_id=43).

For China the national level agriculture and non-agriculture employment and GDP was obtained from the National statistics yearbook 2013. GDP is in constant 2004 prices.