Agricultural Productivity, Pay-Gap, and Non-Farm Development: Contribution to Structural Transformation in India

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Abstract: There had been a massive outflow of agricultural workforce during the past decade in India. Ironically, this was the period when real farm wages were rising, agricultural prices were improving, and national policies were supporting farmers. This efflux, even under favorable environment, raises concerns that whether workers in agriculture are productively employed, and are paid equivalent to their productivity contribution. In short, is there a productivity-pay-gap in agriculture? We explored the presence of productivity-pay-gap in agricultural labor market in India during 1981-2016, possible causes behind it, and its influence on structural transformation. We observed negative productivity-pay-gap in agriculture since 2000s. Wages equaled productivity during 1980s and 1990s, after which productivity lagged behind. Instrumental Variable (2SLS, LIML, GMM) estimates attribute this divergence to a) labor intensification in construction sector and b) introduction of MNREGS-the largest public works program in the country. Against conventional wisdom, increasing agricultural prices fostered agricultural decline, and was found to be the major driver of transformation. It explained 43 percent of total agricultural decline, followed by the productivity-pay-gap (25 percent). Capital intensification in non-agriculture (16 percent) and investing in public agricultural research & education (16 percent) were found to be the other potential drivers of transformation.

Key words: Productivity-pay-gap, Geweke decomposition, instrumental variables (2SLS, LIML, GMM), structural transformation, agriculture, India.

JEL Codes: O110, O530, N550, C360

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INTRODUCTION

Structural change theories describe the share of workforce in least productive sector declines with economic progress. Workers shifts from traditional sectors like agriculture to modern sectors like manufacturing and services during the development process (Fisher, 1939; Clark, 1940; Lewis, 1954; Ranis & Fei, 1961; Kuznets, 1973). Observing cross-country evidences, the pattern of growth had been similar across the developed world and in much of the Asian countries including Japan and Korea, with variations in Latin American and African regions (Dennis & Iscan, 2009; Neuss, 2019). Manufacturing sector has expanded gradually in the Asian nations with falling share of agriculture both in terms of output and employment. In China, the share of labor has dropped more than a half in agriculture between 1978 and 2004 (Brandt *et al.,* 2008), and industrial absorption of agricultural labor has contributed substantially to the Vietnam's economic growth (Rodrik *et al.,* 2016). The pattern of change had rather been different in India. The transformation has been 'atypical' (Goel & Echavarria, 2015) where the service sector's contribution expanded dramatically before the manufacturing attaining the peak. The share of output and employment in agriculture has declined consistently. India has brought down the share agricultural workforce[1] in total workforce to 55 percent during 2011 from a 70 percent during 1951[2].

While the pace of decline had been slower in employment than in agricultural output, the pattern of change brings interesting questions. Especially, the two decades - 1960s and 2000s are of great interest. Population Census shows that the 1960s witnessed an absolute decline of 21 million farmers. Three decades later, the 2000s again registered a decline of around 8.5 million farmers from agriculture. Unlike 1960s, which witnessed an addition of 16 million agricultural laborers signaling much of the farmers have turned into agricultural laborers, the 2000s registered an increase of 38 million agricultural laborers against a decline of just 8.5 million farmers. Oppositely, the 1970s, when technological gains of green revolution were diffusing wider, added more farmers than laborers. About 14 million new farmers entered in agriculture, while there had been an addition of just 8 million laborers during this decade. During 1980s, more or less equal number of farmers and laborers entered in the workforce. Despite all these compositional changes, total agricultural workforce continued to increase.

The compositional changes are reflected less frequently in Population Census as it is decadal in nature. Observing with Employment and Unemployment Survey (EUS) estimates of the National Sample Survey Office (NSSO) of India, which are quinquennial in nature and record employment particulars of households at a national scale[3], one shall find interesting deviations, especially since 1990s (see appendix 1) when the country introduced structural

[1] 'agricultural workforce' comprises both cultivators (farmers) and agricultural laborers.

[2] Population Census estimates as reported in MoAFW (2016a, pp.15).

[3] The employment survey records responses of around 100,000 households in each quinquennial round.

reforms and adopted the model of liberalization, privatization and globalization (LPG). For instance, while the census estimates show a persistent increase in the (absolute) size of agricultural workforce since 1991, the NSSO estimates indicate a sharp turn down after 2004-05. Further, while the census estimates record a decline of about 8.5 million farmers during 2000s, the survey estimates record an increase of about 30 million between 1999-00 and 2004-05, followed by a huge decline of about 21.3 million between 2004-05 and 2011-12 (Mehrotra *et al*., 2014).

While differences exist among the sources on the pattern of change, similarity lies in providing evidences to a declining size of farmers in recent years. Estimates in both these sources, between 2001 and 2011 in the census and between 2004-05 and 2011-12 in the EUS survey, show millions of farmers are quitting agriculture. Interestingly, the period after 2004-05 is noted in India for 'agricultural growth recovery' after a decade long deceleration (World Bank, 2014; Chand and Parappurathu, 2012). Agricultural output (NSDP) has increased faster despite of shift of labor out of agriculture (Balaji & Babu, 2020) and agricultural growth turned more inclusive across regions (Balaji & Pal, 2014). The terms of trade improved in favor of agriculture since then (MoAFW, 2016b), and public expenditure on agriculture and irrigation increased across states (Bathla, 2017). The Government's support in the form of increased allocations for research as well was observed (Singh & Pal, 2015). Why do farmers still quit agriculture? Turning into casual labor market in agriculture, the survey estimates also show an absolute decline of 15 million laborers between 2004-05 and 2011-12. Given that the real farm wages were rising during this period (Himanshu & Kundu, 2016), what caused casual workers as well to leave agriculture? The withdrawal of farmers when agriculture performed well, and of laborers when wages rose, stands paradoxical. The study is an attempt to understand possible causes.

DRIVERS OF STRUCTURAL TRANSFORMATION

Empirical studies refer three major forces driving transformation in the long-run. *First*, nonhomothetic preferences explained by the *Engel's law* resulting in relative decline in food prices; *second,* changes in relative factor intensities described by the *Rybczynski theorem* that propose capital accumulation encourage capital-intensive sector at the expense of labor-intensive sector (Rybczynski, 1955; Anderson, 1987); and *third*, differential rates of technological progress between sectors (Esposti, 2012; Martin & Warr, 1994 & 1993; Anderson, 1987). Other factors, like the level of income per capita, governance and institutional reforms (Mensah *et al.*, 2016), reforms in factor markets and industry structure (Chen *et al.*, 2011) and international trade (Uy *et al.*, 2013; Teignier, 2017) are also found to influence structural change. In Indian context, increase in agricultural productivity (Himanshu & Kundu, 2016) and growth in construction sector (Gulati *et al.*, 2014) have been the potential causes.

The attempt to understand *productivity-pay-gap* as a factor to influence structural change is rather limited. This factor is explained as a primary cause of divergence in labor market equilibrium and resulting unemployment in an economy (Lopez & Silva, 2011; Madson, 1994) but not as a cause that reallocates workers between different sectors. When such gap exists in sector like agriculture, which employs around half of the total workforce in a highly populated country like India, it would lead to inter-sectoral labor shift. For example, when payments turn low in agriculture than labor productivity, upon access, workers would shift out of agriculture to low-skill demanding construction like occupations. In fact, even when earnings are on par with productivity, one would expect such shift when the shifting-in sectors offer higher (real) wages. In short, the behavioral factor that operate at household level to decide between farm and nonfarm choices is *productivity-pay-gap* in the former case, and is relative *wage-differentials* in the latter case. One could refer the former as *push factor*, and the later as *pull factor*.

Foundations in wage theories imply as long as workers are compensated for their productivity contribution, there exists incentives to offer labor services, and firms/farms tend to hire more labor unless marginal wages outweigh productivity gains. In the absence of frictions in competitive labor market, equilibrium is set when wage equals marginal labor productivity. Disequilibrium arises when workers turn more productive, or when wages raise beyond productivity. While the former raises demand for labor, the later ceases hiring of labor or releases labor to other sectors. The difference along this divergent path is known as *productivity-pay-gap*.

By theory, deviations in equilibrium are observed to be 'temporary' and are expected to vanish over long-run. Still, empirical literature provides evidences on existence of disequilibria (Elgin & Kuzubas, 2013; Bruno and Sachs, 1985). Deviations would emerge from different sources. Technological and human capital factors affect labor productivity. In India, shifting towards high-yielding dwarf varieties since mid-1960s and emergence of skilled agricultural workers following tracterization/mechanization are obvious examples in agriculture. Price and income factors influence wages. When 'demand-pull' and/or 'cost-push' factors exert inflationary pressure, the workers would demand for higher wages despite of no additional productivity gains, hence widening the gap. Policy choices have potential strength to alter productivity-pay relations. One would relate rolling out of public works programs/social safety net programs at larger scale as an example. The launch of Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS) since 2006 in India, and consequent shifts in wages are well documented (Berg *et al.*, 2018; Himanshu & Kundu, 2016; Gulati *et al.*, 2014;

Nadhanael, 2012). Since labor inflow in rest of the sectors is pulled back, wages tend to rise beyond productivity, leading to a diverging gap. Absence of labor unions and formal contracts are the other factors one would expect to cause divergence (Lopez & Silva, 2011; Zavodny, 1999), which are common in the agricultural labor market in India.

We believe, during the study period in India, that *wage-productivity-disequilibrium* in agriculture might have had a greater role in conditioning labor reallocation for the following reasons. *First*, observations increasingly point out distress factors in agriculture than wage-gains as the causes of nonfarm development (Jatav & Sen, 2013; Abraham, 2009), resulting in feminization of agriculture (Patnaik *et al.*, 2018) and casualization of nonfarm workforce in the country (Jatav, 2010). The Economic Survey 2017-18 notes that outmigration has favored men over women and this has intensified participation of women in agriculture, highlighting the need to address the differences in access of farm related services to the women (MoF, 2018). *Second*, there had always been wage gains in construction, trade, transport, finance and real estate to the agricultural workforce. But outflow had predominantly been into construction than any other sector. We believe the absence of need to acquire new skills and to be more literate in the construction sector, which stands for no additional demand to the low-skilled agricultural workforce to enter into construction, is the prime cause of successful absorption.

For example, using Mehrotra *et al.*'s (2014) estimates, one could observe a decline of around 21 million farmers and 15 million laborers from agriculture was accompanied by an increase of 25 million construction sector workers between 2004-05 and 2011-12. Though one would not strictly assume entire addition in construction came from agriculture, it is highly likely since there exists a limited possibility of workers flowing into construction from other nonagricultural enterprises as wages are already high. On the other side, there exists demand for human capital factors like literacy and skill that restrict agricultural workers moving into high wage sectors like trade and communication. This point outs that growth in demand in labor intensive construction sector, along with low entry barriers than the wage gain is the proximate cause of labor flow.

Third, we attribute certain policy choices like MNREGS to reduce agricultural labor supply. The households covered under the scheme jumped from 21 million during the inception year 2006-07 to 51 million in 2017-18. Impact of this supplementary employment program on farm wages are frequently noted (Gulati *et al.*, 2014; *Reddy et al.*, 2014). Following that, we believe *wage-differentials* form one among different causes that produce *productivity-pay-gap* in agriculture, which in turn explains relative decline of agriculture. The manuscript attempts to study the changes in agricultural labor market in the above context. *First*, it explores the existence of *productivity-pay-gap* in agriculture and traces its stability in the long-run. Importance of such exercise could not be underestimated as the implications are multifarious. A minimal gap would imply proper functioning of agricultural labor market and demand-supply signals respond to each other. Rather, deviations in equilibrium would help to understand agrarian distress on one side and inter-sectoral labor flow to the other side. *Second*, it attempts to explore causes behind this *productivity-pay-gap*, and *third*, it estimates influence of this gap in speeding-up transformation.

DATA AND METHODOLOGY

We followed survey based estimates backed by the fact that most of the empirical research maintain to employ survey estimates to observe major changes in economic structure at the national level (Gibson *et al.*, 2017; Lanjouw & Murgai, 2009; Ravallion & Datt, 1996). Further, unlike census estimates, they offer analytical flexibility ranging from individuals to households, from regional to national, and from annual to quinquennial scale.

***Factor-shares, Technology and Prices*:**

Following Martin and Warr (1993 & 1994) and Esposti (2012), we modelled transformation driven by factor intensities, technological differences and farm-nonfarm prices, but depart in following aspects. The capital-labor ratio described in *Rybczynski* theorem was reconstructed as the ratio of capital-labor ratios in non-agriculture to agriculture. This was backed by the assumption that capital-labor adjustments within and between farm and nonfarm sectors interact together to bring transformation rather than an outcome of interaction between capital intensive nonfarm sector and labor intensive agricultural sector. In fact, agriculture had been more capital intensive than the construction sector during the study period. Average share of labor income had been 78 percent in construction but 55 percent in agriculture. The labor and capital shares in farm and nonfarm sectors were used for this purpose. To obtain estimates for nonfarm sector as a whole, factor shares were aggregated using GVA estimates as weights. For example, since labor and capital shares in nonfarm sector are distributed across 26 sub-sectors, one would not obtain factor intensities simply by averaging these sub-sectoral estimates. Rather, appropriate estimates could be obtained by multiplying sub-sectoral GVA estimates with corresponding labor and capital share estimates, and aggregating them as a single series.

Technological differences were captured through research and development (R&D) expenditure[4] incurred in farm and nonfarm sectors respectively. On similar fashion mentioned

[4] R&D stock was not available

above, the R&D variable was constructed as a ratio of R&D expenditure per agriculture worker to expenditure per worker in nonagricultural sector. Since private sector expenditure in agriculture was not available, and information contained in literature (Pray & Nagarajan, 2014) would generate less precise trend upon interpolation/extrapolation, public sector expenditure alone was considered. The expenditure on public agricultural research and education provided in Pal (2017) was used for this purpose. The expenditure series provided by the Department of Science and Technology (DST) for the total economy, comprising both public and private sectors was used to derive nonfarm R&D expenditure by subtracting agricultural expenditure. Both farm and nonfarm series were normalized by workforce employed in respective sectors. The GVA deflators (2011-12=100) were used to arrive factor intensities and technological variables at real terms. The same deflators were used to construct terms of trade between agriculture and non-agriculture, which is simply the ratio of agricultural and nonagricultural prices. The workforce employed in MNREGS was obtained from the Ministry of Rural Development, and employment share in construction sector was estimated using India-KLEMS database.

***Constructing the Productivity-Pay-Gap*:**

Constructing productivity measures in structural change context possess definite challenges (Herrendorf & Schoellman, 2015; Gollin *et al.*, 2014). Similarly, equating the productivity estimates with market wages under classical marginalists' assumption of absence of market frictions and presence of competitive labor market to explain pay differences could as well be questioned (Krueger & Summers, 1988). Even when one does so, under simple framework, one could derive labor productivities in different years using production function approach that model output as a function of labor and capital. In the absence of labor-hours based sectoral employment estimates, while the time-series of agricultural workforce could be derived from the panel of quinquennial household survey sources through interpolation, obtaining capital stock would turn the task difficult. Even when such series is constructed or available, when labor productivities are estimated using standard Cobb-Douglas approach[5], questions might arise on marginal productivity estimates as they are derived from a *constant* elasticity parameter.

Rather, one would derive labor productivity series using factor shares if available[6]. The Reserve Bank of India in its recent report provided labor and capital share estimates for the period 1981-2016 along with employment and output characteristics of 27 major sub-sectors for India[7]. We obtained marginal productivity estimates using the annual labor share series for agriculture, and average productivity as the ratio of Gross Value Added (GVA) to the workforce employed. Average wages in agriculture were computed as the weighted average of wages reported by the self-employed, regular and casual workers in agriculture, using an earlier version of the report[8] where wage estimates were available till 2011-12. The series was extrapolated till 2015-16 using the linear parameters obtained after accounting for structural breaks in the wage series[9], and was deflated by consumer prices index (agricultural laborers, 2011-12=100) to arrive at real terms. The marginal productivity estimates were deflated by the agricultural GVA

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[5] The product of elasticity and average productivity provide marginal productivity in Cobb-Douglas framework.

[6] The labor (workforce) in agriculture include both farmers and agricultural laborers

[7] The database (India KLEMS) is available at https://rbi.org.in/Scripts/BS_PressReleaseDisplay.aspx?prid=43504

[8] Available at http://rbidocs.rbi.org.in/rdocs/content/docs/KLEMS09122016.xls

[9] We used Zivot & Andrews's (1992) procedure to decide breakpoint and fitted linear spline function to estimate parameters before and after break. These estimates were used to forecast wage estimates between 2012-13 and 2015-16.

deflators (2011-12=100). We define the differences in wage and productivity over years as *productivity-pay-gap* or *wage-productivity-gap*[10].

***Endogenous Linkages and Modeling Transformation*:**

As structural change emerges through multi-sector linkages (Johnston & Mellor, 1961; De Janvry, 2010), necessary pre-requisite before modelling and solving the system would be to establish direction of causality among expected drivers of change and explore the possibility of feedback relations. One would take the association of agricultural and nonagricultural wages with prices (Kundu, 2018; Nadhanael, 2012) as example for Indian case. Further, causality would vary between short-run and long-run, like wages would respond to prices in short-run, but would vanish in long-run with extraneous shocks. Rather, investments once made on roads and other infrastructure will have a lasting effect on productivity. The Granger (1969) test doesn't account for instantaneous/contemporaneous correlation in a data with short-run frequency. Having a set of annual time series in the present study, to account for contemporaneous relation along with long run causality and feedback, we followed the procedure described by Geweke (1982). It measures linear dependence among, say two series X and Y, as the sum of measure of linear feedback from X to Y, from Y to X, and an instantaneous linear feedback between X and Y[11].

[10] *Wage-productivity-gap* is the inverse of productivity-pay-gap

[11] The decomposition procedure could incorporate multiple time series. A detailed technical discussion can be found in Geweke (1982)

For simplicity, assume a two variable (X, Y) vector autoregression (VAR) representation of the form

$$Y_t = \sum_{i=1}^{m} \gamma_{2i} X_{t-i} + \sum_{i=1}^{m} \delta_{2i} Y_{t-i} + \xi_{1t} \qquad \text{(1)}$$

$$X_t = \sum_{i=1}^{m} \lambda_{2i} X_{t-i} + \sum_{i=1}^{m} \phi_{2i} Y_{t-i} + \xi_{2t} \qquad \text{(2)}$$

where ξ_{1t} and ξ_{2t} are errors that are serially uncorrelated. Still, there may exist a contemporaneous relation with them. The variance-covariance matrix $\sum_{\xi}$ can be portioned as

$$\sum_{\xi} = \begin{bmatrix} \sum_{11} & \sum_{12} \\ \sum_{12}' & \sum_{22} \end{bmatrix}$$

where $\sum_{ij} = E\left[\xi_{it} \xi_{it}'\right]$, i, j=1, 2. When $\left|\sum_{11}\right| = \left|\sum_{1}\right|$, we say X granger causes Y where $\sum_{1} = E\left[\varepsilon_{1t} \varepsilon'_{1t}\right]$ is obtained from

$$Y_t = \sum_{i=1}^{m} \delta_{1i} Y_{t-i} + \varepsilon_{1t} \cdot$$

The contemporaneous correlation can be obtained from the VAR representation

$$Y_t = \sum_{i=0}^{m} \gamma_{3i} X_{t-i} + \sum_{i=1}^{m} \delta_{3i} Y_{t-i} + \xi_{1t} \qquad \text{(3)}$$

$$X_t = \sum_{i=1}^{m} \lambda_{3i} X_{t-i} + \sum_{i=0}^{m} \phi_{3i} Y_{t-i} + \xi_{2t} \qquad \text{(4)}$$

only when $\left|\sum_{11}\right| > \left|\sum_{\xi 1}\right|$ and $\left|\sum_{22}\right| > \left|\sum_{\xi 2}\right|$. The measures of linear feedback developed by Geweke (1982) is shown in Table 1. Upon existence of causality and feed back in the long-run, one would adhere to Vector Auto egression (VAR) or Vector Error Correction (VEC) based models for estimating parameters of drivers of structural change[12]. A VAR(*p*) with X_t as exogenous variable can be written as

$$Y_t = V + A_1 Y_{t-1} + \dots + A_p Y_{t-p} + B_0 X_t + B_1 X_{t-1} + \dots + B_s X_{t-s} + u_t \qquad t \in \{-\infty, \infty\}$$

--------------- (5)

where $Y_t = (y_{1t}, \dots, y_{Kt})$ is a *Kx1* random vector; A_1 through A_p are *KxK* matrices of parameters; X_t is an *Mx1* vector of exogenous variables, B_0 through B_s are *KxM* matrices of coefficients; V is a Kx1 vector of parameters; and u_t is assumed to be white noise *i.e.*, $E(u_t) = 0$; $E(u_t u_t^{'} = \Sigma)$ and $E(u_t u_s^{'} = 0)$ for t≠s. Note that K=4 in

___Insert Table 1. here___

present case that refer three traditional factors namely relative capital-labor intensity, relative R&D expenditure and terms of trade, and a behavioral variable *wage-productivity-gap*. One would assume population growth as an exogenous factor. Upon non-stationarity and cointegration among series, the above VAR equation (excluding exogenous variable) can be written as a VECM form of

[12] Note that the Geweke's (1982) procedure itself follows a VAR system to observe short-run and long-run causality.

$$\Delta Y_t = V + \Pi Y_{t-1} + \sum_{i=1}^{p-1} \Gamma_i \Delta Y_{t-i} + \varepsilon_t \qquad \text{--------------- (6)}$$

where $\Pi = \sum_{j=1}^{j=p} A_j - I_k$ and $\Gamma = -\sum_{j=i+1}^{j=p} A_j$. The V and ε_t are identical. Note that in a VAR system, each variable is assumed to be correlated with lagged values of its own and other variables. When bi-directional causality in fact doesn't exists, estimating a VAR/VECM would imply specification error and be less meaningful[13]. In such case, one would opt for linear models that address endogeneity. We used instrumental variables (IV) approach when bi-directional causality didn't exist, if not in all but most of the economic variables. In the IV based framework, we modelled structural change as a function of relative factor intensities, technological differences and terms of trade, and added the behavioral variable *wage-productivity-gap* as an additional factor. This additional variable was assumed endogenous, and explained with two major instruments *i.e.* a policy shock variable representing number of workers participating in the MNREGS program; and a pull factor described as the share of construction sector labor in total workforce[14]. We modelled the process of structural transformation as

$$ST_t = \beta_0 + \beta_1 WPG_t + \gamma_1 KLR_t + \gamma_2 RDR_t + \gamma_3 ToT_t + \upsilon_t \qquad \text{--------------- (7)}$$

$$WPG_t = \delta_0 + Z_1 CON_t + Z_2 PWP_t + \xi_t \qquad \text{--------------- (8)}$$

[13] The pros and cons of VAR based modelling could be found in Cooley & LeRoy (1985), Runkle (1987), Stock & Watson (2001) and Christiano (2012), among others.

[14] We justify these instruments in results and discussion section.

where ST=share of agricultural workers in total workers; KLR=K-L ratio in non-agriculture/K-L ratio in agriculture; RDR=R&D expenditure in agriculture/ R&D expenditure in nonagriculture; ToT=Agricultural GVA deflator/non-agricultural GVA deflator; WPG=Real wage/marginal productivity of labor in agriculture; CON=share of construction sector workers in total workforce and PWP=number of households benefitted under the public works program MNREGS. By order and rank conditions, one would observe both equations 3 and 4 are *over-identified*. Hence, a Two-Stage Least Squares (2SLS) method can be used to solve the system. The two instruments in equation-4 are reduced through an auxiliary regression as a single instrument in stage-1 upon regressing WPG_t on all predetermined variables in the system, and substituting the predicted values in equation-3. Since Limited Information Maximum Likelihood (LIML) estimators possess better small sample properties and are more resistant when the instruments are weak, and Generalized Method of Moments (GMM) provides efficient estimators in presence of heteroscedasticity, we employed them as robustness tests.

RESULTS AND DISCUSSION

Wage-Productivity relationships in agriculture:

To begin with, we examined the trends in wage and marginal productivity in agriculture. A visual assay informed wage roughly equaled productivity during 1980s and 1990s, after which productivity lagged behind, after accounting for inflation faced by the agricultural workforce, and prices realized in market for food (Figure 1). Empirical results rather report a reciprocal trend in both advanced (Bivens & Mishel, 2015; Ravikumar & Shao, 2016; Karanassau & Sala, 2014; Fleck *et al.*, 2011; Feldstein, 2008) and developing (Bhattacharya *et al.*, 2011;

Biesebroeck, 2011) economies, mostly in nonfarm sectors, with wages rarely surpassing productivity (Ghose, 2005)[15]. Statistical tests offered further insights in this trend. More precisely, they showed the pace of wage and productivity growth started diverging since mid-2000s. Structural break test[16] indicated the years 2006 and 2005 at which wage and productivity inclined to a new path (Table 2). One could recall the public works program MNREGS came into force since the year 2006-07, casting doubt on raising wages by crowding out agricultural workers. Further, we could observe a quick response of wage to productivity shift, shown by the breakpoints occurring within a year.

___Insert Figure 1. here___

___Insert Table 2. here___

What lead them to shift to a new direction? Labor productivity increments jumped 5.5 times after 2005 in agriculture, from 0.86 Rs/day to 4.74/day annually[17]. One could hardly attribute capital intensification behind this productivity shift. Labor share rarely declined, which one could refer with an increase in capital share[18], as shown by the stagnant coefficients 0.04 against agriculture in both the periods. The R&D expenditure as well witnessed no major boost,

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[15] We found limited literature for agriculture sector. Still, nonagricultural wage-productivity trends in India as well follow international observations with productivity surpassing wages during the study period, as one would note in Figure 1.

[16] We used STATA's *sbsingle* to identify the break.

[17] The spline function coefficients measure annual rate of change in variable concerned, thus, the value 4.738 against marginal labor in agriculture in Table 2 indicate productivity increased by Rs.4.738/day/labor each year in agriculture.

[18] Labor share (%) = 100-Capital share (%).

and contribution to productivity could hence only be marginal. One might not look for prices and inflation to explain improvements in labor productivity. To the other side, real agricultural wage increased from 1.87 Rs/day to 9.60 Rs/day, a 5.1 times increase after the year 2006. As aware, one would not readily point out increase in wage as a response to inflation as real wage already accounts for it. Much of the unexplained could then be attributed to the forces operating outside the sector.

We believe the following factors to act behind wage-productivity divergence. The productivity shifted since 2005 not by raising capital or R&D expenditure. Rather, it was by reallocating sizeable labor to nonfarm sector without affecting agricultural output. Figure 2 shows an absolute decline of 55.2 million agricultural workers between 2004-05 and 2015-16. Despite such shock, the GVA continued to grow positively with 3.5 percent a year. It is the *ability to sustain output growth despite of labor withdrawal* we attribute behind shift in labor productivity since 2005 in agriculture[19]. In fact, much of the wage-productivity divergence is due to shift in wage than in productivity. While labor productivity rose by Rs.4.7 Rs/day annually since 2006, real wages doubled to Rs. 9.6/day, signaling non-productivity related factors operating on wages.

___Insert Figure 2. Here___

___Insert Figure 3. Here___

[19] We believe increase in speed of convergence in land productivity as shown in Balaji & Pal (2014) and a faster diversification within agriculture towards high-value-agricultural commodities like fruits and vegetables and allied agricultural products like milk, meat, egg and fish to sustain high output growth in agriculture.

This guided us to look on two major factors. The first factor we believed behind the surge in agricultural real wages was the output growth in construction sector and resulting increase in demand for labor. The real GVA growth jumped from 4.9 percent between 1981-2000 to 8.1 percent between 2001 & 2016[20]. Being labor-intensive than agriculture[21], construction sector successfully absorbed more labor consistently. In fact, construction sector is labor intensive than most of the nonagricultural sectors. Following growth, a stagnant share of construction workers during 1990s rose exponentially since then (Figure 2). We attribute this consistency to the nature of demand, which requires no/low additional skill from the unskilled agricultural workforce entering in this sector. Even when required, in Marshall's words, we assume skill acquisition as *quasi-bottleneck*, and the sector could train them in relatively shorter period. Sustained output growth and ability to absorb labor in presence of relative wage gains in construction contributed a major share in over labor reallocation in the economy.

The second factor we believed is a shift in labor supply towards the public works program–MNREGS. Aiming to provide supplementary wages to the under-employed and surplus rural labor, a legislation was enacted during 2004 through National Rural Employment Guarantee Bill, and passed during 2005 by the houses of parliament. During the year 2006-07, around 21 million households were provided employment under the scheme, which eventually rose to 51 million during the year 2017-18. We observe in Figure 3 a decline in agricultural workers of around 55 million between 2004-05 and 2015-16, providing an idea that MNREGS crowd-out agricultural workforce[22]. Though the program was designed to be carried out at off-

[20] Growth rates are CAGR estimates.

[21] The share of labor in GVA is between 75 percent -80 percent in construction against 55 percent in agriculture.

[22] The data series used in the study doesn't include the MGNREGS workers.

seasons, rolling out of the plan was found to increase the bargaining power of agricultural workers (Reddy *et al.*, 2014), pushing up wages.

Before solving the system, the existence of bidirectional causality was probed and results are presented in Table 3 (see appendix 2). Note that the decomposition test was carried out to decide between time series and cross-section based methods to solve the system but not to design the direction of causality itself. For example, following long-run causality between the variables ST and KLR, one would observe ST granger caused KLR but KLR doesn't granger caused ST, which says transformation process altered the relative capital-labor ratio but not *vice-versa*. Similar was the relation observed between RDR and ST. While ST granger caused RDR, RDR didn't granger caused ST. While the statistical absence of feedback and the direction of causality can be questioned on empirical sense, one could ultimately observe no long-run bi-directional causality among most of the economic variables. Similar was the results of short-run direct one to conclude. Out of six variables studied, just three of them confirmed bi-directional short-run causality. Technically, the results disclosed lagged values of a variable barely helps to explain present values of other variables.

___Insert Table 3. Here___

On the ground of direction of causality and non-existence of reverse causality on one side, and following the observations that rising wages are primary cause of wage-productivity divergence and labor-intensification in construction sector and implementation of MNREGS are the proximate causes of wage growth on the other side, we preferred instrumental variable regression to solve the system. A Two-Stage Least Squares (2SLS) technique was used for this purpose. As mentioned, the GMM and LIML estimates were obtained for robustness check.

Following IV estimation using three different methods, heteroscedasticity was diagnosed with the statistics of Pagan & Hall (1983), Koenker (1981), Breusch & Pagan (1979), Cook & Weisberg (1983), Godfrey (1978) and White, (1982). Relevance of chosen instruments was tested with statistics of Bound *et al.* (1995) and validation was assessed with statistics of Sargan (1958), Basmann (1960), Anderson & Rubin (1950) and Hansen (1982). Endogeneity assumption for the productivity-pay-gap variable was tested with statistics of Durbin (1954), Wu (1974), Hausman (1978).

Drivers of Structural Transformation:

It is essential before drawing inferences on drivers of transformation to ascertain robustness of the estimates obtained. Heteroskedastic residuals were disproved against the null, hence the 2SLS estimators are efficient (Table 4). Still, one could opt for GMM and the estimates are asymptotically equivalent to 2SLS estimates. We found no reportable differences in 2SLS and GMM estimates on almost all variables in the system. A relatively high partial R^2 and F statistics ascertained correlation of chosen instruments with the endogenous regressor. Sargan's and Basmann's test statistics in case of 2SLS, Basmann's and Anderson-Rubin's in case of LIML and Hansen's J statistic in case of GMM confirmed instruments are independent from the observable error process. Statistics of Durbin, Wu-Hausman and C tests asserted endogeneity in the variable specified and Wald statistics indicated absence of structural breaks in the coefficients. Thus, expectations on different estimates are completely satisfied through different test statistics.

Before turning into the importance of wage-productivity-gap in structural transformation, we would confirm with the empirical properties of first-stage regression. As hypothesized, the chosen instruments were highly significant, and hence are informative in the model. A one percent increase in MNREG workers was found to increase the wage-productivity-gap by 0.06 percent. Rather, the effect on this gap caused by labor expansion in construction was more than seven times higher, indicated by the coefficient 0.45. This proportion roughly matches with the estimates of Gulati *et al.*, (2014), who obtained the coefficients 0.03 and 0.28 for MNREGS and construction sector GDP respectively while explaining agricultural wages. Though the context is slightly different, the observation arise from the present research duly matches with their conclusion that construction sector is 4 to 6 times more effective in raising agricultural wages than MNREGS.

___Insert Table 4. Here___

What does the estimated coefficients refer for? Especially, we focus the elasticity coefficient of construction sector labor share[23] in the first stage regression that stands at 0.45 with highly significant *p*-value. The growth of labor in post-2000 period had been 9.4 percent a year in the sector, which translates to a 4.2 percent increase in wage-productivity gap in agriculture annually. Given that the divergence grew 2.4 percent a year in reality[24], it stands that speed of divergence was brought down by improvement in agricultural prices, shown by a more than unitary elasticity of -1.13 against the terms of trade variable. One would justify the inverse relation against the fact that higher are the relative agricultural prices, higher is the incentive to remain in agriculture, and hence lesser is the wage-productivity gap. To the other side, capital

[23] As MNREGS data cover last 10 years and obtain zero values for rest of the period, we avoided drawing detailed inferences.

[24] CAGR estimate

intensification has helped to reduce the gap to some extent, mainly through productivity improvements. One would conclude from the first-stage regression that better prices for food at the market and increased public agricultural investments would help to reduce wage-productivity-gap in agriculture in presence of opposite forces like construction sector growth which tend to raise agricultural wages.

The traditional drivers namely terms of trade, capital intensity and technological progress were found to accelerate structural change. The estimated elasticities were -0.48, -0.17 and -0.18 respectively and were highly significant. Terms of trade explained 43 percent of agricultural decline, followed by relative capital intensity and R&D expenditure in agriculture, each explaining 16 percent of decline respectively[25]. By theory, agricultural prices are expected to decline over long-run relative to the nonagricultural prices, leading to a shift of labor towards nonfarm occupations. The present study observed that even when agricultural prices improve, one could observe labor moving towards high paying occupations. During the period 1981-2016, terms of trade was improving rather than deteriorating, especially at faster rate since mid-2000s. Still, the agricultural workforce continued to migrate more rapidly. We doubt the inability of price gains to reach farmers, and resulting *status-quo* behind the continuance[26]. Further, we doubt net revenue increments that adjust costs in cultivation, rather than mere prices, decide labor mobility.

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[25] The shares are simply the ratio of a given coefficient to the sum of all coefficients, multiplied by 100.

[26] Though the statement highly demands empirical proof, lack of availability farmer's share in consumer's prices restrict us verifying.

Technological progress is believed to be slow in agriculture. Given the assumption, increasing R&D expenditure relatively faster in agriculture would release more labor since technologies are labor saving in nature. During the study period, the share of R&D expenditure to GVA increased more rapidly in agriculture than in nonagriculture sector. For example, the data used in the present analysis mark a gradual but steady increase from 0.32 percent in 1980-81 to 0.66 percent in 2015-16 for agriculture. To the other end, while the share was double than that of agriculture since beginning[27], the trend was inconsistent in nonagricultural sector hovering between 0.8 percent and 1.0 percent. Increasing expenditure for research and development in relative but not absolute term have helped to displace labor from agriculture.

Similarly, capital intensification was defined in relative terms, not as precisely described as to reflect the *Rybczynski* theorem. Still, one could expect similar effect described by the theorem and a negative relation with agricultural sector labor share. Agricultural sector had remained labor intensive with a more than unitary labor-capital ratio, and declined marginally from 1.27 in 1980-81 to 1.22 to 2015-16. The nonagricultural sector rather displaced more labor with capital, indicating a steeper decline from 1.22 in 1980-81 to 0.78 in 2008, followed by a slight increase to 0.92 in 2015-16. As expected, a one percent increase in nonagricultural KL ratio with respect to agriculture helped to bring down the agricultural labor share by 0.17 percent, equal to the contribution of R&D expenditure.

[27] 0.67 percent during 1980-81

CONCLUSIONS AND POLICY IMPLICATIONS

When wage falls behind productivity, one could expect workers shift to a new profession. The present study found agricultural workforce received wages above their productivity contribution in India since 2000s, and the divergence between them had increased even after adjusting for inflation. Still, the share of agricultural workers continued to decline. While this divergence could emerge from wage and productivity related factors, we attribute the former more than the later. Wage grew more rapidly than labor productivity in agriculture, and the major factor behind this rapid wage growth had been a shift in demand for construction workers. Results showed that when the size of workers increased in construction by one percent, it had increased wage-productivity ratio in agriculture by 0.44 percent. The public works program-MNREGS as well had a significant influence in altering the ratio. The effect of productivity enhancing factors like adding more capital replacing labor and raising expenditure for R&D had been marginal, and hence had limited influence.

We observed this divergence explained one-fourth of structural change, measured by a decline in share of agricultural workforce. Much of this decline was due to a relative increase agricultural prices. Terms of trade explained 43 percent of total decline in agricultural workforce. In general, a falling agricultural prices was expected during structural change and this inverse relation is attributed behind transfer of labor from agriculture. Oppositely, the present study observed even when agricultural prices are improving, one could expect a labor shift. This explains the dominance of wage related factors over the productivity enhancing factors in agriculture, and stands that as long as wage tends to rise over productivity as observed in the recent decade, the decline of labor from agriculture would continue. A rise in KL ratio in nonfarm sector and expenditure under R&D in agricultural sector more rapidly with respect to the remaining sector(s) further speeded the structural change process. Each factor contributed 16 percent to the transformation during the study period.

Though the drivers of change were identified, policy choices appear to be complex. The construction sector is expected to continue its growth momentum in the near future. The market forecasts depict infrastructure investment demand of more than US$ 700 billion for the year 2022, driven by the Government's initiatives, public-private partnership, infrastructure needs, housing development and international investment that cover both rural and urban economies. With an ongoing trend, the labor employed in construction could rise to 122 million during the year 2022[28], the year at which the Government of India has targeted to double the farmers' income. This is 52 percent higher than the size of labor employed during the year 2016. Given the elasticity coefficient 0.45 obtained in the present study, it translates the wage-productivity gap to raise to 1.96, *ceteris paribus*. Similar is the trend one could expect with MGNREG scheme. The households covered under the scheme jumped from 21 million during the inception year 2006-07 to 51 million in 2017-18. The pressure on farm wages would hence be much higher even when it continues to employ the 50 million households covered at present in near future.

The implications are not just confined to a given class of labor benefitting from rising wages. The increase in pressure on farm wages would worsen agrarian distress in the country further. Of the working expenses farmers incur, 53 percent in case of rice and 30 percent in case of wheat is spent for labor alone[29]. Given the low benefit-cost ratios in cropping (1.02 and 1.23

[28] The trend since 2004-05 is used to derived the figure

[29] The estimates are averages of labor cost shares in three largest producing states during the year 2015-16 (CoC data). Includes 'opportunity cost' of family labor as well.

in case of rice and wheat respectively during the year 2015-16), one would expect profits to fall down with an increase in wages. The moderating force could then only be the agricultural prices. While the country has observed steep increase in agricultural prices relative to nonagriculture since mid-2000s, the causal factors are less understood.

A relative increase in agricultural investment could result from adjustments in both investments in agriculture and nonagriculture in absolute terms. As one would not expect downsizing of nonagricultural investment, there exists a stronger need to increase agricultural investment. Especially, one could focus fast-growing regions where returns to agricultural investment are relatively high. While private investment is found to crowd-out public investment in the total economy, expecting a similar pattern within agriculture would require credit expansion in agriculture. At present, out of total credit disbursed by different institutions, less than one-fourth[30] is disbursed for asset creation in agriculture, while rest is disbursed for covering working expenses in cultivation. Hence, credit policies that encourage farm asset creation is of great interest. The alternate choice would be to enhance the skills of agriculture workforce to rise their productivity levels, which shall be augmented through training centres and information access on agriculture technologies and adoption. Similarly, raising research and development expenses more rapidly in agriculture relative to the nonagricultural sector would invite increased private sector participation in agriculture. Regulatory and institutional support from the Government, allowing public sector research products and sponsoring for research in

[30] Statistics pertain to the year 2011-12, for which gross estimates are available. The short-term credit disbursed to farmers was to Rs.3467.37 billion, and long-term credit was Rs. 1071.62 billion during this year.

agriculture to the private as observed in past and prioritizing less-attractive Eastern-India in public agricultural research funding could in part help.

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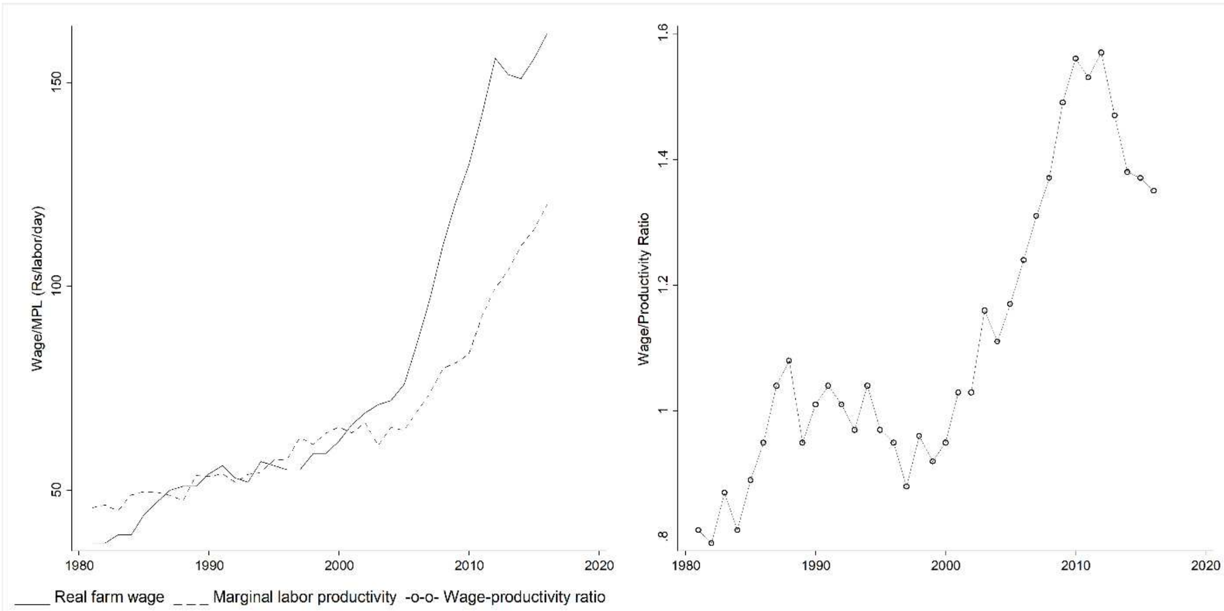
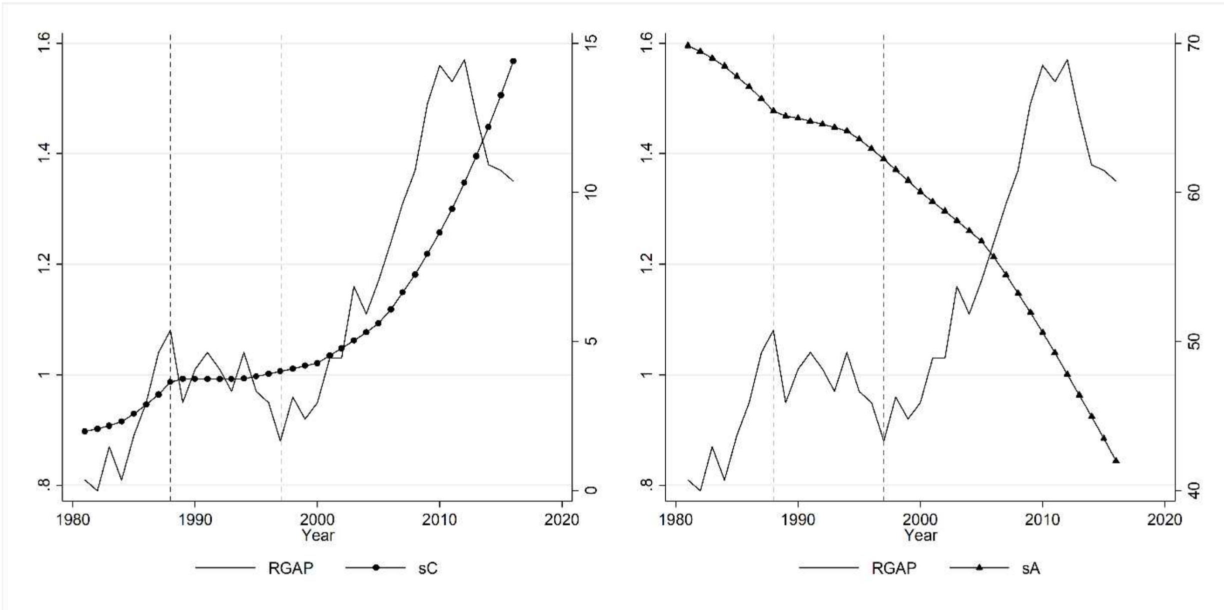
Figure 1. Wage-productivity gap in agriculture (All-India, 1981-2016)



Note: Wage and productivity are in real terms

Source: Based on KLEMS database

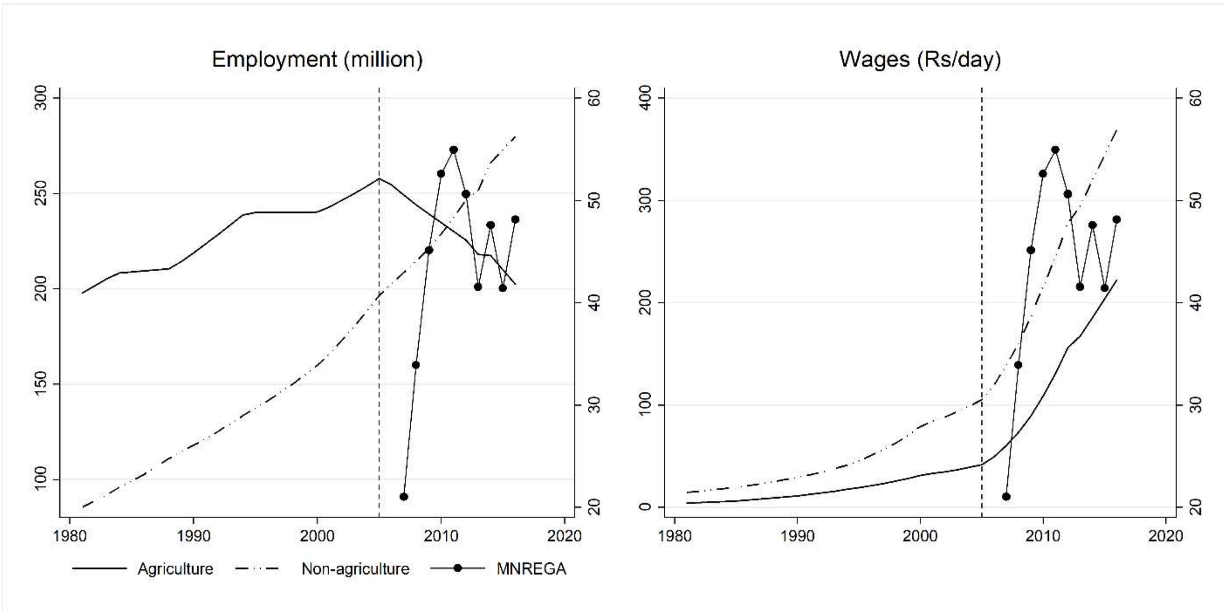
Figure 2. Construction sector development and productivity-pay-gap in agriculture (All-India, 1981-2016)



Note: a) X axes represent year; b) values in primary axes in both the panels are wage-productivity ratios (RGAP) in agriculture and are in real (2011-12) terms; c) values in secondary axis at left panel indicate employment share in construction (sC) and at right panel indicate employment share in agriculture (sA); d) first and second reference lines indicate the years 1988 and 1997 respectively in both the panels

Source: Estimated based on KLEMS database

Figure 3. Policy shock (MNREGS) and wage-employment changes (1981-2016)



Note: a) X axes represent year; b) values in secondary axes in both the panels are MNREGA households; c) Wages are at current prices; d) reference lines indicate the year 2005; e) MNREGA started since 2006-07;

Source: Employment and wages are based on KLEMS database; worker statistics of MNREGA are from Ministry of Rural Development

Table 1. Geweke′s Linear Feedback Measure

Linear feedback	Causality measure	Null hypothesis	Test statistic
From X to Y	$F_{X\to Y} = \ln\left(\lvert\Sigma_1\rvert / \lvert\Sigma_{11}\rvert\right)$	$H_0 : F_{X\to Y} = 0$ (X doesn't cause Y)	$(T-m)\hat{F}_{X\to Y} \sim \chi^{2(m)}$
From Y to X	$F_{Y\to X} = \ln\left(\lvert\Sigma_2\rvert / \lvert\Sigma_{22}\rvert\right)$	$H_0 : F_{Y\to X} = 0$ (Y doesn't cause X)	$(T-m)\hat{F}_{Y\to X} \sim \chi^{2(m)}$
Instantaneous	$F_{X.Y} = \ln\left(\lvert\Sigma_{11}\rvert / \lvert\Sigma_{\xi 1}\rvert\right)$ $F_{X.Y} = \ln\left(\lvert\Sigma_{22}\rvert / \lvert\Sigma_{\xi 2}\rvert\right)$	$H_0 : F_{X.Y} = 0$ (Non-instantaneous causality)	$(T-m)\hat{F}_{X.Y} \sim \chi^{2(1)}$
Total correlation	$F_{X,Y} = \ln\left(\lvert\Sigma_1\rvert / \lvert\Sigma_{\xi 1}\rvert\right)$ $F_{X,Y} = \ln\left(\lvert\Sigma_2\rvert / \lvert\Sigma_{\xi 2}\rvert\right)$	$H_0 : F_{X,Y} = 0$ (No linear dependence)	$(T-m)\hat{F}_{X,Y} \sim \chi^{2(2m+1)}$

Source: Adopted from Chong & Calderon (2000), pp.75

Table 2. Structural breaks in growth in key variables

Variable	Sector	Break point	Wald Statistic†	Spline function coefficients††	
				Pre-break	Post-break
Labor share in GVA (%)	AG	2001	18.58 (0.00)	-0.04 (0.03)	-0.042 (0.11)
	NAG	2005	49.94 (0.00)	-0.19 (0.00)	-0.246 (0.06)
Real wages (Rs/day)	AG	2006	354.66 (0.00)	1.87 (0.00)	9.596 (0.00)
	NAG	1998	190.36 (0.00)	-0.70 (0.06)	8.071 (0.00)
Marginal labor productivity (Rs/day)	AG	2005	569.26 (0.00)	0.86 (0.00)	4.738 (0.00)
	NAG	2009	262.14 (0.00)	5.80 (0.00)	19.172 (0.00)
R&D expenditure share to GVA (%)	AG	2000	12.97 (0.03)	0.01 (0.00)	0.010 (0.00)
	NAG	1990	30.06 (0.00)	0.01(0.18)	-0.004 (0.06)
GVA deflators (2011-12=100)	AG	2007	1165.56 (0.00)	2.00 (0.00)	9.040 (0.00)
	NAG	2006	235.13 (0.00)	2.33 (0.00)	5.820 (0.00)
Consumer price index (2011-12=100)	AG	2008	741.73 (0.00)	2.15 (0.00)	9.422 (0.00)
	NAG	2008	662.65 (0.00)	2.28 (0.00)	9.185 (0.00)

Note: a) Variables are in real terms; b) AG=Agriculture; NAG=Non-agriculture; c) Figures in parentheses are p values; d) †supremum Wald statistics; e) †† Linear spline function was fitted using breakpoints identified.

Table 3. Causality and feedback: decomposition results

Variables						
	ST	KLR	RDR	ToT	WPG	CON
Granger Causation						
ST		Y	Y			
KLR			Y			
RDR						
ToT	Y				Y	
WPG		Y		Y		
CON	Y	Y	Y	Y		
Instantaneous feedback						
	ST	KLR	RDR	ToT	WPG	CON
ST						Y
KLR						
RDR				Y		
ToT			Y			
WPG						Y
CON	Y				Y	

Note: a) Y refers presence of causality; b) Causality arise from 'row' to 'column'; c) 'U' and 'B' are based on significance of causality at 5% and blank cells represent no causal relation; d) Statistics for the variable PWP is not displayed as it takes zero values for most of the years, but included in decomposition.

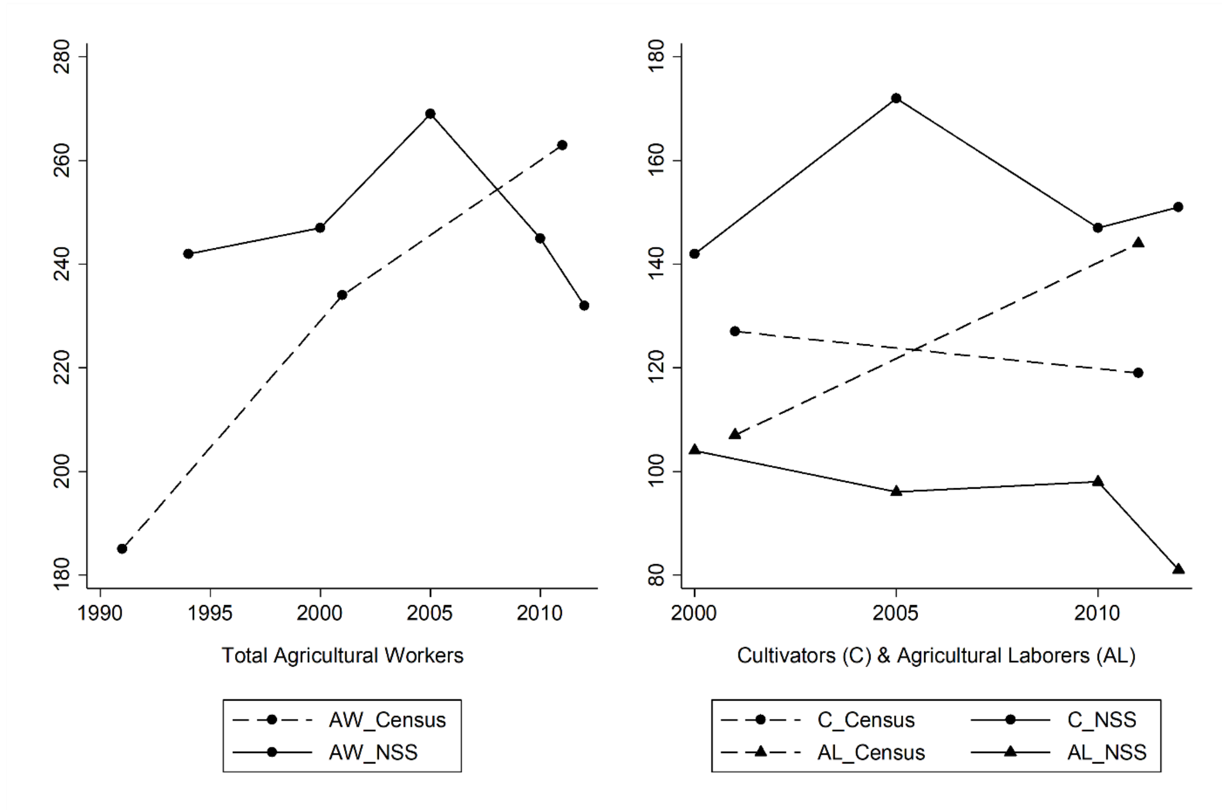
Table 4. Instrumental variables (IV) estimates

Variables	2SLS	LIML	GMM
First stage regression			
Relative capital-labor ratio	-0.203 (0.110)	-0.203 (0.147)	-0.203 (0.110)
Relative R&D expenditure ratio	-0.084 (0.427)	-0.084 (0.434)	-0.084 (0.427)
Terms of trade	-1.131 (0.000)	-1.131 (0.000)	-1.131 (0.000)
MNREG employment	0.060 (0.000)	0.060 (0.000)	0.060 (0.000)
Share of construction sector employment	0.448 (0.000)	0.448 (0.000)	0.448 (0.000)
Constant	-1.032 (0.000)	-1.032 (0.000)	-1.032 (0.000)
Instrumental Variable Regression			
Wage-productivity gap in agriculture	-0.278 (0.000)	-0.277 (0.000)	-0.293 (0.000)
Relative capital-labor ratio	-0.174 (0.003)	-0.173 (0.001)	-0.163 (0.006)
Relative R&D expenditure ratio	-0.179 (0.001)	-0.209 (0.000)	-0.180 (0.002)
Terms of trade	-0.476 (0.000)	-0.453 (0.000)	-0.462 (0.000)
Constant	-0.948 (0.000)	-1.006 (0.000)	-0.945 (0.000)
Tests	**Statistic**		
a) Heteroskedasticity			
Pagan-Hall general test	12.523 (0.897)		13.523 (0.853)
Pagan-Hall test (assumed normality)	7.254 (0.996)		8.451 (0.988)
White/Koenker nR^2 test	21.924 (0.345)		25.749 (0.174)

Breusch-Pagan/Godfrey/Cook-Weisberg	13.092 (0.873)		20.789 (0.410)
b) Instrument relevance			
Partial R^2	0.760		0.760
F	47.600 (0.000)		47.600 (0.000)
c) Instrument validity			
Sargan's test	3.457 (0.063)		
Basmann's test	3.765 (0.052)	3.675 (0.065)	
Anderson-Rubin test		4.410 (0.036)	
Hansen's J test			3.875 (0.049)
d) Endogeneity			
Durbin's test	17.010 (0.000)		
Wu-Hausman's test	26.872 (0.000)		
C (difference-in-Sargan) test			6.862 (0.009)
e) Parameter stability			
supremum Wald test	16.411 (0.090)		

Note: Small sample correction is made while estimation; figures in parentheses are p-values

Appendix 1. Differences in Census and Survey (NSS) based Estimates



Note: Values in X axes are in million numbers

Source: Census estimates are as reported in MoAFW(2016a); Survey estimates are as in Mehrotra et al. (2014)

Appendix 2. Results of Geweke′s Decomposition

Causality/Feedback	χ^2 value	*p*-value
Granger Causation		
eST -> rKLR	6.360	0.042
eST -> rRDR	18.937	0.000
eST -> gvaTOT	3.387	0.184
eST -> rG	0.007	0.996
eST -> eCN	1.866	0.393
eST -> mnreg	1.981	0.371
rKLR -> eST	5.350	0.069
rKLR -> rRDR	13.636	0.001
rKLR -> gvaTOT	0.841	0.657
rKLR -> rG	1.037	0.595
rKLR -> eCN	5.079	0.079
rKLR -> mnreg	9.251	0.010
rRDR -> eST	1.025	0.599
rRDR -> rKLR	1.187	0.552
rRDR -> gvaTOT	1.493	0.474
rRDR -> rG	4.177	0.124
rRDR -> eCN	5.286	0.071
rRDR -> mnreg	0.080	0.961
gvaTOT -> eST	8.985	0.011

gvaTOT -> rKLR	4.564	0.102
gvaTOT -> rRDR	3.940	0.139
gvaTOT -> rG	13.183	0.001
gvaTOT -> eCN	0.172	0.917
gvaTOT -> mnreg	2.359	0.307
rG -> eST	1.112	0.573
rG -> rKLR	11.823	0.003
rG -> rRDR	3.752	0.153
rG -> gvaTOT	6.901	0.032
rG -> eCN	0.679	0.712
rG -> mnreg	1.611	0.447
eCN -> eST	11.511	0.003
eCN -> rKLR	7.134	0.028
eCN -> rRDR	8.267	0.016
eCN -> gvaTOT	10.200	0.006
eCN -> rG	2.694	0.260
eCN -> mnreg	0.447	0.800
mnreg -> eST	2.306	0.316
mnreg -> rKLR	15.536	0.000
mnreg -> rRDR	1.218	0.544
mnreg -> gvaTOT	11.860	0.003
mnreg -> rG	6.769	0.034
mnreg -> eCN	0.775	0.679

Instantaneous feedback		
eST <-> rKLR	3.057	0.080
eST <-> rRDR	2.001	0.157
eST <-> gvaTOT	0.399	0.527
eST <-> rG	1.132	0.287
eST <-> eCN	6.062	0.014
eST <-> mnreg	7.859	0.005
rKLR <-> rRDR	0.145	0.703
rKLR <-> gvaTOT	1.233	0.267
rKLR <-> rG	0.377	0.539
rKLR <-> eCN	0.826	0.363
rKLR <-> mnreg	7.502	0.006
rRDR <-> gvaTOT	6.476	0.011
rRDR <-> rG	0.359	0.549
rRDR <-> eCN	0.289	0.591
rRDR <-> mnreg	1.450	0.229
gvaTOT <-> rG	0.407	0.524
gvaTOT <-> eCN	0.028	0.867
gvaTOT <-> mnreg	1.637	0.201
rG <-> eCN	7.511	0.006
rG <-> mnreg	2.374	0.123
eCN <-> mnreg	0.001	0.972