*[Preliminary Draft]*

# Effect of Flood on Rural Agricultural Wages in Indian States: An Empirical Analysis

***Yashobanta Parida***[1]

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***Abstract***

The study examines the effect of floods on rural agricultural wages in 15 major Indian states covering periods from 1983 to 2011. Multiple factors are responsible for increasing rural agricultural wages in Indian states; flood impact is one of them. Pooled Mean Group (PMG) estimates show that flood impact measured in terms of economic losses and area affected by flood have a positive impact on rural agricultural wages in the long-run. The long-run positive impact is caused by damage to physical and human capital stock and adverse impact on the agricultural labour market through a shortage of rural labour supply. The econometric result further show that pull factors such as employment opportunities in rural non-farm sectors has significantly increased real agricultural wages in the long-run as a result increased demand for labour in rural non-farm sectors and at the same time decline demand for labour in farm sectors. The study also analyzes push factors such as government expenditures on rural development and agricultural productivity. These factors can significantly increase rural agricultural wages through increased demand for labour in rural areas. For robust results, the study uses development indicators measured in terms of per capita income, road density and availability of banking facilities as explanatory variables in this analysis. The results indicate that per capita income, road density and availability of banking facilities cannot minimize flood impact on agricultural wages in long-run.

***Keywords:*** *Agricultural wages; Flood impact; Non-agricultural employment; Per capita income; Rural development expenditure: PMG estimation*

***JEL Classification:*** *J31; Q54; J21; H54; C3*

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*[1] PhD Scholar in Economics, Centre for International Trade and Development, Jawaharlal Nehru University, New Delhi-110067. This article is part of my PhD thesis. I would like to thank my supervisor Dr. Rashmi Rekha Barua & Co-supervisor Prof. B. N. Goldar for their valuable comments and suggestions.*

***E-mail:*** *yash_parida@rediffmail.com* ; *yashparida@gmail.com*

## 1. Introduction

Natural disasters are recurrent phenomenon in India. Every year, different regions of India experience various form of natural disasters, but chronically flood disaster is one of them. Various factors such as geo-climatic conditions as well as high degree of socio-economic vulnerability in different regions are responsible for increasing flood disaster trend in Indian states. India is second largest flood affected nations after Bangladesh (Centre for Research on the Epidemiology of Disasters (CRED, 2004)). National Flood Commission (NFC) has estimated[2] that around 40 million hectares of land in India is flood prone. Frequent occurrence of floods not only affects agricultural output but also affects rural economy through damage of human and physical capital stocks and escalating fiscal pressure on both the State and Central governments in India. India lost around 0.46[3] percent of GDP annually and crop losses is estimated around 0.18 percent of GDP, damage to private and public properties are 0.25 and 0.21 percentages of GDP respectively and around 6 percent populations were affected each year due to flood during 1980-2011.The state-wise vulnerability measured in terms of average annual flood damage as percentage of state GSDP is highest in Bihar followed by Andhra Pradesh, Assam, Kerala, Odisha and so on, and lowest in Madhya Pradesh during 1983-2011. Around 8 out of 15 states, suffered more than 0.5 per cent of average annual flood damage as a percentage of state GSDP (shown in Figure A.1). However, average annual area affected by floods as percentage of state geographical area is highest in Bihar followed by Assam, West Bengal, Kerala and lowest in Rajasthan (shown in Figure A.2). These impacts vary depending on severity, magnitude and duration of the floods. Extreme flood events affect welfare of rural households through different channels such as decline in agricultural productivity and agricultural wages (Paul and Rasid, 1993; Azam, 1993; Ravallion, 1995; Banerjee, 2007; Banerjee, 2010; Mueller and Quisumbing, 2011; Poaponsakorn and Meethom, 2013). Moreover, these impacts also slow down economic

[2] In 1980 Rashtriya Barh Ayog (RBA) or National Flood Commission has estimated state-wise liable to flood affected area "by adding the maxima of flood affected area (1953-78) in any year to the area protected up to 1978 and then deducting portion of the protected area included in the flood affected area due to failure of protection works" . For further details, see the "Report of Working Group on Flood Management and Region Specific Issues for XII Plan" , Page No -95, 2011, Planning Commission, Government of India.

[3] All India flood damages estimates by the Author. Total damage includes damage to private and public properties. Damage to private properties includes house damages and crop damage.

activities causing workers to migrate from agricultural sectors to non-agricultural sectors in search of higher wage earnings (Hornbeck and Naidu, 2012; Mueller and Quisumbing, 2011). Similarly, moderate and lower flood events significantly increase agricultural productivity, agricultural wages, and economic growth through enhancing fertility of lands (Brammer, 1988; Banerjee, 2007; Loayza et.al, 2012; Banerjee, 2010).

Apart from the flood disaster impact, weather variation has significantly reduced crop yields in India due to absence of long-run adaptation measures (Guiteras, 2007). However, rainfall volatility adversely affects female-to-male wage ratio (Mahajan, 2017) and significantly increases non-agricultural labor supply and agricultural wages in India (Ito and Kurosaki, 2009; Mahajan, 2017; Emran and Shilpi, 2014; Bandyopadhyay and Skoufias, 2015; Skoufias et.al 2017). In India, excess rainfall or scarcity of rainfall has not only adversely affected the agricultural output and employment, but also affected agricultural wage income.

Agricultural wage income is one of the major income sources of rural households because more than 64 per cent of rural workforce[4] depends on agriculture sector for their sustenance. Thus, agricultural wage income plays a significant role in determining economic condition of rural households and helps to reduce rural poverty (Kijima and Lanjouw, 2005; Datt and Ravallion, 1998). In India, a host of factors determine rural agricultural wages. The low return to investment in agricultural sectors is responsible for lowering rural agriculture wages in India. However, other factors such as increasing demand for labour in non-farm sectors and scarcity of workers for performing agricultural activities have an opposite effect and thus responsible for increasing rural agriculture wages in Indian states.

There are other exogenous factors such as frequent occurrence of natural disasters which cause adverse impacts in the rural labour market, via reducing productivity of agriculture and allied sectors and consequently employment in these sectors. Employment opportunities in agricultural sectors heavily depend on weather related events. Any deviation of employment directly affects wage earnings of rural households. Rose (2001) suggests that rural households prefer to work in non-farm sectors for maintaining minimum income level once hit by a disaster shock. An extreme flood event affects household's economic conditions through a rise in poverty levels and

[4] Report of Employment and Unemployment Survey (68th Round, 2011-12).

threatens food security due to damage of agriculture crops as well as household assets. There are other channels through which disaster events adversely affect different aspects of human life, such as deteriorating human health conditions as a result of environmental degradation. All these negative impacts create uncertainties in regular wage earnings of rural households. Lower income securities among the rural households force them to migrate from agricultural sectors to non-agricultural sectors in search of permanent and higher wage earnings.

Only a few empirical studies have addressed the impact of natural disasters on labour market conditions in terms of employment and wages. The study by Banerjee (2007) examined effects of floods on agricultural wages in Bangladesh taking into account demand-side factors. The present study incorporates both demand and supply side factors to analyze the impact of floods on rural agricultural wages in 15 major Indian states from 1983 to 2011. The study examines two main research hypotheses. First, the study examines the effect of floods on annual real agricultural wages after controlling pull factors (employment opportunities in rural non-farm sectors) and push factors (public expenditure on rural development and agricultural productivity). Second, the study looks into the impact of floods on real agricultural wages earned during flood months in particular.

To the best of author's knowledge, this is the first empirical study which has used state-level disaster data along with a unique rural employment data to examine the impact of floods on rural agricultural wages in Indian states. This study not only contributes to the economics of disaster literature but also provides useful inputs for structuring suitable agricultural labour market policies and flood management policies that would improve welfare of rural households. The rest of the study is organized as follows. Section 2 provides a detailed literature review which analyzed disaster impact on labour market as well as economic sectors in both developing and developed countries. Section 3 analyzes state-wise rural employment as well as rural agricultural wage trends in Indian states. Section 4 describes the data sources and econometric identification strategy. Section 5 discusses the empirical results. Finally, discussion and conclusions are provided in section 6.

## 2. Review of literature

There are various studies which empirically examine the impact of floods and rainfall volatility on agricultural wages and agricultural productivity in Bangladesh. Azam (1993) analyzed the effects of floods on rural real wages in Bangladesh using monthly data from July 1981 to June 1989. The results show that area affected by flood has negative impacts on real wages. Paul and Rasid (1993) show that rice production suffers damage by 4 percent due to floods in Bangladesh. Banerjee (2007) examined the impacts of flood on agricultural wages in Bangladesh using district wise monthly flood data from 1979-2000. The study finds that flood has positive impacts on agricultural wages in long-run. The empirical results further indicated that agricultural wages are higher in more flood prone districts. The study also finds that agricultural wages decline by 14 per cent in inundated areas during extreme floods in short-run. The study also shows that agricultural productivity has positive impacts on agricultural wages in Bangladesh. Banerjee (2010) shows that extreme flood events reduce crop yields, while normal flood events increasing agricultural productivity post flood months in Bangladesh. Mueller and Quisumbing (2011) evaluate impacts of the 1998 flood on agricultural and non-agricultural wages in Bangladesh. They found that real wages of both agricultural and non-agricultural workers are lower in short-run. Further, the study also found that workers out-migrate from agriculture to non-agricultural sectors due to lower agricultural wages. Bandyopadhyay and Skoufias (2015) examined the relationship between rainfall volatility and rural occupational diversification using nationally household representative data combining with rainfall data at the *Upazila* level in Bangladesh. They found that rainfall volatility is responsible for pushing labour force to choose diverse occupation in Bangladesh.

Rahman (2009) examined the determinants of agricultural wages in Bangladesh using annual data from 1949 to 1979. The results show that agricultural productivity is one of the most important factors determining rise in rural real wages in Bangladesh, both in short-run and in long-run. Jones Palmer and Parikh (1998) examined the relationship between agricultural wages, price of rice and agricultural productivity using time series data in Bangladesh. They found that in long-run agricultural wages are positively related with rice price and agricultural productivity.

Next, let us consider the studies for India. Some studies have examined the determinants of agricultural wages and agricultural productivity in context of India. Sidhu (1988) empirically examined the determinants of agricultural wages using district wise survey data in Haryana and Punjab during 1975-1976. The study shows that agricultural productivity has positive impact on agricultural wages, while supply of labour has a negative impact on agricultural wages. Sato (2004) examined the determinants of agricultural wages in Indian states using three rounds of National Sample Survey (NSS) data. The study found that agricultural productivity and employment in non-farm sectors have significantly increased real agricultural wages in Indian states. Jayachandran (2006) analyzed the impact of agricultural productivity on male agricultural wages using district-level panel data in India from 1956 to 1987. Using rainfall as an instrument for agricultural productivity, this study concludes that agricultural productivity has significantly increased real male wage in Indian districts. This effect is less significant in those districts which have made more progress in terms of infrastructure such as better roads connectivity and banking facilities.

There are a few studies which examine the impact of rainfall volatility on agricultural wages and occupational choices of rural agricultural households in India. Ito and Kurosaki (2009) investigated the effects of rainfall on the non-agricultural labor supply of rural households in India. The results of the study show that rainfall volatility has significantly impacted the non-agricultural labor supply. Mahajan (2017) examined the impacts of rainfall on gender wise wage gap using district level panel data obtained from National Sample Survey covering periods 1993 to 2007. The results show that rainfall shocks are positively correlated with both male and female wages. The study further shows that rainfall shock is positively correlated with female-to-male wage ratio in rice cultivated areas and those areas which highly depend on rainfall. This implies that high rainfall increases female-to-male wage ratio, while low rainfall reduces the same. Skoufias et.al (2017) investigated rainfall volatility and occupational choices among the rural households using district-wise national representative household data in India. The study reveals that rural agricultural households shift occupation from agriculture to non-agricultural sectors due to high variability in rainfall pattern.

Next, other empirical studies examine the relation between poverty status and non-farm employment in India. Eswaran et al (2009) examines evolution of poverty in India through agricultural wages and employment. They argue that agricultural productivity and sectoral labour flow has significantly increased agricultural wages and helped to reduce poverty in India.

Lanjouw and Murgai (2009) examined the relationship between rural occupational diversification and poverty using various rounds of NSS region-wise data in India. They found that poverty is lower due to increased employment shares in non-farm sectors and rising agricultural wages. Imai et.al (2013) examined the impact of rural non-farm employment on poverty reduction in India and Vietnam. The study found that rural non-farm employment has significantly increased consumption per capita in India and Vietnam. Further, the study also shows that greater participation in rural non-farm sectors has significantly reduced poverty in India. Kumar et.al (2011) found that presence of rural non-agricultural sectors have significantly reduced rural poverty in India.

Flood disaster and rainfall volatility not only affects the labour market outcomes in developing countries such as India and Bangladesh, but also affects labour market conditions in other countries. A couple of studies have empirically examined the impact of natural disaster on labour market outcomes in the context of developed and developing countries. Mueller and Osgood (2009) examined the impact of droughts on Brazilian labour markets using three rounds of household survey data. They found severe droughts have adversely impacted rural wages. Belasen and Polachek (2009) examined the effects of hurricanes on local labor markets in Florida using quarterly census of employment and wages data. The estimates based on Generalized Difference in Difference (GDD) reveal that hurricane has significantly increased wage earnings of workers in Florida up to 4 percent, and at the same time, it has decreased wage earnings in the neighboring counties by same percentage points. The study also shows that hurricane has adversely impacted labour supply in Florida. Hornbeck and Naidu (2012) evaluated the impacts of Mississippi Flood of 1927 on agricultural development in United States. The study shows that the flood has caused adverse impacts on out immigration of black population. Thus the landowners in flooded regions have modernized and mechanized their agricultural sectors due to shortage of black populations. Poaponsakorn and Meethom (2013) examined the effects of floods on household income and expenditure in 26 provinces of Thailand using socio-economic survey data. The results based on difference-in-difference estimates show that flood have negative impacts on money and wage income of middle class households in the flooded regions. Kirchberger (2014) examined the effects of large earthquakes on labour markets in terms of wages and employment in different sectors of the economy in Indonesia using family life survey data set. The study shows that growth of agricultural wages is significantly higher in earthquake affected regions. The reason behind this is that the demand for labour in construction sectors increase due to heavy damages of public and private properties in aftermath of earthquake. This causes a labour supply shortage in agriculture relative to labour demand which drives up the agricultural wages. Dasilva and Grossi (2001) found that in rural areas of Brazil, a larger number of workers left farm activities due to increased employment opportunities in non-farm sectors, especially in construction sectors. Further, the study found that rural agricultural households earn lower incomes compared to those working in both farm and nonfarm sectors.

## 3. Overview of rural employment and agricultural wages in Indian states

The agricultural sector is the most important sectors in Indian economy. It not only provides employment opportunities to rural population, but also contributes to Gross Domestic Products. This sector helps to reduce rural poverty and enhance food security for the nation as a whole. Around, 58 per cent of rural households depend on agriculture for their livelihood. However, the share of agriculture sector to Gross Domestic Product has significantly declined from 36.4 percent in 1983 to 13 percent in 2013. Still, agriculture sectors registers greater employment compared to rural non-farm sectors. Table-1 shows the trend of rural employment and its growth rate in different sectors of the economy.

**Table 1: Pattern of rural employment in different sectors**

| | **Rural employment (%)** | | | | | | | **Growth rate of rural employment*** | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **Employment sectors** | 38th (1983) | 43rd (1987-88) | 50th (1993-94) | 55th (1999-00) | 61st (2004-05) | 66th (2009-10) | 68th (2011-12) | 1983-1987 | 1993-2011 | 1983-2011 |
| ***Agriculture*** | **81.2** | **78.2** | **78.4** | **76.2** | **72.5** | **68.0** | **64.1** | **0.02** | **-0.07** | **0.11** |
| 1.Manufacturing | 6.8 | 7.2 | 7.0 | 7.4 | 8.1 | 7.2 | 8.6 | 0.13 | 0.40 | 0.79 |
| 2.Trade, hotel & restaurant | 3.5 | 4.0 | 4.3 | 5.1 | 6.2 | 6.5 | 6.5 | 0.22 | 0.73 | 1.63 |
| 3. Construction | **1.6** | **3.3** | **2.4** | **3.3** | **4.9** | **9.4** | **11.1** | **1.15** | **4.30** | **8.47** |
| 4. Transport, storage & communication | 1.1 | 1.3 | 1.4 | 2.1 | 2.5 | 2.9 | 3.0 | 0.26 | 1.35 | 2.80 |
| 5. Mining & quarrying | 0.5 | 0.6 | 0.6 | 0.5 | 0.5 | 0.6 | 0.4 | 0.28 | -0.16 | 0.26 |
| 6. Other services | 5.3 | 5.3 | 5.9 | 5.3 | 5.3 | 5.4 | 6.3 | 0.06 | 0.23 | 0.68 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| ***Sub-total non-agriculture (1 to 6)*** | **18.8** | **21.8** | **21.6** | **23.8** | **27.5** | **32.0** | **35.9** | **0.23** | **0.90** | **1.69** |

***Note:*** Compiled by author from various NSS employment and unemployment reports.* Growth rate is calculated using absolute employment figure.

Employment share in rural agricultural sectors has significantly declined from 81.4 percent in 1983 to 64.1 percent in 2011. At the same time, employment in rural non-farm sectors has increased from 18.8 percent to 35.9 percent. The growth rate of rural non-agricultural employment sectors is 15 times higher than the growth of agricultural employment during the same periods. The growth rate of employment in non-farm sectors in post and per reform periods is higher than the growth rate of agricultural employment. A number of factors explain lowering of employment in agricultural sectors, such as low return in agricultural activities depressing wage earnings; and occurrence of frequent natural disasters that directly affects welfare of rural households. The employment growth in construction sector is the highest as it shows an increase from 1.6 percent to 11.6 percent during 1983 to 2011. Other sectors include, transport, storage & communication had an employment growth of 2.80 percent; trade, hotel & restaurant registered 1.63 percent employment growth; manufacturing experienced 0.79 percent growth in employment. The overall employment growth rate of construction sector is the highest among the other non-farm sectors because of massive investment directed towards rural road construction and rural development including rural house construction. This causes a significant rise in demand for labour in construction sectors. The employment trend of agricultural and non-agricultural sectors and the associated compound annual growth rates for 15 major states in India are shown in Table A.2. The data clearly show that agricultural employment share is highest in Madhya Pradesh followed by Rajasthan, Maharashtra and so on, but lowest in Kerala in 1983. In early 1980’s rural population was heavily depended on agricultural sectors compared to rural non-agricultural sectors. After economic reforms in Indian economy, dependency on agriculture sector has significantly declined because of increasing employment opportunities in other rural non-farm sectors such as manufacturing, service and construction sectors. This trend is continuing for all states till 2011. The Compound Annual Growth Rate (CAGR) of rural agricultural employment is negative for 10 states out of 15 states from 1983 to 2011. The employment share of non-agricultural sectors is highest in Kerala followed by West Bengal, Tamil Nadu and so on and, lowest in Madhya Pradesh in the year 1983. However, the share of non-agricultural employment continuously increased in all states from early 1980's till 2011 due to increasing demand for labour in those sectors. Rural workers move from agriculture to non-agricultural sectors in search of permanent sources of income and for a better livelihood. The dependency on agricultural sectors dramatically declined due to low return from agricultural activities. The CAGR of rural non-agricultural sectors is highest in Rajasthan and lowest in Kerala but the growth rates remain positive for all states from 1983 to 2011. The share of agricultural workers in post reform period has significantly declined in all states. However, share of non-agricultural worker has increased during the same periods in all states.

Apart from analyzing state-wise employment trends in agriculture, the study also analyses Compound Annual Growth Rate (CAGR) of construction-GSDP and agricultural-GSDP various states as shown in Figure A.3. The findings indicate that the CAGR of construction-GSDP is higher compared to the agriculture-GSDP in all states from 1983 to 2011. Higher demand for labour in construction sector results due to rapid urbanization and large-scale investment in infrastructure development in different states of India. Among the states, the CAGR growth rate of construction-GSDP is highest in Bihar and lowest in Odisha. However, the rate of agriculture-GSDP is highest in Maharashtra and lowest in Odisha.

### 3.1 Rural agricultural wages in Indian states

The livelihood of rural household depends on agricultural wages and employment opportunity of agricultural sectors. Any deviation of wage earnings adversely impacts welfare of rural households. The dependency on rural agricultural sectors has continuously declined due to increased uncertainty of income and wage earnings in agricultural sectors. Still, this sector provides more employment compared to any other rural sectors. Around 64 per cent of rural workforce depends on agricultural sectors as shown in Table-1. The workforce participation rate in both male and female worker in agriculture sectors has declined 77.5 percent to 59.4 percent and 87.5 percent to 74.9 percent respectively from 1983 to 2011. The trend shows that female workers heavily depend on agricultural sector compared to male workers due to various socio-economic and cultural factors. The rural employment in non-farm sectors for both male and female has increased 22.5 to 40.6 percent and 12.5 to 25.1 percent respectively in the same periods (38th and 68$^{th}$ rounds of NSS Employment and Unemployment reports). This trend shows that in one hand there occurs a shortage of labour in rural agricultural sectors, and in the other hand increased demand for labour in rural non-farm sectors increases rural agricultural wages (this is called Trickle Down Hypothesis by Bhalla, 1993; Vaidyanthan, 1994). The all-India annual real agricultural wages in 2004-05 bases are shown in Figure A. 4. The graph shows that the annual real agricultural wages significantly increasing from Rs 40 in 1983 to Rs 90 in 2011. Similarly, agricultural wages in flood months remain slightly higher than the annual agricultural wages during the same periods due to high demand for labour for performing agriculture activities. Other factors such as scarcity of agricultural land and introduction of labour-saving technology (called Residual Sector Hypothesis by Vaidyanathan, 1986; Visaria and Basant, 1993), heavy urbanization and overall economic development are responsible for increasing rural farm wages in Indian states. The expenditure on rural development and introduction of public funded programme such as MGNRGS and food security programme are responsible for increasing rural farm wages because of increasing the demand for labour in rural area. Other exogenous factor such as "flood impact" is also responsible for increasing rural farm wages. As a result, rural workers out migrate from agricultural sectors to non-agriculture sectors.

The state-wise CAGR of real agricultural wages is shown in Figure A.5. The growth of agricultural wages is highest in Tamil Nadu probably due to higher workforce participation rate in non-agricultural sectors after Kerala as shown in Table A.2 followed by Karnataka, Odisha, and Kerala and so on and lowest in Rajasthan. Similarly, Kerala has ranked fourth in terms of growth rate of agricultural wages because work force participation rate in non-farm sectors is highest compare to any other states as shown in Table A.2. However, Odisha has ranked third and Bihar has ranked fifth in terms of growth rate of agricultural wages. It clearly shows that poverty rate has significantly declined in two states due to high growth of agricultural wages in the same periods. Similarly, Gujarat has lowest wage growth rate among the states, still rural workforce heavily depends on agricultural sectors after booming of the construction-GSDP. There are other socio-economic factors such as overall growth of GSDP as well as implementation of various social welfare programmes and disaster impacts that are responsible for higher growth rate of farm wage in Indian states.

The state-wise annual real agricultural wages and real agricultural wages in flood months are shown in Table A. 3. The ranks of states are categorized based on annual real wages in 2011.

Four states namely Kerala, Haryana Punjab and Tamil Nadu have relatively in higher annual agricultural wages (greater than equal 150 per day) seemed to be socio-economic factors. For example, higher wage paid to workers in ploughing activities and lower workforce participation rate in agricultural sectors in Kerala are responsible for higher wage rate compared to other states. The higher per capita income and lower poverty rate in these four states are major causes of higher agricultural wages. However, states such as Andhra Pradesh, Rajasthan and Bihar fall under medium agricultural wage rate because the CAGR of non-farm sectors is highest in those states. The states such as Gujarat, Maharashtra and Madhya Pradesh fall under low agricultural wages categories because rural workers in those states still heavily depends on agriculture sectors as shown in Table A.2. In sum, apart from pull and push factors there is another exogenous *pull* factor 'flood impacts' which is also responsible for increasing rural agricultural wages through a damage of agricultural output, damages of houses and population affected and also affects food security as well as human health. Rural households are unable to sustain their livelihood due to lower income securities and low return of agricultural sectors. This leads to increased outmigration of rural workforce from agricultural sectors to non-agricultural sectors.

## 4. Empirical specification and data sources

This section explains empirical identification and data sources of the present study. The agricultural wage data are obtained from *Agricultural Wages in India (AWI)* published by the Directorate of Economics and Statistics (DES), Ministry of Agriculture, Government of India. The methodology of collecting agricultural wage data by the DES for different agricultural operations such as ploughing, sowing, weeding, reaping and harvesting etcetera in selected villages (centers) are based on daily wages within the districts across Indian states. DES provides state-wise monthly nominal agriculture wages for male workers in different agricultural operations on a monthly basis for 15 Indian states for a particular agricultural year that starts from July and ends in June of the following year. The state-level average monthly nominal wage data for female agricultural workers for a few states such as AP, Karnataka, Maharashtra and Rajasthan are reported in year 1997-98. I have used monthly nominal agricultural wages for male workers in analytical and empirical analysis. For empirical purpose, I have converted the monthly nominal wage date for an agriculture year to calendar year. Then, I have constructed a simple average of monthly wage data and converted it to annual wage. Real wage is constructed by deflating annual nominal wage with the Consumer Price Index (CPI) for agriculture laborers for the base year (2004-05). Finally, I have compiled nominal wage for the flood months by taking a simple average for four months over July to October. In India, major floods usually occur during the months of July till October due to active monsoon. The real wage for the flood months is constructed by deflating nominal wage with Consumer Price Index (CPI) available for the same month for agriculture laborers for the base year (2004-05).

The state-wise flood disaster related statistics such as area affected by flood, flood damage and population affected by floods are obtained from the Central Water Commission (CWC), Government of India (GoI). Other flood related information for a few states, namely Tamil Nadu and Odisha are taken from United Nations Office for Disaster Risk Reduction (UNISDR; http://www.desinventar.net/DesInventar/results.jsp). However, year-wise flood disaster data for the state of Bihar are available from Flood Management Information Systems, Government of Bihar. The country-wise flood related information is available from Dartmouth Flood Observatory (DFO; http://floodobservatory.colorado.edu). The country-wise all forms of natural disaster are available from EM-DAT database compiled by the Centre for Research on the Epidemiology of Disasters (CRED), Catholic University of Louvain in Belgium. There is some missing information in the CWC data set, for example, data on population affected has been reported in case of some states for some respective years, but area affected and damages caused by floods are not reported for the same years. In that case, I have matched the international database with the CWC database to fill up the missing observations.

The study has used different control variables such state-wise rural employment in agriculture and non-agricultural sectors. In India, state-wise rural employment data are available for different rounds of Employment and Unemployment Survey reports. These surveys are conducted by National Sample Survey Office (NSSO), Ministry of Statistics and Program Implementation, GoI every five[5] years to collect different household-level information regarding employment and unemployment status of individuals. Except quinquennial survey, NSSO

[5] It is called quinquennial survey on Employment and Unemployment Situation in India or thick rounds. This survey covers more households both in rural and urban areas.

collects employment and unemployment and consumer expenditure data annually[6], but not for all consecutive year. The NSSO report also provides state-wise rural workforce[7] participation rate and rural agricultural workforce participation rate in Usual[8] Principal and Subsidiary Status (UPSS). Rural employment includes both agriculture and non-agricultural employment. Non-agricultural[9]employment includes various sectors such as manufacturing, trade, hotel & restaurant, construction, transport, storage & communication, mining & quarrying, electricity, gas & water and services sectors. Similarly, employment in agriculture sectors includes crops and plantation, livestock, forestry and fishing. For empirical purpose, I have compiled workforce participation rates for total rural employment and agricultural employments from 19 rounds[10] of NSSO reports. Then, I have estimated the number of total rural employment and rural agricultural employment using state-wise census[11] population. Method of linear interpolation is used to fill up employment data for the missing years when no NSSO survey was conducted.

State-wise population data are available from the census of India, which normally takes place within ten years. I have used different census years such as 1981, 1991, 2001 and 2011. The state-wise total population and rural population is linearly interpolated for the years, when no census was conducted. Similarly, Gross State Domestic Product (GSDP), agricultural sector GSDP and construction sector GSDP, both at current and constant prices, are obtained from the Ministry of Statistics and Program Implementation, GoI. The data on state government expenditure such as rural development expenditure and total government expenditure are available from the various volumes of State Finance Reports published by the Reserve Bank of India (RBI). State-wise road length data are obtained from *Basic Road Statistics of India*,

[6] It is called Household Consumer Expenditure and Employment Situation in India or thin round. This survey conducted annually covering less households comparing to quinquennial survey or thick round. First time NSSO combine collected Household Employment data with Household consumer Expenditure data since 45th (1989-90) round.

[7] Workforce participation rate is ratio of employed person to total population.

[8] Principal Status: A person worked for long time in a year preceding the date of survey. Subsidiary Status: A person worked different economic activity in short-term basis other than principal status.

[9] Non-agriculture employment = Total rural employment - Agricultural employment

[10] NSSO Reports: 1983, 1987, 1989, 1991, 1993, 1994,1995,1997,1998,1999,2000,2001,2002,2003,2004,2005,2007,2009,2011.

[11] Census of India takes place within ten years for example 1981, 1991, 2001 and 2011.

Ministry of Road Transport and Highways, GoI. State-wise numbers of bank offices are available from the various volumes of Basic Statistical Returns, RBI. For empirical purpose, I have normalized other control variables and summary and definition of all variables are shown in Table A.4.

Using state-level panel data for 15 major Indian states from 1983 to 2011, the study examines the dynamic relationship between real agricultural wages and flood disaster impacts. In dynamic panel data, the static fixed effect estimates produced biased and inconsistent results due to correlation between lagged values of dependent variable and error terms. However, various empirical studies have applied GMM-difference estimator proposed by Arellano and Bond (1991) and the GMM-system estimator proposed by Arellano and Bover (1995) and Blundell and Bond (1998), to examine the dynamic relationship among variables using panel data. The GMM method produces consistent estimates of parameters in the presence of endogenous regressors. This method also controls endogeneity through internal instrument mechanism. It controls for both time and state specific effects in dynamic micro panel data, when cross section (N) is larger than time period (T). Roodman (2006) argued that in macro panel data, when the number of time periods (T) is larger than the numbers of cross section units (N), GMM estimates produce spurious results due to a large number of instruments generated in the process, and it may reject the validity of instruments. The GMM estimate also imposes homogeneity of slope coefficient and allows only the intercept to vary across cross section units. This estimate is inappropriate for larger time periods in panel data due to non-stationary issue of the variable. However, Pesaran and Shin (1999) argued that homogeneity assumption of the slope coefficient under GMM estimation can produce inconsistent results unless the slope coefficients are truly identical.

The Mean Group (MG) estimation technique proposed by Pesaran and Smith (1995) helps to estimate separate regressions for each state and calculates unweighted average of state specific coefficients. The MG estimates work well in long panel data for at least 20 to 30 cross section units (Samargandi et al, 2015). This estimation allows intercepts, short-run coefficient, long-run coefficient, speed of adjustment and error variances and these coefficients are heterogeneous across states. There are N(2k + 3) parameters to be estimated. Each equation has *2k* exogenous coefficients, coefficient of lagged dependent variable, an intercept and variance. In small sample, this model estimates downward bias for coefficient of the lagged dependent variable. However, the estimates are more sensitive to outliers in small cross section units (Favara, 2003). Additionally, Dynamic Fixed Effects (DFE) restricts all slope coefficients, speed of adjustment and error variances to be equal across all states but intercepts vary across the states. In other words, DFE estimates (N-1)(2k + 2) parameters. Each equation has ‘k’ long-run and short-run coefficients plus coefficient of lagged dependent variable and a common variance. However, in case of small sample size, DFE produces inconsistent and biased results due to correlation between lag dependent variable and error term (Baltagi, Griffin and Xiong, 2000).

Apart from the above analysis, the study has employed Pooled Mean Group (PMG) model proposed by Pesaran et al. (1999) for estimating consistent results. The study uses PMG[12] model for several reasons. First, PMG model estimates consistent long-run relationship among the variables without testing panel unit root test of individual variables through maximum likelihood estimation procedure. This implies that the error correction term is negative and statistically significant and not lower than negative 2 (Loayza & Ranciere, 2006). Second, PMG estimates control endogeneity by adding the optimal lag length for both dependent and independent variables (Pesaran et al., 1999). Finally, it produces best results in terms of consistency and efficiency of the parameters. This estimator restricts the assumption of homogeneity of long-run slope coefficients across states, but it allows the short-run coefficients including intercept and speed of adjustment to vary across states. Based on Pesaran et al. (1999), the error correction form of autoregressive distributed lag ARDL *(p,q)* specification explained by (Loayza & Ranciere, 2006) is as follows:

$$\Delta RAW_{i,t} = \sum_{j=1}^{p-1} \gamma_j^i \, \Delta RAW_{i,t-j} + \sum_{j=0}^{q-1} \delta_j^i \, \Delta X_{i,t-j} + \varphi^i \left[ RAW_{i,t-1} - \left\{ \beta_0^i + \beta_1^i X_{i,t-j} \right\} \right] + \epsilon_{it} \qquad (1)$$

Where $p$ is lag length of dependent variable, $q$ is lag length of explanatory variables, i denote states, t denotes time, RAW is natural logarithm of real agricultural wages, X represents the set of explanatory variables such as flood damage[13], area affected by floods, workforce participation rate in non-farming[14] sectors, agriculture productivity, expenditure on rural development,

[12] First, the PMG estimator is an intermediate estimator between MG and DFE and estimates (N-1)K parameters.

[13] Flood damage includes public and private properties such as damage of roads, crop damage and house damage.

[14] Rural non-farming activities: A person works other than agriculture and allied sectors such as rural construction, manufacturing, service, Trade, hotel & restaurant, Mining & quarrying, Transport, storage & communication and other sectors.

workforce participation rate in agriculture employment, γ represents short-run coefficient of lag dependent variable, δ represents short-run coefficient of independent variables, β represents the long-run coefficients and φ is the speed of adjustment[15] to the long-run equilibrium. The square bracket in equation (1) represents the restricted long-run regression, which is homogenous across the states, which is derived from the following equation.

$$RAW_{i,t} = \beta_0^i + \beta_1^i X_{i,t} + \mu_{i,t}, \text{ Where } \mu_{i,t} \sim I(0) \qquad (2)$$

The outcome variable of my study is natural logarithm of annual real agricultural wages and natural logarithm of real agricultural wage in flood months. The PMG model estimates long-run, short-run as well as error correction coefficients. The long-run coefficient is homogenous for all states, but short-run coefficient and error correction term vary across states.

## 5. Empirical results: Effect of flood damages and non-farm employment on real agricultural wages

In this section, the study examines effects of flood damage on real agriculture wages using equation (1). The outcome variables in Model-1 and Model-2 are annual real agricultural wages and real agricultural wages in flood months respectively. The estimates of PMG are shown in Table-5. In Model-1 and Model-2, the coefficient of flood damage over state Gross State Domestic Product (GSDP) is positive and statistically significant in long-run, the coefficient is negative and statistically insignificant in short-run. This shows that higher intensity of flood damage has significantly increased annual real rural agricultural wages and real agricultural wages during flood months in the long-run. This finding is consistent with Banerjee (2007). Frequent occurrence of floods in rural areas adversely affects agricultural crop production and impoverishes lives of rural poor. Lower crop production due to floods increases uncertainty of income earnings of rural households, thus deteriorating their standards of living. Thus, rural workers migrate from agriculture to non-agricultural sectors for regular employment and higher wage earnings.

[15] The speed of adjustment should be negative and significant, which shows that there exists a long-run relation among the variables in my model.

**Table 5: Flood damages, non-farm employment and agricultural productivity**

| Variable | Pooled Mean Group | Pooled Mean Group |
|---|---|---|
| | Model-1 | Model-2@ |
| ***Long-run coefficients*** | | |
| Ln(Flood damages/State-GSDP) | 0.0164**<br>(0.0076) | 0.0149**<br>(0.0061) |
| (Rural non-farm employment/Rural employment) % | 0.0061***<br>(0.0023) | 0.0066***<br>(0.0021) |
| Ln(Agricultural productivity) | 0.6163***<br>(0.0420) | 0.5802***<br>(0.0427) |
| Ln(Rural development expenditure /Total expenditure) | 0.0074**<br>( 0.0034) | 0.0059**<br>( 0.0029) |
| ***Convergence coefficient*** | -0.3151***<br>(0.0529) | -0.4453***<br>(0.0634) |
| ***Short-run coefficients*** | | |
| ΔLn(Flood damages/State-GSDP) | -0.0025<br>(0.0016) | -0.0026<br>(0.0021) |
| Δ(Rural non-farm employment/Rural employment)% | 0.0008<br>(0.0008) | 0.0018**<br>(0.0009) |
| ΔLn (Agricultural productivity) | -0.1499***<br>(0.0416) | -0.1453<br>(0.0922) |
| ΔLn (Rural development expenditure/Total expenditure) | 0.0002<br>(0.0015) | 0.0003<br>(0.0017) |
| Intercept | 0.2504***<br>(0.0625) | 0.3761***<br>(0.0726) |
| No of states | 15 | 15 |
| No of obs | 420 | 420 |

***Note:*** *** p<0.01, ** p<0.05, * p<0.1 denotes level of significance at 1,5 and 10% respectively. The lag structure of all models is ARDL (1, 1, 1, 1, 1) and controlling for state and time effects. Dependent variable for Model-1 is Ln (Annual real agricultural wage). @ Dependent variable for Model-2 is Ln (Real agricultural wage in flood months).

As a result, out-migration generates labour shortage for performing farming related activities in the agricultural sector, which ultimately causes a rise in rural agricultural wages. The coefficient of non-farm employment is positive correlated with real agriculture wages in both models in long-run, but statistically significant in short-run in Model-2. This implies that higher workforce participation rate in non-farming sectors increases the rural agricultural wage due to migration of rural workers from agricultural sectors to non-farm sectors in search of higher and regular wage earnings. The rural workforce participation rate in agriculture and allied sectors has declined from 81.4 per cent in 1983 to 64.1 per cent in 2011. During the same time period, the rural workforce participation rate in non-agriculture sector has increased from 18.6 percent to 35.9 percent as shown in Table-1. This trend clearly shows that rural workers have migrated from agricultural sectors to non-agricultural sectors, especially construction[16] sectors as agricultural income is highly uncertain due to chronic floods in Indian states. Thus a growing tendency to move from the low productive sector to high productivity sectors of the economy is observed in long-run as well as short-run too. However, the coefficient of agricultural productivity is positively related with real agriculture wage in Model-1 and Model-2. The estimates show that 1 percent increase in agricultural productivity increases in real wage by 0.616 percent in Model-1 and 0.580 percent in Model-2 respectively in long-run. Higher agricultural productivity generates favorable demand for rural agricultural labour, and higher demand for labour in agricultural sector raises the real wage. The coefficient of rural development expenditure is positively related with agricultural wage in long-run in both models. The results show that expenditure on rural development activities increases the demand for labour in rural areas, which in turn enhances rural wages due to greater bargaining power of the rural workers. The error correction coefficients are negative and significant in both models. The results show that there exists a long-run relationship among the variables.

Next, I have used area affected by flood instead of flood damage, and estimated equation (1) using PMG estimation technique. The estimates are shown in Table A.6. The coefficient of area affected by flood is positive and statistically significant in long-run in both models after controlling other variables. The results reveal that the area affected by flood has significantly increased real agriculture wages for various reasons that are analyzed in section 5.1. However, the short-run coefficient of area affected by flood is negative and statistically significant in Model-1. This result is consistent with (Azam, 1993; Banerjee, 2010; Mueller and Quisumbing, 2011). Frequent floods disaster adversely affects agricultural productivity and rural labour market in short-run. Lower crop harvest diminishes the demand for labour in rural areas, which leads to a decline in real agricultural wages in short-run. Another long-run coefficients such as non-farm employment, agricultural productivity and expenditure on rural development are

[16] The workforce participation rate of rural construction sectors has been increase 1.6 per cent in 1983 to 11.1 per cent in 2011. The growth rate of workforce participation rate in rural construction sector is highest (8.47% from 1983 to 2011) compare to the any other rural sectors.

positive and statistically significant. This is consistent with my earlier estimation results shown in Table-5. Again, the error-correction coefficient is negative and significant. It shows that there exists a long-run relationship among the variables.

### 5.1 Effect of flood damages and role of construction sector on real agricultural wages

In this section, the study has examined the effect of flood damage and construction-GSDP on real agriculture wages. I have used state-wise construction-GSDP instead rural non-farm employment as an explanatory variable. This rural constriction sector provides more employment compare to any other rural sectors over the periods. The employment opportunity in rural construction sector has increased 1.6 percent to 11.1 percent during 1983 to 2011 (see Table 1). The study estimates equation (1) using PMG model and results are shown in Table-7. In the empirical estimation, I have used a ratio of construction-GSDP to state-GSDP instead of non-farm employment. The construction sector is prominent in terms of non-farm employment generation and contributes to state GSDP significantly. Rural male employment in construction sectors has increased from 2.2 percent in 1983 to 13 percent in 2011 due to increase in private and public investments for infrastructure development ($38^{th}$ round, 1983 and $68^{th}$ round, 2011 NSS employment and unemployment reports). In Model-1 and Model-2, the coefficient of flood damage over state-GSDP is positive and statistically significant in long-run, which shows that 1 percent increase in flood damage over state-GSDP, increases the annual real agricultural wages by 0.0150 percent and increases the real agricultural wages during flood months by 0.0118 percent. Rural workers become more vulnerable during the flood months due to lack of agricultural employment. It is difficult for the rural households to cope with flood and sustain their livelihoods particularly during flood months. These factors force rural labour to move out from agricultural to non-agricultural sectors in search of permanent and higher wage earnings. The coefficient of construction-GSDP over state-GSDP is positively correlated with rural agricultural wages in long-run in both models. The results show that rapid growth of construction sectors due to heavy public investment in infrastructure development such as road, railways and ports as well as growing private real estate business and urbanization pull down rural workers from low return sectors to high return sectors. Statistics show that the share of construction in national GDP has increased from 6.1 percent to 6.9 percent from 2002-03 to 2006-07 due to heavy government expenditure towards rural and urban infrastructure. These factors create demand for labour in construction sectors; as a result rural workforce participation rate in these sectors has increased from 1.6 percent to 11.1 percent during 1983 to 2011 as shown in Table-1. This causes agricultural wages to rise, through a creation of labour shortage in agriculture and allied activities.

**Table 7: Flood damages, agricultural productivity and construction-GSDP**

| Variable | Pooled Mean Group | Pooled Mean Group |
|---|---|---|
| | Model-1 | Model-2@ |
| ***Long-run coefficients*** | | |
| Ln(Flood damages/State-GSDP) | 0.0150*<br>(0.0078) | 0.0118*<br>(0.0063) |
| Ln(Construction-GSDP/State-GSDP) | 0.1221***<br>(0.0033) | 0.0826**<br>(0.0406) |
| Ln(Agricultural productivity) | 0.6101***<br>(0.0443) | 0.6022***<br>(0.0447) |
| Ln(Rural development expenditure/Total expenditure) | 0.0078**<br>(0.0035) | 0.0060*<br>(0.0032) |
| ***Convergence coefficient*** | -0.3513***<br>(0.0491) | -0.4419***<br>(0.0639) |
| ***Short-run coefficients*** | | |
| ΔLn(Flood damage/State-GSDP) | -0.0029*<br>(0.0016) | -0.0032<br>(0.0639) |
| ΔLn(Construction-GSDP/State-GSDP) | 0.0249<br>(0.0016) | 0.0277<br>(0.0924) |
| ΔLn(Agricultural productivity) | -0.1755***<br>(0.0513) | -0.1517<br>(0.0928) |
| ΔLn(Rural development expenditure/Total expenditure) | -0.0003<br>(0.0012) | 0.0006<br>(0.0019) |
| Intercept | 0.4257***<br>(0.0771) | 0.4794***<br>(0.0826) |
| No of states | 15 | 15 |
| No of obs | 420 | 420 |

***Note:*** *** $p<0.01$, ** $p<0.05$, * $p<0.1$ denotes level of significance at 1,5 and 10% respectively. The lag structure of all models is ARDL (1, 1, 1, 1,1) and controlling for state and time effects. Dependent variable for Model-1 is Ln (Annual real agricultural wages). @ Dependent variable for Model-2 is Ln (Real agricultural wage in flood months).

Thus, it is observed that during the period 1983 to 2011, rural workforce participation rate in agricultural sectors has declined from 81.4 percent to 64.1 percent and agricultural wages have increased. The control variables such as agricultural productivity, rural development expenditure are positively correlated with real agricultural wages in long-run. This finding is consistent with the earlier findings of the present study as shown in Table-5 and Table A.6. However, the short-run coefficient of flood damage over state-GSDP is negatively associated and statistically significant in Model-1. The results show that any short-term crisis like flood pull down real wages through impacts spread over different sectors of the economy. This result is again consistent with the earlier findings of the study as shown in Table A.6. Again the error correction term is negative and significant in both models.

Next, the study examines the effect of area affected by flood and construction-GSDP on agricultural wages. For estimation purposes, I have used area affected by flood instead of flood damages and omitted agricultural productivity variable in equation (1). The results of PMG estimates are shown in Table A.8. In Model-1, the long-run coefficient of area affected by flood is positive and significant after controlling construction-GSDP and rural development expenditure. However, the short-run coefficient of area affected by flood is negative and significant in Model-1. The long-run coefficients of construction-GSDP over state-GSDP are positive and significant in both models, while the coefficient of error correction term is negative and significant in both models.

### 5.2 Robust result

The *pull* factors such as construction-GSDP and increased employment opportunities in rural non-farm sectors and *push* factors such as expenditure on rural development and agricultural productivity are responsible for rising real agricultural wages in Indian states. Apart from these, flood impacts also serve as another pull factor that increases rural real agricultural wages. Frequent occurrences of flood adversely impacts household welfare through a rise in poverty, threatening food security, and destroying physical assets and human capital. All these factors reduce household income and causes rural worker migration from agriculture sectors to non-agriculture sectors. This leads to increasing the rural agricultural wages due to shortage of workers in agricultural sectors. To check for robustness of the estimates, I have used Per Capita Income (PCI) instead of workforce participation in non-farming sectors and employment in agriculture sector instead of agricultural productivity to estimate equation (1). For all models, I have used one[17] period lag of dependent and independent variables based on Schwartz Bayesian criterion[18]. Optimal lag length can be chosen based on data structure and time dimension of the data. In annual macro data it should be one period lag as it reduces degrees of freedom and estimates additional parameters. The PMG estimates are shown in Table-9. In Model-1 and Model-2, the long-run coefficient of flood damage over GSDP is still positive and significant in both models after controlling PCI and employment of agriculture sector. The coefficient of employment in agriculture sector is negatively correlated with real agricultural wages in long-run, implying that agricultural labour supply plays an important role in determining rural agricultural wages. This results show that excess labour supply in agricultural sector would significantly reduce rural agricultural wages. However, the long-run coefficients of real PCI are positive and significant in both models. This shows that economic development has significantly increased real agricultural wages.

**Table 9: Flood damages, employment in agriculture and PCI**

| Variable | Pooled Mean Group | Pooled Mean Group |
|---|---|---|
| | Model-1 | Model-2@ |
| ***Long-run coefficients*** | | |
| Ln(Flood damages/State-GSDP) | 0.0323***<br>(0.0090) | 0.0178**<br>(0.0076) |
| (Employment in agriculture /Rural employment) % | -0.0061*<br>(0.0034) | -0.0099***<br>(0.0029) |
| Ln(Real PCI) | 0.5421***<br>(0.0501) | 0.4264***<br>(0.0434) |
| ***Convergence coefficient*** | -0.2959***<br>(0.0408) | -0.3989***<br>(0.0397) |
| ***Short-run coefficients*** | | |
| ΔLn(Flood damage/State-GSDP) | -0.0044***<br>(0.0015) | -0.0027<br>(0.0021) |
| Δ( Employment in agriculture / Rural employment) | -0.0004<br>(0.0007) | -0.0008<br>(0.0009) |

[17] The time dimension is not long enough to over extend the lags; one can impose a common lag structure across countries (see Loayza & Ranciere, 2006; Pesaran et al., 1999).

[18] I have also estimated same models using Eviews-9 and selected one lag of all variables based on Schwartz Bayesian criterion in ARDL model and also introduced the time trend in my models. All results are available upon request.

| | | |
|---|---|---|
| $\Delta$Ln(Real PCI) | -0.4164***<br>(0.1377) | -0.4333***<br>(0.1865) |
| Intercept | - 0.1346***<br>(0.0268) | 0.3419***<br>(0.0400) |
| No of states | 15 | 15 |
| No of obs | 420 | 420 |

***Note:*** *** $p<0.01$, ** $p<0.05$, * $p<0.1$ denotes level of significance at 1,5 and 10% respectively. The lag structure of all models is ARDL (1, 1, 1, 1) and controlling for state and time effects. Dependent variable for Model-1 is Ln (Annual real agricultural wage). @ Dependent variable for Model-2 is Ln (Real agricultural wage in flood months).

The reason behind that, the states with better performing non-farm sectors such as manufacturing, services, and construction, mining & quarrying sectors require more labour, causing a shift of rural workforce from primary sectors to non-farm sectors. The short-run coefficient of flood damage is negative and significant in Model-1. This result is consistent with earlier a finding as shown in Table-5 and Table-7. The error correction term also negative and significant in both models, which shows that there exists a long-run relationship among the variables. Next, study estimate impact of flood measured in terms of area affected by floods on rural agricultural wages using equation (1). The PMG estimates are shown in Table A.10. The long-run coefficient of area affected by flood and real PCI is positive and significant in both models. However, employment in agriculture is negatively correlated with agricultural wages in long-run, while area affected by flood is negatively correlated with real rural agricultural wages in the short-run. Again the error correction term is negative and statistically significant in both models. The overall estimates are consistent throughout the models.

The study further shows that effect of flood on agricultural wage after controlling economic development measures in terms of road density and availability of banking facilities as explanatory variables in this study. The PMG estimates are shown in Table A.11. The coefficient of flood damage over GSDP is still positively correlated with agricultural wages in long-run in both models after controlling road density and availability of banking facilities. The study further shows that availability of better road and banking facilities has significantly increased the agricultural wages in long-run. Overall result show that road density and availability of banking facilities cannot minimize the flood impacts on rural agricultural wage in long-run.

## 6: Conclusion and discussion

This study examined the effect of floods on rural real agricultural wages in Indian states using state-level panel data covering periods from 1983 to 2011. The PMG estimates show that the error correction term is negative and statistically significant in all models, which implies that there exists a long-run relationship among the variables. The econometric results further indicate that pull factors such as higher rural workforce participation rate in rural non-farm sectors and growth of construction sectors create an upward pressure on the rural agricultural wages in the long-run as a significant proportion of rural workers move from farm sectors to non-farm sectors in search of stable wage earnings. Moreover, the push factors such as expenditures on rural development and agricultural productivity have significantly increased rural agricultural wages in the long-run through generating a favorable demand for rural laborers.

Apart from pull and push factors, there is another exogenous pull factor such as flood damages and area affected by flood have a positive impact on real agricultural wages in long-run. Any catastrophe situation like flood adversely affects welfare of rural households through damage of agricultural crops, damage of household assets and creating a direct impact on the agricultural labour market conditions. Those impacts significantly reduce income of the rural households, which have increased the poverty levels as well as threatening food securities. As a consequence of reduced income security rural workers are forced to migrate from agriculture to non-farm sectors. It also creates lower labour supply in agricultural sectors, which leads to an increase the rural agricultural wages in Indian states. Another interesting finding of the study is that the flood impact tends to lower the rural agricultural wages in short-run. Frequent flood disasters directly affect livelihood of rural household in short-run and rural households are usually not capable of adopting coping strategies to mitigate flood impacts. For that reason, rural workers compromise to work at a lower wage rate to sustain their livelihood in the short-run.

As a robustness check on the results, the study examines effect of flood on rural agricultural wages, controlling for per capita income, road density and availability of bank facilities as explanatory variables. The PMG estimates show that per capita income is positively correlated with rural agricultural wages in long-run. Higher per capita income, a proxy of economic development in Indian states has significantly increased rural agricultural wages via creation of higher labour demand in manufacturing, service and construction sectors. However, excess labour supply in agricultural sector pulls down the agricultural wages. The study further reveals that availability of better road infrastructure and banking facilities cannot diminish flood impact on agricultural wages in long-run.

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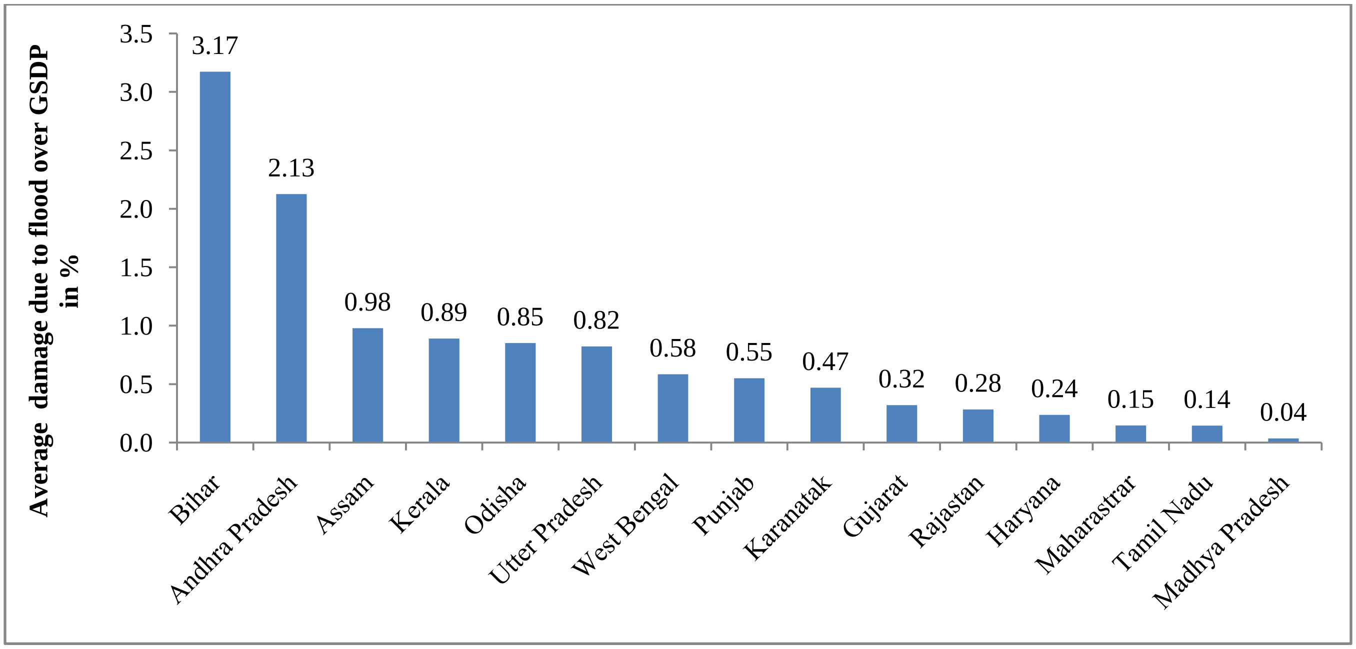
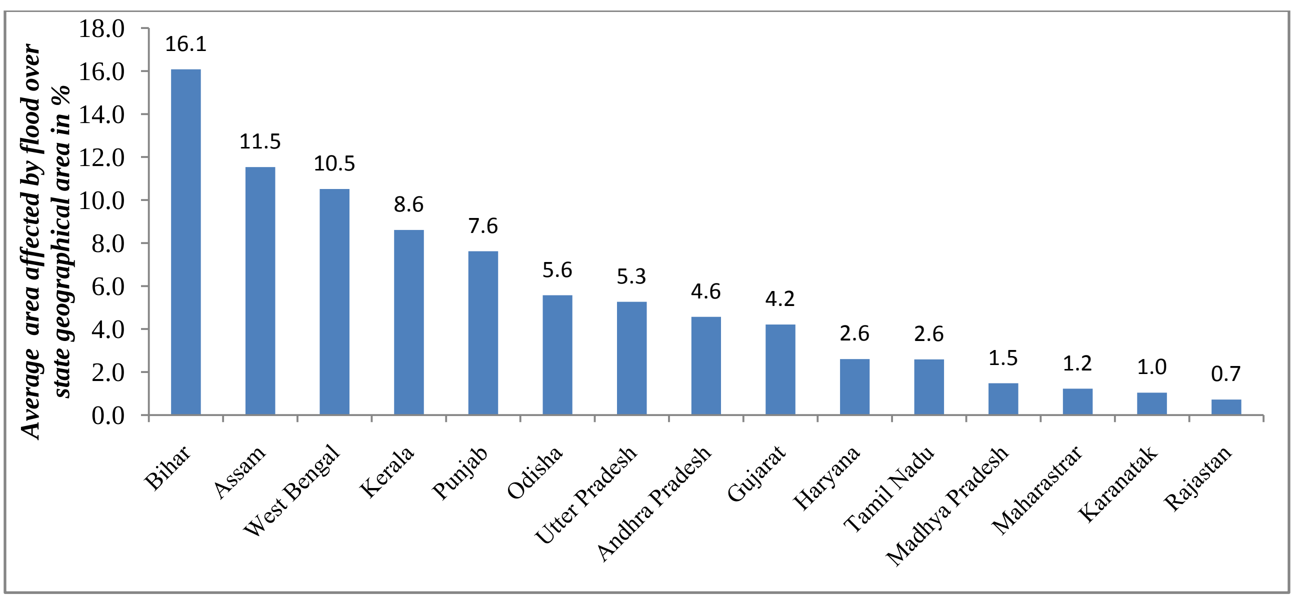
## Appendix A

**Figure A.1: Average total damage due to floods per Rupee of state-GSDP during 1983-2011**




***Note:*** Author calculation.

**Figure A.2: Average area affected due to floods over state geographic area during 1983-2011**



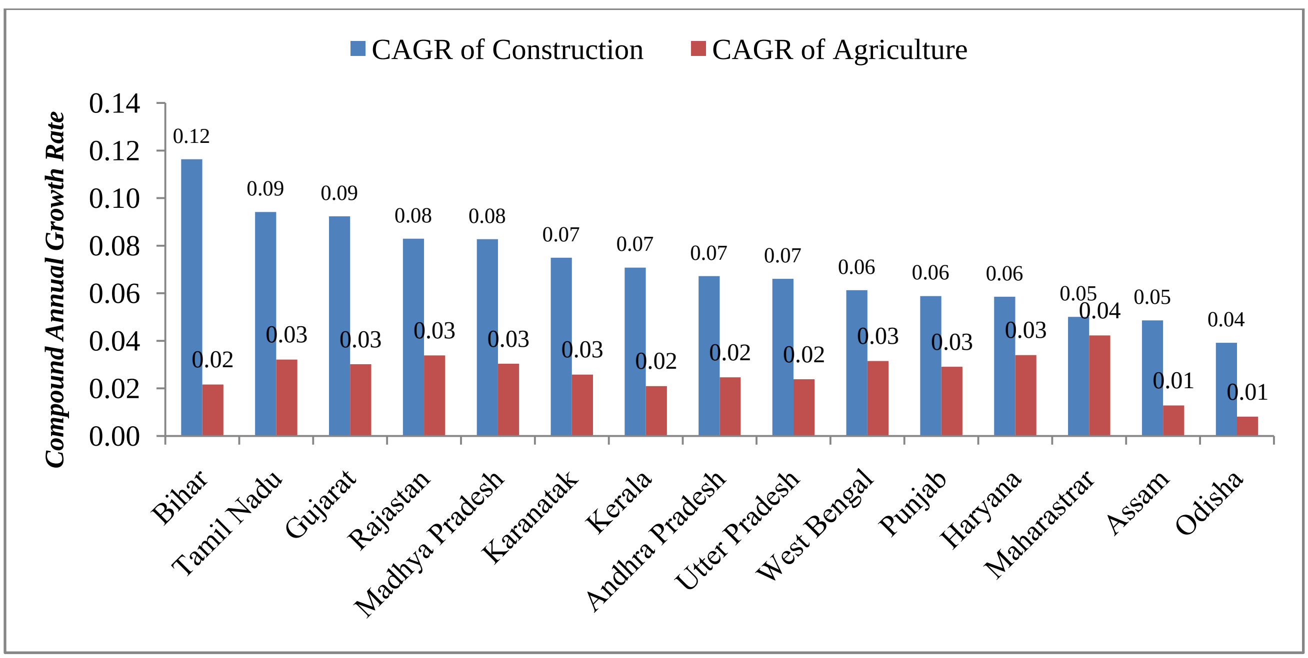

***Note:*** Author calculation.

**Table A.2: State-wise rural employment in agricultural and non-agricultural sectors**

| States | Share of agricultural worker | | | | | Share of non-agricultural worker | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1983 | 1993 | 2004 | 2011 | CAGR* (1983-2011) | 1983 | 1993 | 2004 | 2011 | CAGR*(1983 - 2011) |
| Kerala | 0.63 | 0.56 | 0.42 | 0.31 | -0.036 | 0.37 | 0.44 | 0.58 | 0.69 | 0.010 |
| Tamil Nadu | 0.74 | 0.70 | 0.65 | 0.51 | -0.017 | 0.26 | 0.30 | 0.35 | 0.49 | 0.020 |
| Punjab | 0.82 | 0.75 | 0.67 | 0.52 | -0.014 | 0.18 | 0.25 | 0.33 | 0.48 | 0.038 |
| West Bengal | 0.73 | 0.63 | 0.63 | 0.53 | 0.000 | 0.27 | 0.37 | 0.37 | 0.47 | 0.032 |
| Haryana | 0.77 | 0.72 | 0.64 | 0.58 | 0.000 | 0.23 | 0.28 | 0.36 | 0.42 | 0.032 |
| Rajasthan | 0.87 | 0.80 | 0.73 | 0.61 | -0.004 | 0.13 | 0.20 | 0.27 | 0.39 | 0.048 |
| Assam | 0.79 | 0.79 | 0.74 | 0.62 | 0.002 | 0.21 | 0.21 | 0.26 | 0.38 | 0.032 |
| Odisha | 0.79 | 0.81 | 0.69 | 0.62 | -0.001 | 0.21 | 0.19 | 0.31 | 0.38 | 0.029 |
| Utter Pradesh | 0.82 | 0.80 | 0.73 | 0.64 | 0.002 | 0.18 | 0.20 | 0.27 | 0.36 | 0.036 |
| Bihar | 0.83 | 0.84 | 0.78 | 0.68 | -0.012 | 0.17 | 0.16 | 0.22 | 0.32 | 0.020 |
| Andhra Pradesh | 0.80 | 0.79 | 0.72 | 0.70 | -0.001 | 0.20 | 0.21 | 0.28 | 0.30 | 0.019 |
| Karnataka | 0.84 | 0.81 | 0.81 | 0.70 | -0.003 | 0.16 | 0.19 | 0.19 | 0.30 | 0.026 |
| Madhya Pradesh | 0.90 | 0.90 | 0.82 | 0.72 | -0.014 | 0.10 | 0.10 | 0.18 | 0.28 | 0.031 |
| Gujarat | 0.84 | 0.79 | 0.77 | 0.75 | 0.000 | 0.16 | 0.21 | 0.23 | 0.25 | 0.023 |
| Maharashtra | 0.86 | 0.83 | 0.80 | 0.77 | 0.002 | 0.14 | 0.17 | 0.20 | 0.23 | 0.023 |

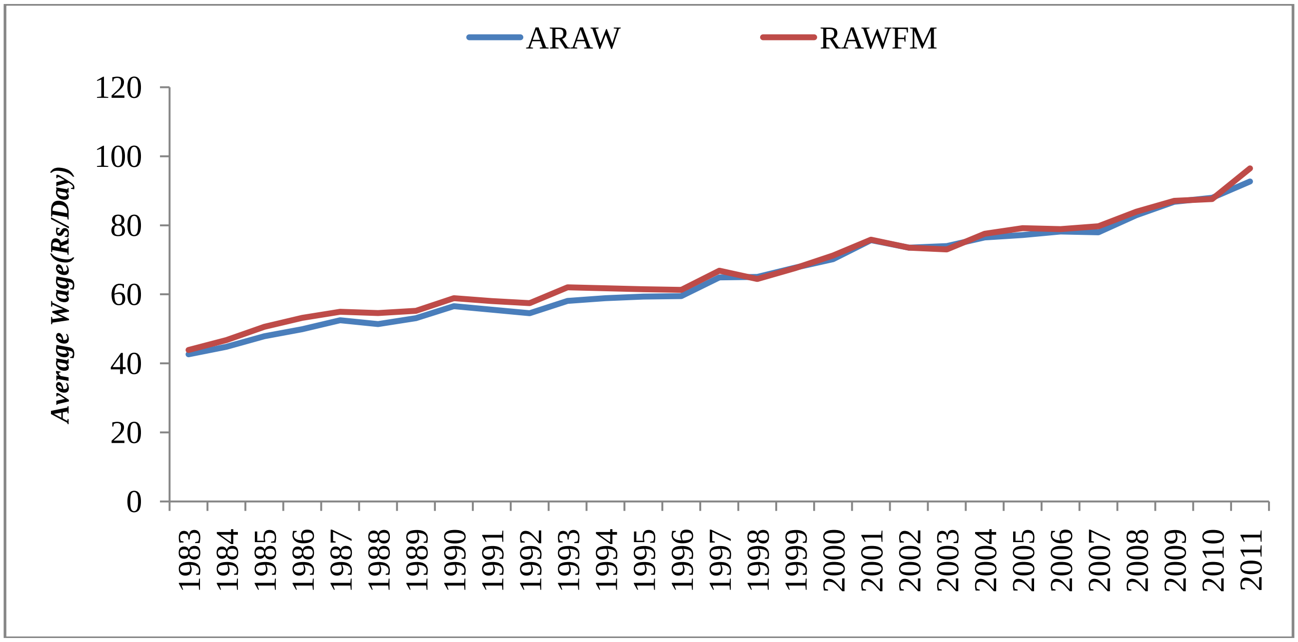
***Note:*** Author calculation. * Compound annual growth rate is calculated using absolute employment figure.

**Figure A.3: CAGR of construction-GSDP and agriculture-GSDP sectors from 1983-2011 by states**



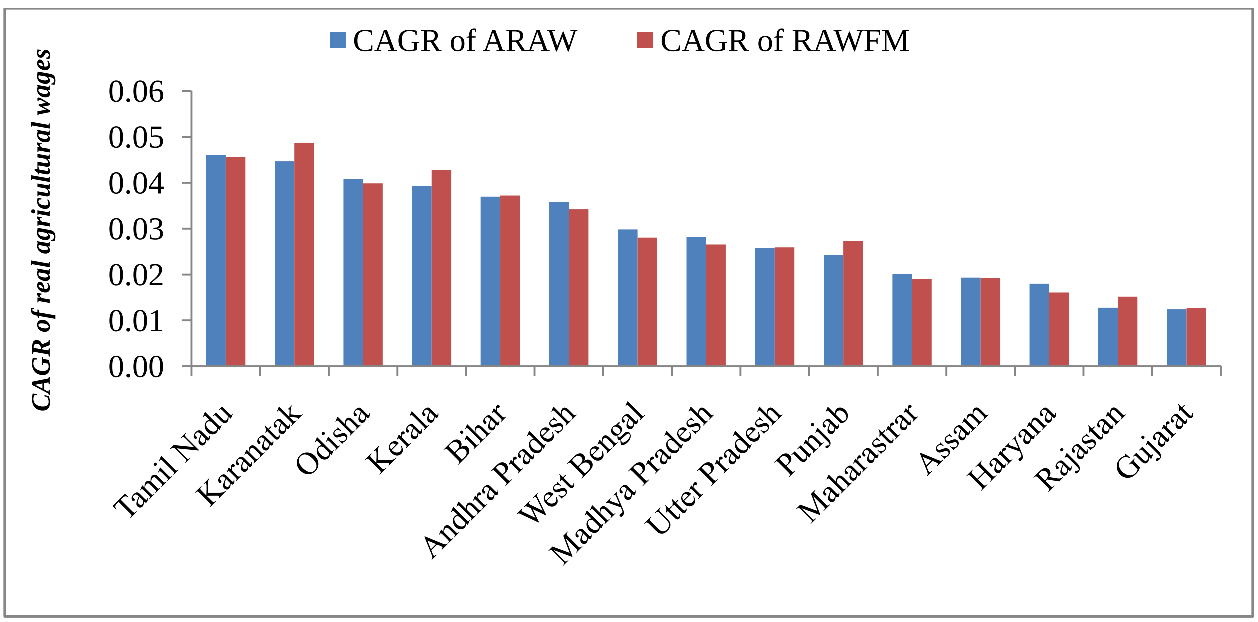

***Note:*** Author calculation. CAGR-Compound Annual Growth Rate.

**Figure A.4: Trends in rural real agricultural wages at all-India level (Base year: 2004-05)**




***Note:*** Author calculation. Source: Agricultural Wages in India. **ARAW**- Annual Real Agricultural wages. **RAWFM-** Real Agricultural Wage in Flood Months.

**Figure A.5: State-wise CAGR of real agricultural wages during 1983-2011**




***Note:*** Author calculation. Source: Agricultural Wages in India. CAGR - Compound Annual Growth Rate. **ARAW**- Annual Real Agricultural wages. **RAWFM-** Real Agricultural Wage in Flood Months.

**Table A. 3: Trends of real rural agricultural wages in Indian state (Base year: 2004-05)**

| States | Annual real agricultural wages ( Rs/ Day) | | | | | Real agricultural wage in flood months ( Rs/ Day) | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | 1983 | 1993 | 2003 | 2008 | 2011 | 1983 | 1993 | 2003 | 2008 | 2011 |
| ***High wage rate*** | | | | | | | | | | |
| Kerala | 67 | 96 | 184 | 228 | 198 | 63 | 96 | 166 | 221 | 203 |
| Haryana | 78 | 99 | 103 | 111 | 129 | 85 | 104 | 105 | 115 | 133 |
| Punjab | 66 | 97 | 90 | 86 | 128 | 69 | 101 | 93 | 94 | 146 |
| Tamil Nadu | 30 | 48 | 67 | 71 | 105 | 31 | 50 | 69 | 74 | 110 |
| ***Medium wage rate*** | | | | | | | | | | |
| Andhra Pradesh | 36 | 47 | 51 | 75 | 95 | 37 | 49 | 53 | 77 | 96 |
| Rajasthan | 61 | 58 | 77 | 87 | 88 | 63 | 62 | 78 | 82 | 96 |
| Karnataka | 25 | 35 | 57 | 77 | 86 | 24 | 39 | 61 | 85 | 93 |
| Bihar | 29 | 40 | 59 | 66 | 81 | 28 | 40 | 58 | 65 | 78 |
| Utter Pradesh | 39 | 51 | 65 | 69 | 79 | 40 | 54 | 64 | 69 | 82 |
| Assam | 44 | 58 | 58 | 62 | 75 | 46 | 58 | 62 | 60 | 79 |
| ***Low wage rate*** | | | | | | | | | | |
| Gujarat | 52 | 53 | 72 | 80 | 74 | 54 | 55 | 71 | 82 | 76 |
| West Bengal | 31 | 71 | 76 | 82 | 71 | 32 | 72 | 70 | 83 | 70 |
| Odisha | 21 | 39 | 45 | 44 | 65 | 23 | 42 | 45 | 45 | 68 |
| Madhya Pradesh | 29 | 26 | 49 | 55 | 64 | 31 | 49 | 45 | 57 | 65 |
| Maharashtra | 30 | 53 | 56 | 50 | 52 | 30 | 59 | 56 | 49 | 52 |

***Note:*** Author calculation. Source: Agricultural Wages in India.

**Table A.6: Area affected by floods, rural non-farm employments and agricultural productivity**

| Variable | Pooled Mean Group | Pooled Mean Group |
|---|---|---|
| | Model-1 | Model-2@ |
| ***Long-run coefficients*** | | |
| Ln (Area affected by flood/State geographical area) | 0.0165**<br>( 0.0077) | 0.0107*<br>(0.0062) |
| (Rural non-firm employment/Rural employment)% | 0.0053**<br>(0.0022) | 0.0086***<br>(0.0022) |
| Ln (Agricultural productivity) | 0.5953***<br>(0.0401) | 0.4447***<br>(0.0439) |
| Ln ( Rural development expenditure/Total expenditure) | 0.0085**<br>(0.0034) | 0.0053*<br>(0.0031) |
| ***Convergence coefficient*** | -0.3254*** | -0.4261*** |

| | | |
|---|---|---|
| | (0.0545) | (0.0636) |
| ***Short-run coefficients*** | | |
| Δ Ln(Area affected by flood/State geographical area) | -0.0053*** (0.0015) | -0.0016 (0.0021) |
| Δ(Rural non-farm employment/Rural employment)% | 0.0017* ( 0.0010) | 0.0027*** (0.0009) |
| ΔLn(Agricultural productivity) | -0.1531*** (0.0501) | -0.1085 (0.0903) |
| ΔLn(Rural development expenditure/Total expenditure) | 0.0000 (0.0015) | 0.0000 (0.0017) |
| Intercept | 0.2709*** (0.0667) | 0.6614*** (0.1160) |
| No of states | 15 | 15 |
| No of obs | 420 | 420 |

***Note:*** *** p<0.01, ** p<0.05, * p<0.1 denotes level of significance at 1,5 and 10% respectively. The lag structure of all models is ARDL (1, 1, 1, 1,1) and controlling for state and time effects. Dependent variable for Model-1 is Ln (Annual real agricultural wage). @ Dependent variable for Model-2 is Ln (Real agricultural wage in flood months).

**Table A.8: Area affected by floods, agricultural productivity and construction-GSDP**

| Variable | Pooled Mean Group | Pooled Mean Group |
|---|---|---|
| | Model-1 | Model-2@ |
| ***Long-run coefficients*** | | |
| Ln(Area affected by flood/State geographical area) | 0.0281* (0.0151) | 0.0029 (0.0103) |
| Ln(Construction-GSDP/State-GSDP) | 0.5645*** (0.0780) | 0.4439*** (0.0526) |
| Ln(Rural development expenditure/Total expenditure) | -0.0001 (0.0080) | 0.0036 (0.0056) |
| ***Convergence coefficient*** | -0.1737*** (0.0309) | -0.2839*** (0.0536) |
| ***Short-run coefficients*** | | |
| ΔLn(Area affected by flood/State geographical area) | -0.0049*** (0.0018) | 0.0001 (0.0019) |
| ΔLn(Construction-GSDP/State-GSDP) | 0.0204 (0.0549) | 0.0007 (0.0822) |
| ΔLn(Rural development expenditure/Total expenditure) | -0.0004 (0.0012) | -0.0012 (0.0017) |
| Intercept | 1.0158*** (0.1709) | 1.5308*** (0.2790) |

| | | |
|---|---|---|
| No of states | 15 | 15 |
| No of obs | 420 | 420 |

***Note:*** *** p<0.01, ** p<0.05, * p<0.1 denotes level of significance at 1,5 and 10% respectively. The lag structure of all models is ARDL (1, 1, 1, 1) and controlling for state and time effects. Dependent variable for Model-1 is Ln (Annual real agricultural wage). @ Dependent variable for Model-2 is Ln (Real agricultural wage in flood months).

**Table A.10: Area affected by floods, employment in agriculture and PCI**

| Variable | Pooled Mean Group | Pooled Mean Group |
|---|---|---|
| | Model-1 | Model-2@ |
| ***Long-run coefficients*** | | |
| Ln(Area affected by flood/ State geographical area) | 0.0225** (0.0091) | 0.0115* (0.0063) |
| (Employment in agriculture/Rural employment)% | -0.0088** (0.0034) | -0.0113*** (0.0028) |
| Ln ( Rural development expenditure /Total expenditure) | 0.0006 (0.0043) | 0.0026 (0.0035) |
| Ln(Real PCI) | 0.5293*** (0.0531) | 0.3281*** (0.0397) |
| ***Convergence coefficient*** | -0.2695*** (0.0447) | -0.3966*** (0.0518) |
| ***Short-run coefficients*** | | |
| ΔLn(Area affected by flood/State geographical area) | -0.0047*** (0.0017) | -0.0006 (0.0021) |
| Δ( Employment in agriculture /Rural employment)% | -0.0005 (0.0009) | -0.0017** (0.0008) |
| ΔLn(Rural development expenditure/Total expenditure) | 0.0022* (0.0013) | 0.0008 (0.0013) |
| ΔLn(Real PCI) | -0.3851*** (0.1334) | -0.3321** (0.1795) |
| Intercept | - 0.0595*** (0.0187) | 0.7390*** (0.0992) |
| No of states | 15 | 15 |
| No of obs | 420 | 420 |

***Note:*** *** p<0.01, ** p<0.05, * p<0.1 denotes level of significance at 1,5 and 10% respectively. The lag structure of all models is ARDL (1, 1, 1, 1,1) and controlling for state and time effects. Dependent variable for Model-1 is Ln (Annual real agricultural wage). @ Dependent variable for Model-2 is Ln (Real agricultural wage in flood months).

**Table A.11: Damage due to flood, rural non-agriculture employment and road density**

| Variable | Pooled Mean Group Model-1 | Pooled Mean Group Model-2@ |
|---|---|---|
| ***Long-run coefficients*** | | |
| Ln(Flood damages/State-GSDP) | 0.0209***<br>(0.0080) | 0.0178**<br>(0.0069) |
| (Rural non-farm employment/Rural employment) % | 0.0115***<br>(0.0030) | 0.0104***<br>(0.0024) |
| Ln(Number of banks per million population) | 0.7860***<br>(0.1538) | 0.3079***<br>(0.1068) |
| Ln(Road density per 100 sq.km of area) | 0.6637***<br>(0.0571) | 0.4752***<br>(0.0453) |
| ***Convergence coefficient*** | -0.2294***<br>(0.0541) | -0.4035***<br>(0.0788) |
| ***Short-run coefficients*** | | |
| ΔLn(Flood damage/State-GSDP) | -0.0013<br>(0.0018) | -0.0023<br>(0.0019) |
| Δ(Rural non-farm employment/Rural employment) % | 0.0004<br>(0.0017) | 0.0007<br>(0.0012) |
| ΔLn(Number of banks per million population) | -0.1487<br>(0.2444) | -0.0744<br>(0.3077) |
| ΔLn(Road density per 100 sq.km of area) | -0.0749<br>(0.0626) | 0.0352<br>(0.0707) |
| Intercept | 0.4908***<br>(0.1227) | 0.2685***<br>(0.0638) |
| No of states | 15 | 15 |
| No of obs | 420 | 420 |

***Note:*** *** p<0.01, ** p<0.05, * p<0.1 denotes level of significance at 1,5 and 10% respectively. The lag structure of all models is ARDL (1, 1, 1, 1, 1) and controlling for state and time effects. Dependent variable for Model-1 is Ln (Annual real agricultural wage). @ Dependent variable for Model-2 is Ln (Real agricultural wage in flood months).

**Table A.4: Definition of variables and summary statistics**

| Variables | Definition of Variables | Obs | Mean | Std. Dev. | Min | Max |
|---|---|---|---|---|---|---|
| Annual real agricultural wages | Simple average of state-wise monthly agricultural wages in calendar year in Rupee and deflated by the Consumer Price Index (CPI) for agriculture laborers for the base year (2004-05). | 435 | 65.34 | 32.25 | 21 | 244 |
| Real agricultural wages in flood months | Simple average of flood months agricultural wages (July to October) in Rupee and deflated by the same months of Consumer Price Index (CPI) for agriculture laborers for the base (2004-05). | 435 | 66.97 | 32.67 | 23 | 250 |
| Flood damages/State-GSDP | Total flood damages include crop damage, house damage and public utility damage Rs in lakh over State GSDP | 435 | 0.007 | 0.036 | 0 | 0.688 |
| Area affected by flood/State geographical area | Total area affected by floods including crop area in million hector over state geographical area in million hector | 435 | 0.052 | 0.094 | 0 | 0.641 |
| Non-farm employment/ Rural employment (%) | Non-farm employments include manufacturing, service, construction and mining and query over total rural employment. | 435 | 26.14 | 10.10 | 9.10 | 68.58 |
| Employment in agriculture /Rural employment (%) | Employment in rural farm sectors includes plantation, fishing and forestry over total rural employments. | 435 | 73.86 | 10.10 | 31.42 | 90.90 |
| Agricultural productivity | State-wise agricultural GSDP Rs in lakh over crop area in 1000 hectors. | 435 | 495.59 | 996.76 | 66.07 | 7235.67 |
| Rural development expenditure/Total expenditure | State government expenditure for rural development Rs in lakh over total state government expenditure. | 435 | 0.029 | 0.024 | 1.93e-08 | 0.112 |
| Construction-GSDP/State-GSDP | Construction-GSDP Rs in lakh over state-GSDP Rs in lakh | 435 | 0.070 | 0.023 | 0.029 | 0.155 |

| | | | | | | |
|---|---|---|---|---|---|---|
| Real PCI | State-wise real GSDP Rs in lakh over state-wise population | 435 | 22688 | 13032 | 4861 | 69785 |
| Number of banks per million population | Number of bank offices per million state population | 435 | 72.76 | 19.57 | 34.99 | 140.39 |
| Road density per 100 sq.km of area | State-wise total road length per 100 Sq. Kms | 435 | 113.02 | 94.04 | 24.38 | 554.39 |