Rainfall Variability and Macroeconomic Performance:A Case Study of India, 1952–2013 <Preliminary Version>

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Abstract
The present and emerging climate change highlights the need to understand the impact of weather shocks on the economy in the context of macroeconomic dynamism. In this regard, the present paper develops an empirical framework applicable to macro-data such as GDP to distinguish the impact of weather shocks on agricultural production, the indirect impact on non-agricultural production through its impact on agriculture, and the direct impact on non-agricultural production. For policymakers, distinguishing the direct and indirect impact on non-agriculture is critical in deciding the proper and efficient allocation of limited resources to adaptation and mitigation efforts. The present paper applies the developed framework to assess the impact of rainfall variability on India's macroeconomic performance during 1952 to 2013 as a case study, finding that rainfall's impact on non-agriculture is mostly rooted in its impact on agriculture. In this way, the paper contributes to the growing climate-economy literature. (147 words)

Keywords
Business cycle, Environment and Development, Monsoon, Agriculture, Kalman filter

Classification Codes: E32, O11, O53, Q19, Q54, Q56

1. Introduction

In the age of climate change, understanding the impact of weather and climate on the economy in the context of macroeconomic dynamism is critically important. The precise identification of the impact routes and their magnitude is particularly vital as a cornerstone. The literature on the climate–economy relationship is growing rapidly, as reviewed by Dell et al. (2014) in the *Journal of Economic Literature*, and confirms the broad effects of weather and climate on agriculture, industry, services, aggregate output, labor productivity, heath and mortality, and political instability. In the literature, assessments of macro-level impact will become more and more crucial for developing countries, as they can provide straightforward information to policymakers to help their design of adaptation and mitigation strategies and consideration of the appropriate level and allocation of public support to implement such strategies. This is especially the case in light of the agreements made at the 2015 Paris Climate Conference, COP21, which include the engagement of developing economies.

The present paper contributes to the advancement of the literature by developing an empirical framework that is applicable to macro-data such as GDP statistics, which can be used to distinguish the impact of weather shocks on non-agriculture's growth cycle through its impact on agricultural performance (referred to as the ‘indirect’ impact in this paper) from the ‘direct’ impact of weather shocks on the non-agricultural growth cycle. For policymakers, distinguishing the direct and indirect impact is critical. If the impact on non-agriculture is mainly through agriculture, it is thus rational to allocate more toward measures in the agricultural sector. If the direct impact on non-agricultural production is large enough, it may help counter the skeptical view on the breadth of climate change’s influence that sees it as an issue limited to the agricultural sector and other sectors deeply associated with natural environments.

The empirical framework adopts a two-stage estimation approach, conducting first a regression of agriculture on weather and, then, a regression of non-agriculture on weather. This framework overcomes the difficulty of multicollinearity and endogeneity problems arising from a correlation between agriculture and weather variations. Namely, the first-stage regression distinguishes agriculture’s unique shock from the weather shock, and then uses the result in the second-stage equation. The two-stage estimation framework also helps avoid potential errors arising from the changing sectoral share of agriculture and non-agriculture when assessing the impact of weather on aggregate output in rapidly growing developing countries by using long-run data covering several decades. Many developing countries are experiencing a rapid structural change into non-agrarian economies, and the susceptibility of agriculture and non-agriculture to weather shocks is essentially very different, with being the former much more affected. More importantly, the framework is simple and easy to modify to suit the interest of researchers.

The paper applies the empirical framework in an assessment of the impact of rainfall variability on India's macroeconomic performance during the period 1952–2013 as a case study. Firstly, average impacts during the period are estimated by generalized least squares (GLS), confirming the validity of the framework in terms of its ability to distinguish the direct and indirect impacts of a weather shock on non-agricultural production's growth. Secondly, time-varying impacts are estimated using a Kalman filter, and vividly depict the time series changes of rainfall variability's impact on output with a decomposition of those on agriculture, as well as direct and indirect impacts on non-agriculture.

India is chosen as a case since it is one of the major players in the response to climate change and a representative country with respect to population and economic size under the sphere of the Asian Monsoon, the seasonal winds blowing from the Arabian Sea to South Asia that bring majority of the annual rainfall to the area. A more practical reason is that India is well documented in terms of its economic development (Basu and Maertens, 2007), with long-term data available in regard to both weather and economics. Rainfall variability is of focus in contrast with temperature because it has been of traditional interest in India as will be reviewed.

In essence, the present paper responds to three important points raised by Dell et al. (2014). First is the need for the augmentation of research to assess the growth effects of weather shocks, which is contrasted with ‘level’ effect as will be further reviewed in the next section. Second is the necessity to reveal the specific mechanism how the weather affects economy to help target potential interventions. This includes the need of research on how weather affects non-agricultural sector facing some skepticism unlike agricultural sector. Third is the sophistication of functional form in integrated assessment model (IAM), which is a primary tool to assess the economy-climate relationship. In particular, damage function which captures how economy is affected by climate change has to be upgraded. Achieving the third point requires the research on the first and the second point. The third point is also pointed out many other researches including the other cornerstone review by Tol (2009), in the *Journal of Economic Perspectives*.

The rest of the paper is structured as follows: The second section introduces the background and the third sets out the empirical framework. The fourth section implements the econometric analyses and includes a demonstration of the results, interpretation and related discussions. The fifth section provides conclusions.

2. Background

2.1 Weather Shocks and Growth

The comprehensive literature review by Dell et al. (2014) provides a guideline for new research in the climate–economy field. According to this work, the preceding literature has emphasized more the level effect of climate conditions on income level, and established evidence that an economy under higher temperature conditions has a lower income level. Sector-wise, agriculture has been the focus of studies of climate impacts (ibid). In comparison, assessments of weather variability on output performance beyond agriculture has been relatively rare, although studies on the impact of weather shocks on growth have started to emerge (ibid).

Dell et al. (2012) examined the impact of temperature shocks on the growth of per capita GDP, agricultural output and industrial output growth during 1950 to 2003 in 125 countries. Their study confirmed the significant negative impacts of higher temperatures lowering the growth rates of per capita GDP and agricultural and industrial outputs in poor countries, but not in rich countries. Barrios et al. (2010) examined the impact of rainfall and temperature anomalies on per capita GDP growth in 22 Sub-Saharan African countries between 1960 and 1990. That study found that higher rainfall deviation is associated with faster growth, but it did not find a significant impact of temperature shocks on growth. On the other hand, Abidoye and Odusola (2015) examined the impact of temperature shocks on per capita GDP growth in 34 African countries during 1961 to 2009, and found that positive temperature deviation lowers growth.

These researches basically estimated the below reduced form equation exploiting annual data with some variations to meet the interests of each research:

$$g_{i,t} = \beta c_{i,t} + \gamma Z_{i,t} + \mu_i + \theta_{it} + \varepsilon_{i,t} \quad \text{(eq.1)}$$

where *t* and *i* indexes respectively time and a country, *g* is an explained variable (i.e. growth rate of interest variable), *c*, *z* denotes explanatory variables of growth rate, weather shocks, and control variables. μ and θ are fixed country characteristic and time fixed effect respectively. β and γ are parameters capturing the effects of weather shocks and control variables respectively. ε denotes an *i.i.d* shock.

There are two major ways to improve the above estimation, which the present paper tries to address. First is that the parameter for weather variations, β, is time-varying in nature when regressed on aggregate output growth in the long run, given that the examined developing countries experienced a rapid decline of agriculture’s share in outputs in the long run. If agricultural production is much more susceptive to weather variation than non-agriculture, the impact of weather shocks on aggregate output should also decline over time. Second, those studies did not examine the underlying mechanisms how weather shock affects economic performance including the transmission of the shocks among agriculture and non-agriculture. Even if the significant impact of weather on non-agriculture is confirmed, it can be rooted in the impact of weather shocks on agriculture.

2.2 India's Development

This subsection will review the development of India, the case study country. First, this subsection will show that the country has continued to be under the significant influence of rainfall variability, and the rainfall–economy relationship has been of great and traditional interest at various levels. Second, it will also review its economic and agricultural development of the past 60 years. Third, India's experience of climate change will also be touched upon.

The Monsoon, the seasonal winds, brings 70–90% of India's annual rainfall during June to September, and influences agricultural production and sometimes induces floods, droughts and other natural disasters. Therefore, dealing with rainfall variability is a longstanding and current challenge for India, being traceable back to rainmaking rituals to invoke rain and a rich harvest in ancient times (Jossie and Sudhir, 2012). Accordingly, India's public interest in the Monsoon is high. Starting with predictions by meteorologists, day-by-day precipitation is monitored and broadcast through newspapers and other mass media outlets in the Monsoon season. A survey examining the participation of rural Indian households in rainfall insurance in 2004 demonstrates that people recognize rainfall deficiency as a key risk (Giné et al., 2008). Rainfall-income relationship is so close in rural India, and rainfall shocks can work as a valid predictor for riot incidence (Sarsons 2015)

The Monsoon is also of interest to economists monitoring and forecasting India's economic performance. For example, the International Monetary Fund and the Asian Development Bank, two representative economic surveillants of the region, often refer to the impacts of the Monsoon in their economic reports on India. Reviewing India's economic development since 1950, Mohan (2008) observes that the slow economic growth has been largely characterized by slow agricultural growth despite the notably reduced share of agriculture in outputs, and agricultural performance continues to be affected by rainfall even in recent years.

As Mohan's view exemplifies, the Monsoon–agriculture relationship has been well recognized and extensive research has been undertaken. Taking a selection of recent examples, Singh et al. (2011) analyzed the impact of droughts and floods on food grain production at the crop level, and found that rice is more susceptible to climate extremes than other products. Subash and Gangwar (2014) closely examined the rainfall and rice production relationship at the district level in India, and found that the impact varies among the regions and that July's precipitation is more influential in regard to rice production than other months in the Monsoon period.

On the other hand, quantifications of the macroeconomic impact have been rare in the Indian context despite the huge interests. Virmani (2006) and Gadgil and Gadgil (2006) are the two rare studies examining the macro-impact of the Monsoon on aggregate and agricultural production. Virmani (2006) analyzed the relationship of rainfall deviation from the mean with growth rates of GDP and agricultural production between 1951 and 2003 by Ordinary Least Squares (OLS) regression. The work confirmed there are significant influences on both GDP and agriculture, and estimated that a 1% rainfall deviation increases the growth of GDP by 0.16% and that of agricultural output by 0.36%. The study also argued that rainfall fluctuation accounts for 45% of GDP variation based on the value of R-squares.

The second study by Gadgil and Gadgil (2006) looked at the data between 1951 and 2004. It examined impacts of the deviation of the Monsoon rainfall from its long-run average on the deviations of GDP and agricultural production, and estimated that a 1% rainfall deviation leads to a 0.16% GDP deviation and 0.45% agricultural output deviation. With respect to changes over time, Gadgil and Gadgil (2006) confirmed that the Monsoon's impact on crop production is lower in the period 1981–2004 compared with that in 1951–1980, while they did not find a decline in rainfall's impact on GDP.

The economic development of India over the past six decades has been dramatic. The sectoral structure changed dramatically into a non-agrarian economy, with a plunge in agriculture's share in GDP from 52% in 1951 to 14% in 2013, although the decline of agriculture's share in employment is slower than its share in GDP: from 74% in 1960 (Binswanger-Mkhize, 2012) to 50% in 2013 (World Bank, 2015). In the expenditure phase, capital formation's share rose from 12% in 1952 to 32% in 2013, and private consumption's share decreased from 87% to 60% during the same period. The growth pace moved from the traditional low Hindu-growth of around 3–4% from the 1950s through the 1980s to high growth rates of over 8% in the mid-2000s (Basu and Maertens, 2007; Mohan, 2008). The source of growth is a topic of great debate, including the role of liberalization policy (e.g. p.16–21, Panagariya, 2008), investment and saving (e.g. Basu, 2008; Sultan and Haque, 2011), and productivity growth (e.g. Rodrik and Subramanian, 2004; Robertson, 2012). Most agree that the widespread reforms in the 1990s have sustained the high growth (Robertson, 2010).

Similarly, agricultural development has also been dramatic. Despite its declining share in aggregate output, agricultural production quadrupled to broadly match the demand for food due to population growth between 1950 and 2010, supported by the introduction of high-yield varieties, increased use of chemical fertilizer from the mid-1960s onwards (known as the 'green revolution'; see Cagliarini and Rush, 2011), and various market and land policy reforms, including those on distribution, access to finance, and subsidies (p.311–325, Panagariya, 2008). The improvements in water management over the decades, including an expansion of irrigated land, have mitigated the impact of rainfall fluctuation on production (Cagliarini and Rush, 2011). This development signals the changes in the agricultural sector's susceptibility to rainfall variability over the time. Trade liberalization after the 1991 reform is regarded as having helped agricultural exports through the depreciation of the Indian currency and the decline in the relative price of agricultural products relative to industrial products (Ahluwalia, 2002)

The linkage between agriculture and non-agriculture has been a recurrent theme in India's economic policy – stunted agricultural growth has been argued to have created barriers for industrial development even after the early 1990s and in recent years (Jha, 2010). The positive relationship between agricultural output per head and non-farm employment is verified by various studies (Coppard, 2001). The impact of rainfall on an individual's economic behavior is fundamental. The rural household male increases his hours of work to smooth income and hence consumption in response to unanticipated shocks (Kochar, 1999). Risk-sharing mechanisms intended to address weather shocks have also been developed. Some rural households address shocks by contingent transfers (Townsend, 1994; Morduch, 2005), enabled by spatially dispersed relatives due to rural-to-rural marriage migration (Rosenzweig and Stark, 1989), and, more recently, via rainfall insurance (Giné et al., 2008).

The development of India's business cycle in the past 60 years has also to be touched because an examination of GDP variability, even if the emphasis is on the association with rainfall, is fundamentally an examination of the business cycle. Ghate et al. (2013) examined the Indian business cycle from 1951 to 2010 with an emphasis on the changes before and after the 1991 reform. They asserted that the persistence of Indian economy has risen to the level of developed economies but that its volatilities remain at the level of developing economies in the post-reform period. Note that the business cycles of developing economies vary, but are generally more volatile and shorter than those of developed economies (Rand and Tarp, 2002; Agénor et al., 2000). The shorter persistence of developing economies is regarded to reflect their insufficient capacity to address economic shocks (Rand and Tarp, 2002).

Finally, it is worth noting that some studies are emerging addressing the growing risk of climate change in regard to India, particularly that the risk of low rainfall is rising in both of frequency and intensity. Kumar et al. (2013) examined the changes between 1901 and 2010, and concluded that droughts have become more frequent and intensive in the 1977–2010 period compared with the earlier period. Similarly, Sooraj et al. (2013) have asserted that the recent decade of 1998–2009 has had more drought events compared with the earlier two decades of 1979–1997 in Central India.

3. Developing an Empirical Framework

3.1. Basic Setting

Based on the review in the previous section, the following two-sector model is proposed. The aggregate production at year *t*, Y_t is composed of agricultural production, A_t, and non-agricultural production, N_t. The share of agriculture in total output is θ_t^a and that of non-agriculture is $\theta_t^n = (1-\theta_t^a)$.

$$Y_t = A_t + N_t \qquad \text{(eq.2)}$$
$$A_t = \theta_t^a Y_t \qquad \text{(eq.3)}$$
$$N_t = \theta_t^n Y_t = (1-\theta_t^a)\, Y_t \qquad \text{(eq.4)}$$

The productions of each sector are composed of the equilibrium or trend components $\hat{A}_t$ and $\widehat{N}_t$ and cyclical components a_t and n_t. The business cycles or growth cycles of each sector, $\tilde{A}_t$ and $\widetilde{N}_t$, can be calculated by cyclical components divided by trend components:

$$A_t = \hat{A}_t + a_t \qquad \text{(eq.5)}$$
$$\tilde{A}_t = a_t / \hat{A}_t \qquad \text{(eq.6)}$$

$$N_t = \widehat{N}_t + n_t \qquad \text{(eq.7)}$$
$$\widetilde{N}_t = n_t / \widehat{N}_t \qquad \text{(eq.8)}$$

The aggregate business cycle, which is defined by the same structure composed of a trend component ($\hat{Y}_t$) and cyclical component (y_t) as agriculture and non-agriculture, is a weighted average of each sector's business cycle by approximation using log linearization:

$$Y_t = \hat{Y}_t + y_t \qquad \text{(eq.9)}$$

$$\tilde{Y}_t = y_t / \hat{Y}_t \qquad \text{(eq.10)}$$

$$\tilde{Y}_t \cong \theta_t^a \tilde{A}_t + \theta_t^n \tilde{N}_t \qquad \text{(eq.11)}$$

As the equation below demonstrates, the cycle of agricultural production is assumed to be a function of weather shocks, w_t . The cycle of non-agricultural production is assumed to be a function of weather shocks (i.e. direct impact on non-agriculture), agricultural production reflecting the weather's impact on non-agriculture through agriculture, and its own past performances:

$$\tilde{A}_t = F(w_t) \qquad \text{(eq.12)}$$

$$\tilde{N}_t = F^N(w_t) + F^A(\tilde{A}_t) + F^{lag}(\tilde{N}_{t-1}, \tilde{N}_{t-2}, \ldots) \quad \text{(eq.13)}$$

3.1 Basic Empirical Framework

This subsection sets out the basic empirical framework to distinguish the direct impact of weather shocks on non-agriculture and indirect impact through a weather shock's impact on agriculture. The weather shock, $\tilde{w}_t$ is exogenous, independent and random. In the case study to follow, the deviation of rainfall from its trend will be the main target of the examination.

$$\tilde{w}_t = e_t^w (i.i.d) \quad \text{(eq.14)}$$

The impact of agriculture is estimated by the following equation:

$$\tilde{A}_t = \beta_A \tilde{w}_t + e_t^A (i.i.d) \quad \text{(eq.15)}$$

where β_A is a parameter capturing the impact of weather shock at time t, $\tilde{w}_t$. e_t^A is agriculture's own shock, not correlated with weather shock. **Equation 15** can be extended to include a lag operator of the past agricultural production or control variables. The cycle of non-agriculture is assumed as follows:

$$\tilde{N}_t = \beta_N^{direct} \tilde{w}_t + \alpha \ \tilde{A}_t + \rho_N \tilde{N}_{t-1} + e_t^N (i.i.d) \quad \text{(eq.16)}$$

where β_n^{direct} is a parameter grasping the direct impact of weather shocks on non-agriculture, and α captures the impact of agricultural production on non-agricultural production. Since α is a key parameter in terms of calculating how far the impact of weather on agriculture affects non-agricultural performance, it is named the 'transmission parameter' in the paper for brevity and convenience. ρ_N is the persistence of non-agriculture, and e_t^N is non-agriculture's own shock.

One of the issues in the framework is that it does not seem to account for an impact of a cyclical component of non-agriculture on that of agriculture, although it accounts for an impact of a cyclical component of agriculture on that of non-agriculture. However, this should not be taken to mean that it ignores the accumulated research on the importance of the rural non-farm economy (RNFE) in rural growth (e.g. Haggblade et al., 2010). The framework assumes that the impact of non-agriculture on agriculture should be captured in the long-run relationship, which is outside the scope of the framework, rather than cyclical components, which is inside of the scope. For instance, one of the crucial positive impacts of RNFE on agriculture is an increased investment in agriculture using non-farm income (ibid). As the investment is generally a long-term decision; people may utilize income from RNFE but not necessarily use their increased spending power immediately upon non-farm income increasing. On the other hand, the impact of agriculture on non-agriculture can be instantaneous, as agro-products serve as inputs in some non-agricultural goods, and non-agricultural production can be adjusted with expectation on agricultural performance, which affects the consumption of farmers generally consisting large part of labor in developing economies. In another aspect, the framework can be considered to assume that farmers produce as much as possible in a given condition and do not adjust production volume based on expectations regarding the performance of non-agriculture. Recall that the performance of non-agriculture is unforeseeable compared with agriculture, whose performance can be predicted to some extent based on weather conditions basically being visible to all players.

Equation 16 can result in biased estimates due to an endogeneity problem associated with $\tilde{A}_t$ and multicollinearity arising from a correlation between $\tilde{A}_t$ and $\widetilde{w}_t$. Therefore, the following equation is derived by substituting $\tilde{A}_t$ in **Equation 16**

with **Equation 15**:

$$\widetilde{N}_t = \left(\beta_N^{direct} + \alpha \quad \beta_A \right) \widetilde{w}_t + \rho_N \widetilde{N}_{t-1} + \alpha \quad e_t^A + e_t^N \qquad \text{(eq.17)}$$

Note that e_t^A can be obtained by estimating **Equation 14** and can be used as an explanatory variable in estimating **Equation 17**. Furthermore, the explanatory variables $\widetilde{w}_t$, $\widetilde{N}_{t-1}$, and e_t^A do not correlate with each other. In other words, multicollinearity and endogeneity are not a concern in the equation, although potential omitted variable bias remains a general concern. An estimation derived via **Equation 17** will provide the overall impact of weather shocks on non-agriculture, β_N^{total}, which is an aggregation of direct impact, β_N^{direct}, and indirect impact, multiplication of impact on agriculture, β_A and the impact transmission parameter, α . For convenience, indirect impact is denoted as $\beta_N^{indirect} (= \alpha \quad \beta_A)$ and therefore $\beta_N^{total} = \beta_N^{direct} + \beta_N^{indirect}$.

By estimating **Equation15** as a first stage and then **Equation 17** as a second stage, the parameters of β_A , β_N^{total} and α can be obtained. Using the results, the direct impact of weather on non-agriculture, β_N^{direct}, indirect impact, $\beta_N^{indirect}$, and impact on aggregate output, $\beta_t \left(= \theta_t^a \beta_A + \theta_t^n \beta_N^{total}\right)$, can also be obtained.

This two-stage approach is a way of avoiding a potential bias arising from the changing share of agriculture in total output. Note that it is more natural to assume that each of agriculture or non-agriculture has relatively constant susceptibility to weather shocks than to assume that the whole economy as an aggregation of agriculture and non-agriculture has constant susceptibility to weather shocks over the several decades.

The below equation is a variation of Equation 16, acknowledging that the changing share of agriculture relative to non-agriculture can also be a target of estimation:

$$\widetilde{N}_t = \beta_N^{total}\widetilde{w}_t + \rho_N\widetilde{N}_{t-1} + \alpha^{\prime}(\frac{\theta_t^a}{\theta_t^n})e_t^{A1} + e_t^n \quad \text{(eq.18)}$$

$$\beta_N^{total} = \beta_N^{direct} + \alpha^{\prime}(\frac{\theta_t^a}{\theta_t^n})\beta_A \quad \text{(eq.19)}$$

Note that θ_t^a and θ_t^n are known from GDP data. In the above equation, $\alpha^{\prime}$ should become more constant and fits more to an assumption of fixed value during the long period. On the other hand, the estimation of β_N^{total} by Equation18 imposing an constraint or assumption that the parameter is fixed, although the true structure is assumed to have an time-varying nature due to changing relative weight of agriculture to non-agriculture, $\frac{\theta_t^a}{\theta_t^n}$ as in **Equation 19**. This is a tricky point requiring careful treatment.

3.3 Extensions

Extension 1: Lagged Impact of Weather. The extension of the above basic case is a case where a lagged weather shock may influence agricultural production at time t. The below is a case where weather shock at t-1 has an impact:

$$\tilde{A}_t = \beta_A^T \widetilde{w}_t + \beta_A^{T-1} \widetilde{w}_{t-1} + e_t^A (i.i.d) \quad \text{(eq.20)}$$

where β_A^T is an impact of weather shock at time t and β_A^{T-1} is an impact of weather shock at time t-1 on agricultural production at time t. In this case, the second-stage equation is as follows:

$$\widetilde{N}_t = \left(\beta_N^{direct} + \alpha \ \beta_A^T\right)\widetilde{w}_t + \rho_N \widetilde{N}_{t-1} + \alpha \ (\beta_A^{T-1} \widetilde{w}_{t-1} + e_t^a) + e_t^n \quad \text{(eq.21)}$$

Given that weather shocks and agriculture's own shocks are i.i.d., the series $\beta_A^{T-1} \widetilde{w}_{t-1} + e_t^a$ should also be i.i.d. Therefore, the inclusion of the lagged impact of weather does not mean that endogeneity or multicollinearity issues affect the estimation of **Equation 17**. In reality, it could be the case, for instance, that the rainfall shock at time t-1 influences the water and soil conditions at time t, and therefore affects production at time t. The indirect impact of rainfall at t-1 on non-agriculture at t is captured by $\alpha \ \beta_A^{T-1} \left(= \beta_{N,t-1}^{indirect}\right)$.

Extension 2: Lagged Impact of Agricultural Production. The second extension is a lagged impact of agricultural production itself. This case entails some complexity in terms of the estimation. In a case where the first order lag has impact, the first-stage equation is as below, where ρ_A captures the persistence of agricultural production:

$$\tilde{A}_t = \beta_A^T \widetilde{w}_t + \rho_A \tilde{A}_{t-1} + e_t^A (i.i.d) \quad \text{(eq.22)}$$

This case, for example, assumes that the production at time t-1 affects production at t via affecting the volume of seeds remained and available for time t production. In this case, the second-stage equation will become:

$$\tilde{N}_t = \left(\beta_N^{direct} + \alpha \quad \beta_A \right) \tilde{w}_t + \rho_N \tilde{N}_{t-1} + \alpha \, \rho_A \tilde{A}_{t-1} + \alpha \quad e_t^a + e_t^n \quad \text{(eq.23)}$$

This equation will require more careful treatment because of endogeneity issues for $\tilde{A}_{t-1}$. The Instrumental Variable method using $\tilde{w}_{t-1}$ as an instrument for $\tilde{A}_{t-1}$ is a candidate for resolving such issues.

4. India, 1952–2013: A Case Study

This section will apply the empirical framework set out in the previous section to assess the impact of rainfall variability on India's agricultural and non-agricultural production during the period 1952–2013 in order to demonstrate its validity. After processing the data in subsection 4.1, two econometric exercise will be conducted. The first exercise will estimate the average impact of rainfall variability during the period by GLS (subsection 4.2). The second exercise will estimate the time-varying impact using a Kalman filter in subsection 4.3. The following subsection will discuss the issues associated with the exercise results. While the major topic of interest is rainfall variability, the research also touches on the impact of temperature shocks where appropriate, given the growing interest in this impact on the economy.

4.1. Data Processing and Description

The data to be examined are all annual and cover the years 1952 to 2013. Economic data were downloaded from the website of the Reserve Bank of India. Aggregate output and agricultural output data were taken from GDP at factor cost series, and non-agriculture data is derived by subtracting agricultural output from aggregate output. These are all based on the Fiscal Year 2004 constant price. Monsoon data is taken from the website of the Indian Meteorological Department, Ministry of Earth Sciences. The precipitation between June and September of each year is used.[1]

All the series are transformed into deviations from trends by Hodrick-Prescott (HP) filters, in the same way as Virmani (2006) employed, to avoid spurious results caused by the rising trends of economic variables and temperatures. Despite some caveats, such as the end-point problem, the HP filter is a widely used method for de-trending. Following Ravn and Uhlig (2002), multiplier λ is set to 100. The reason that the annual growth rates are not adopted is that they have a trend and can induce spurious regression results. On the other hand, deviations from trends are also more neutral to consecutive events – such as two consecutive rainfall shortages two years in a row – than growth rates. The deviations are calculated using the following equation:

$$x^{i} = x^{i,trend} + x^{i,cyclical} \qquad \text{(eq. 24)}$$

$$x^{i,deviation\ from\ trend} = x^{i,cyclical} / x^{i,trend} \qquad \text{(eq. 25)}$$

[1] Rainfall data comes from the Indian Meteorological Department, Ministry of Earth Sciences. http://www.imd.gov.in/section/nhac/dynamic/data.htm (accessed January 2016)
GDP data relies on ‘Handbook of Statistics on Indian Economy 2013-14’ compiled by the Reserve Bank of India. https://www.rbi.org.in/scripts/AnnualPublications.aspx (accessed January 2016)

where x^i are the variables of interest: rainfall, temperature, total output, agricultural output and non-agricultural production. The reason for using HP-filtered rainfall deviation rather than the raw data disclosed by the Indian Meteorological Department is simply because of the conformity of a processing method among data series used in the exercise. The filtered series is almost the same as the data disclosed by the Department; the only exception is the temperature series, which used the $x^{i,cyclical}$ to enable the comparison with existing works, which mostly estimate the marginal impact of 1 Celsius degree. Note that the level of the cyclical components of temperatures is unchanged throughout the examined period (unlike as is the case for economic variables) and there is no need for normalization by **Equation 25**.

Table 1 illustrates the statistical characteristics of the processed series. The means of all the series are almost zero and results of the Augmented Dickey-Fuller test demonstrate that all the series are well de-trended and stationalized. The levels of calculated volatilities are roughly similar to those in Ghate et al. (2013), which are calculated by annual growth rates rather than HP-filtered series. June-to-September rainfall has the highest volatilities among the five series.

Rainfall variability has a significant positive correlation with agriculture at 0.77 (t=9.35) and with aggregate output at 0.57(t=5.38), while it has an insignificant positive correlation with non-agriculture at 0.19 (t=1.49). Agriculture has a significant positive correlation with non-agriculture at 0.31 (=2.54) and aggregate output at 0.79 (t=10.21). Non-agriculture has a positive significant correlation with aggregate output at 0.80(t=10.48). (**Table 2**)

When rainfall drops below 10% of the long-term trend the situation is categorized as a drought in the case of India (Gadgil and Gadgil, 2006). Therefore, the impact of rainfall variability will basically be shown as the impact of a 10% positive or negative deviation from the trend, unless otherwise stated.

4.2. Average Impact, 1952–2013

This section implements the estimation of the average impact of rainfall on macroeconomics during the period 1952–2013 using the empirical framework developed in section 3 and the data as set out in subsection 4.1. Pondering some volatility decline in the examined series over time, GLS estimation will be employed rather than OLS to address the potential concerns on heteroskedasticity. Note that the two-stage approach does address the issue of the rapidly changing share of agriculture and non-agriculture in total output, although the changing nature of the parameters themselves is not addressed. The estimation basically returns the average effects during the years 1952 to 2013.

The results of the first-stage equation (i.e. **Equation 15, 20, 22**) are shown in

Table 3. The estimated impact of rainfall variability at time *t* on the agricultural production cycle at time *t* is significant at 1% in all specifications. The lagged rainfall variability term is also significant at 5% on agricultural production at time t. On the other hand, lagged agricultural production is not significant at 5%. The fitness measured by adjusted R-squares is also high at around 60% in the specifications including the rainfall variability term, but low in the other specification.

Turing to the magnitude of the impact, the 10% negative rainfall deviation at time t is associated with a 3.1–3.2% negative deviation in agricultural production at time t. This is lower than the results of Virmani (2006) at 3.6% and Gadgil and Gadgil (2006) at 4.5%, presumably due to the addition of the recent 10 years (i.e. 2003/04–2013 into the examined sample, where resilience to rainfall variability should have increased due to irrigation and other developments. The 10% negative deviation of lagged rainfall variability is associated with a 0.7% negative deviation in agricultural production from the trend.

Given the increasing attention on the impact of temperature shocks on the economy, a specification incorporating temperature’s deviation from its trend is also conducted. This finds that it is significant at 1% when it is solely included but the fitness is not high, suggesting that temperature variability has much less explanatory power than rainfall variability in regard to the agricultural production cycle.

Furthermore, this specification has significant omitted variable bias due to the exclusion of the rainfall variability term. The temperature variability term is also significant at 5%, when it is included with the rainfall variability term. However, correct measurements of each parameter for rainfall and temperature can be difficult because of multicollinearity arising from the correlation between high temperatures and low rainfall variability in the Monsoon season (**Table 2**). The lower impact of rainfall variability in the specification with temperature variability could be a result of this multicollinearity. Based on the high explanatory power of rainfall compared with temperature and the concerns by the multicollinearity issue, the rest of the exercise will focus solely on the impact of rainfall variability as a representative variable for weather shocks with respect to agricultural performance.

A comprehensive robustness check covering the whole of the two-stage estimation will be set out later by conducting a simulation using formulated hypothetical series to test if the estimation captures the true values of the parameters. Here, I present only two regular robustness checks of the first-stage estimation. The first is on the omitted variable bias. To address the concern, specifications with the addition of inflation measured by Consumer Price Index and Wholesale Price Index and irrigation and arable land expansions are tried. However, none of the added variables are significant at 5%, and therefore the results are not shown in order to save space. The second is a residual test. The statistical nature of the residuals in the first-stage estimation is shown in **Table 4**. Their means are almost zero. They do not correlate with the explanatory variable of rainfall deviation. The null hypotheses of having normal distribution, homoskedasticity, and no serial correlation are not rejected by Jarque-Bera test, the White test or the Lagrange multiplier (LM) tests, respectively for all the specifications with the exception of the normal distribution test for the **A-3** specification – which only includes lagged agricultural production cycle term – and is outlined in **Table 3**.

Based on the results of the first-stage estimation demonstrating high explanatory power and the robustness of rainfall variability terms, the **A-1** and **A-2** specifications – whose explanatory variables are rainfall variability – will be chosen to be used for the second-stage estimation from among the six specifications in **Table 3**. Specifically, the second-stage exercise conducts the estimation of **Equation 17** exploiting the results of the **A-1** specification and that of **Equation 21** exploiting the results of **A-2** specification. Furthermore, variations to account for the changing relative weight of agriculture and non-agriculture like **Equation 18** in case of **Equation 17** will also be conducted. In sum, the above mentioned four specifications will be conducted in the second stage. Note that direct impact of rainfall at time t-1 on non-agriculture is not assumed and not estimated in any specification, while **Equation 17** and **Equation 21** account for the indirect impact of rainfall variability at time t-1 through its impact on non-agriculture.

The estimated results of the second-stage estimation for non-agriculture are displayed in **Table 5**. All of the explanatory variables, rainfall, the transmission parameter from agriculture to non-agriculture, and the persistence of non-agriculture, are significant at 1% and all the four specifications return very similar results.

However, the LM tests for the residual of the second-stage equation suggest there is a possibility of serial correlation (**Table 6**). Therefore, the specifications of the with-MA(1) term are also tested. The results are shown in **Table 7**, which cleared the residual tests including LM tests as shown in **Table 8**. Note that other tests for the residuals than LM test are cleared both in without MA(1) specification as showed in **Table 6.** In specific, their means are almost zero; They do not correlate with the explanatory variable of rainfall deviation, lagged non-agricultural production, and agricultural unique shocks; The null hypotheses of having normal distribution and homoskedasticity are not rejected by the Jarque-Bera test or the White test respectively.

Rainfall variability has a significant impact on non-agriculture at the 1% significance level. The magnitude of the impact on non-agriculture in the with-MA(1) specification estimation is as follows. The 10% negative rainfall deviation from its trend at time t lowers the non-agricultural production at time t by 0.46–0.53% from its trend, which is roughly one-sixth of rainfall variability's impact on agriculture. The indirect impact of rainfall variability at time t, which captures the impact on non-agriculture through rainfall's impact on agriculture, dominates and in fact slightly exceeds the overall impact of rainfall, ranging between 0.47% and 0.58%. The estimation results using the without-MA(1) specification are very similar for the overall impact and for the indirect impact in both significance and magnitude.

On the other hand, the direct impact turns out to be negative in three out of four specifications using the with-MA(1) specifications and positive in all of the specifications using the without-MA(1) specification as well as one of the with-MA(1) specifications, although their magnitudes are marginal, ranging between negative 0.05% and positive 0.02% as the impact of 10% positive deviations. Therefore, the direct impact should be judged as being marginal. In fact, the time-varying estimation in the next subsection will show that it changes over time from negative to positive. This is also why the signs of the direct impact of rainfall variability on non-agriculture are sensitive to specifications as well as the reason that the magnitude of the impact is marginal.

Based on the two-stage estimation results of rainfall's impact on agriculture and non-agriculture, the overall average impact of rainfall variability on GDP during the period 1952–2013 can be calculated. Using the average share of agriculture (33%) and non-agriculture (67%) in GDP during these years, the average impact of 10% positive rainfall deviation at time t on GDP during 1952 to 2013 is positive 1.4%, which is roughly similar to the results seen in the previous works by Virmani (2006) and Gadgil and Gadgil (2006), which showed 1.6%. Combined with the lagged rainfall's impact on agriculture at 0.3%, the average overall impact during 1952 to 2013 on GDP is 1.7%.

A Further Robustness Check by Simulation. Since the two-stage estimation framework developed in the present paper is unique, simulations are also conducted to check if the two-stage empirical framework can estimate the unbiased true parameters if the assumed structure is correct. Specifically, one-thousand series of rainfall variability, agriculture business cycle, and non-agriculture business cycle are produced, using functions of econometric software to produce random shocks whose sizes are similar to actual data sets. Then, the two-stage estimations are conducted to check if the true values are estimated. The results demonstrate that the average estimated values are very close to the true values and the estimations are valid (see the **Appendix** for details of the simulation).

4.3. Time-Varying Impact, 1952–2013

The previous section's empirical framework imposes the assumption that parameters are fixed during the examined period between 1952 and 2013. However, it is natural to assume that the parameters are also time-varying. As reviewed in **section 2**, the resilience of agriculture to rainfall variability should have increased due to irrigation developments and other water management improvements, and the transmission parameter should be changing due to dramatic changes in relative weight of agriculture to non-agriculture. Therefore, this section will estimate time-varying parameters by employing the Kalman filter technique following Hamilton (1994). Based on the results seen in **subsection 4.2**, two basic specifications are chosen. The first specification includes only contemporaneous weather terms and is named the '*without lag*' pattern. The observation equations for the first set are below, which are modifications of **Equation 15 and 17**:

$$\tilde{A}_t = \beta_{A,t}\widetilde{w}_t + e_t^A \sim NID(0,\sigma^A) \quad \text{(eq.26)}$$

$$\widetilde{N}_t = \beta_{N,t}^{total}\widetilde{w}_t + \rho_{N,t}\widetilde{N}_{t-1} + \alpha_t\ e_t^a + e_t^n \sim NID(0,\sigma^N) \quad \text{(eq.27)}$$

The state equations are below:

$$\beta_{A,t+1} = \beta_{A,t} + v_t^A \sim NID(0,\sigma^{vA}) \quad \text{(eq.28)}$$

$$\beta_{N,t+1}^{total} = \beta_{N,t}^{total} + v_t^N \sim NID(0,\sigma^{vN})(\mathrm{NID}) \quad \text{(eq.30)}$$

$$\rho_{N,t+1} = \rho_{N,t} + v_t^\rho \sim NID(0,\sigma^\rho)(\mathrm{NID}) \quad \text{(eq.31)}$$

$$\alpha_{t+1} = \alpha_t + v_t^\alpha \sim NID(0,\sigma^\alpha)(\mathrm{NID}) \quad \text{(eq.32)}$$

The second specification below is a modification of **Equation 20** and **21**:

$$\tilde{A}_t = \beta_{A,t}^{T}\widetilde{w}_t + \beta_{A,t}^{T-1}\widetilde{w}_{t-1} + e_t^A \sim NID(0, \sigma^{A'})(i.i.d) \quad \text{(eq.33)}$$

$$\widetilde{N}_t = \beta_{N,t}^{total}\widetilde{w}_t + \rho_{N,t}\widetilde{N}_{t-1} + \alpha_t\,(\beta_{A}^{T-1}\widetilde{w}_{t-1} + e_t^a) + e_t^n \sim NID(0, \sigma^{N'}) \quad \text{(eq.34)}$$

The state equations are the same for $\rho_{N,t}$, $\beta_{N,t}^{total}$ and α_t , and those for $\beta_{A,t}^{T}$ and $\beta_{A,t}^{T-1}$ are as follows:

$$\beta_{A,t+1}^{T} = \beta_{A,t}^{T} + v_t^{A,T} \sim NID(0, \sigma^{vA'}) \quad \text{(eq.35)}$$

$$\beta_{A,t+1}^{T-1} = \beta_{A,t}^{T-1} + v_t^{A,T-1} \sim NID(0, \sigma^{vA"}) \quad \text{(eq.36)}$$

The decomposition of overall impact on non-agriculture to direct and indirect impacts, and the aggregation to get the overall impact, follows the same procedure as was undertaken in subsection 4.2. Note that the accounting changing relative weight of agriculture to non-agriculture is no more needed (as done in **subsection 4.2)** because the parameters themselves are allowed to alter this subsection's excercise. Note also that the MA(1) term is not added in the second-stage estimation for non-agriculture in order to simplify the estimation. This is allowable, given that the results for the overall estimation for rainfall variability term were similar in the previous subsection's exercise.

Following the standard procedure, the sizes of innovation variance terms (i.e. σ), which minimize the prediction errors for parameters are estimated by maximum likelihood estimation . The results, especially the trends of parameters over time, are plausible as will be demonstrated later. However, the estimated parameters are generally higher than those of the GLS estimation in the previous section as will be shown later, suggesting there is a possibility of overestimation. Therefore, larger sizes of innovation variance, which keep the significance at 5% for the parameter estimation, rather than the size of innovation variance estimated by standard procedures, are also tried to assess the susceptibility of results to the innovation size for reference purposes. Note that larger innovation variation enables us to follow the changes in parameters more quickly and vividly. For convenience, the estimation with the larger innovation variance is named the ‘flex’ pattern, and those using the standard procedure are termed the ‘steady’ pattern in this paper.

In sum, the following four specifications will be tried: ‘steady without lag’, ‘flex without lag’, ‘steady with lag’, and ‘flex with lag’. The results will be shown for each category of rainfall variability’s impacts on agriculture, non-agriculture and then those on GDP in **figures 1 to 8**. In the figures, the results between 1965 and 2013 are shown as the results before 1965 are volatile (i.e. taking some to converge to plausible results), as is often seen when employing a Kalman filter estimation. The comprehensive estimated results are shown only for steady patterns in **Table 9** and **Table 10**, while those for flex patterns, which are conducted for reference purpose, are not shown to save space.

Agriculture. The results of estimating the time-varying impacts of rainfall variability on agricultural production are demonstrated in **Figure 1**. All four patterns demonstrate that the impacts of 10% positive rainfall deviations are elevated to a high of roughly 4% in the late 1970s to early 1980s, and then decline thereafter. The speed of the decline in the flex patterns is faster than that of the steady patterns, as would be expected. The impacts drop to 2% in recent years in the case of the flex pattern, while the steady pattern remains higher at 3% in recent years. The impact of the previous year's rainfall shock (i.e. 10% positive deviation) on agricultural production has continuously decreased from roughly 1.0% to 0.7% in all of the four patterns. This decline in rainfall's impact on agriculture over time is consistent with the findings of Gadgil and Gadgil (2006).

The fluctuations of the above rainfall impacts on agriculture can be interpreted consistently with India's agricultural developments. What follows is a chronological interpretation of such a circumstance. The lower sensitivity to rainfall shocks in the early 1960s can be associated with a massive expansion of sown areas. The expansion of cropland was sustained at a high pace in the 1950s and the early 1960s, and the agricultural production increase prior to the early 1960s was largely due to the expansion in sown areas (Singh, 2000). Thus, additional production in newly cultivated areas may have alleviated or sometimes negated the negative impact of rainfall shortage. From the late 1960s and into the 1970s, a new agricultural strategy of adopting high yielding variety (HYV) seeds, chemical fertilizers, and irrigation facilities called the 'Green Revolution' was implemented to achieve self-sufficiency in food grain (ibid). Since HYV seeds' production performance is susceptive to water conditions, sensitivity to rainfall variability surged and remained high with the increased use of HYV seeds in the late 1960s and 1970s. From the early 1980s, however, susceptibility to rainfall variability decreased steadily as the benefits from the continuous increase in irrigated croplands from the 1970s to the 1990s became visible, overwhelming the increased susceptibility to water conditions due to the increased use of HYV seeds. Agricultural investment is known to have dropped in the early to mid-1980s, due to the decline in public investment resulting from the deterioration in fiscal conditions, but started picking up in the late 1980s and 1990s due to the in surge private investment (Gulati and Bathla, 2001).

Non-Agriculture. The overall impact of rainfall variability on non-agriculture in all the four patterns are similar in trends. The overall impact started to increase in the early 1970s and accelerated in the late 1970s. It continued to increase at a slow pace until the mid-2000s, then dropped in 2009 and has remained at a lowered level until in early 2010s. Focusing on the steady pattern, the detailed results are as follows. The overall impact of 10% positive deviations increases rapidly from a low of 0.4% in the 1960s to over 0.6% in the late 1970s, reaching its peak in the mid-2000s at 0.8% and dropping to 0.7% in 2009 (**Figure 4**). The positive overall impact of rainfall variability is supported by the sustained high indirect impacts (i.e. the impact on non-agriculture through rainfall's impact on agriculture) marked at roughly above 1.0% in the 1970s and 1980s, which decline steadily after the 1990s reaching below 0.6% in the 2000s and early 2010s (**Figure 5**). The indirect impact's decrease is also supported by a continuous decline of the transmission parameter as it is the impact on agriculture multiplied by the transmission parameter (**Figure 2**). On the other hand, the direct impact of the 10% positive rainfall deviation steadily increased from the negative values at below negative 0.5% in the 1960s, turning positive in the early 1990s and reaching 0.3% in the 2000s, with a drop to 0.2% in the early 2010s (**Figure 6**).

There are two key points in the above results. Firstly, the pattern of the direct impact on non-agriculture lags behind the impact on agriculture and indirect impact on non-agriculture by almost two to three decades. This lag can be associated with the slow belief formation process of Indian people in regard to the impact of rainfall on the economy, which will be discussed further in the next subsection. Secondly, the direct impact on non-agriculture changed from negative values in the 1960s to 1980s to positive values in the 1990s to 2010s. The negative value can be interpreted as a result of natural disasters and underdeveloped infrastructure in the country. An interpretation of the positive direct impact will be discussed further in the next subsection, as it is not straightforward.

The Aggregate Impacts on GDP. The overall impacts of rainfall variability on GDP can be obtained by aggregating the results on agriculture and non-agriculture by their respective share in GDP. **Figure 7** demonstrates the results for the steady pattern without lag and **Figure 8** for the steady pattern with lag. The results vividly depict the dynamism of the changes in the weather–economy relationship. The key chronological stories that the aggregated results reflect are as follows. The direct impact on agriculture and its transmission to non-agriculture grew in the 1960s and remained high until the late 1970s, and declined thereafter. Despite the reduced share of agriculture in GDP since the 1980s, agriculture-related impacts of rainfall variability dominate rainfall variability’s impact on the economy as a whole throughout the examined period. On the other hand, the direct impact of rainfall variability on non-agriculture was negative until the 1980s, being vulnerable to natural disasters due to underdeveloped infrastructure. The direct impact on non-agriculture becomes positive in the 1990s and remains so thereafter. In sum then, the impact on non-agriculture is confirmed but a large part of it is rooted in agriculture-related impacts.

4.4 Discussions

This subsection discusses three issues, which are associated with the previous subsection's results on the time-varying impacts.

4.4.1 The Positive Direct Impact on Non-Agriculture and People's Beliefs

The interpretation of a 'positive' direct impact of rainfall variability on non-agriculture is difficult compared with the more straightforward interpretation of negative shocks as a result of natural disasters and underdeveloped infrastructure. The increase of resilience to rainfall shocks through infrastructure development at a maximum only explains changes from negative values to zero. Moreover, it is also not straightforward compared with the indirect impact of rainfall on non-agriculture, which can be considered a natural result of the strong linkage between agriculture and non-agriculture in India.

One of the candidates to explain the positive direct impact is the impacts of rainfall variability information on people's expectations. If people expect good economic performance due to positive rainfall shocks, people may consume and produce more when they see the rainfall shocks. For instance, farmers may consume more in anticipation of future increased income, and non-farm employers produce more due to them expecting more consumption by farmers. The crucial nature of rainfall that it is visible to all people, a fact further augmented by the media's Monsoon reporting, could be a reason why the impact of rainfall variability on people’s expectations can be strong.

If the direct positive impacts are due to people’s expectations, the direct impact can be considered a kind of error arising from the difference between expectations formed by information on rainfall precipitation and its actual impact on agriculture and non-agriculture. This is consistent with the results that indirect impact is much larger than the direct impact. Note that indirect impact captures the impact of ‘actual’ agricultural production on non-agriculture, while other factors related to weather shocks such as the impact of rainfall variability on people’s expectations are not necessarily captured as the indirect impact as understood from the structure of **Equation 16.**

If the direct positive impact on non-agriculture is associated with the rainfall shock’s impact on people’s expectations, how can we interpret the lagged peak of the direct impact compared with that of indirect impact? The indirect impacts peak in the late 1970s and early 1980s, while the direct impact continued to improve to reach a peak in the mid-2000s. Furthermore, the increase of the direct impact in the 1980s, 1990s and early 2000s occurred when the indirect impacts declined continuously.

The lagged peak could be associated with the notions that people’s beliefs change slowly. People expects based on their belief on how rainfall variability affects economy. Lybbert et al. (2007), who examined how people update their beliefs on rainfall performance in Ethiopia and Kenya, argued that people's beliefs take time to alter, even if they are exposed to new information and especially when that new information is ambiguous. This is called confirmation bias. In the case of India, it is natural to assume that people's beliefs were built slowly and steadily through people's experience of an economy in which agriculture's share was high and where the linkage between agriculture and non-agricultural production was growing, such as was seen in the 1970s and 1980s. However, it takes time for people to update their beliefs because assessing the extent of the influence of a reducing agricultural share is difficult for most individuals. Indeed, new information on the reduced share of agriculture in the economy is ambiguous in the sense that how far people should take account of it to make economic decisions is not clear. It is worth recalling that agriculture's impact on non-agricultural production is real for people, even if people recognize the declining importance of agriculture in the economy. If people react to rainfall information based on past experience or old information, the economy may overreact to rain fluctuations and the Monsoon's impact can remain high compared with the real production structure.

4.4.2 The Impact of Temperature on Non-Agriculture

The second candidate to explain the positive direct impact of rainfall shocks on non-agriculture is the possibility that the rainfall shock functions as a proxy for temperature shocks. In India, a precipitation shock is negatively correlated with a temperature shock in the Monsoon season (**Table 2**). Therefore, the positive impact of positive rainfall shocks could be a result of the negative temperature shocks such as increase in productivity or decrease in mortality (Dell.et al. 2014)

The negative impact of high temperatures on the economy is a plausible hypothesis. However, **Figure 9**, which illustrates the residuals of the AR1 estimation for non-agriculture's cyclical component and temperature shocks (i.e. temperature for the all-year average de-trended by the HP filter), raises some difficulties in terms of adopting and even examining the hypothesis. The relationship between temperature shocks and non-agriculture's performance is roughly negative in the pre-1991 reform period, but roughly positive after the 1991 reform. Thus, there emerges the possibility that a high temperature shock can be associated with high growth.

Here, the second-stage equation (**Equation 17**) will be extended as below to include the temperature shock in order to directly examine if it has a positive relationship in the post-1991 reform period:

$$\widetilde{N}_t = \beta_{N,t}^{total}\ \beta_N^{total}\widetilde{w}_t + \rho_N\widetilde{N}_{t-1} + \alpha\ \ e_t^A + \beta_n^{temp1990} * dummy1990 * \tilde{T}_t +$$

$$\beta_n^{temp1991} * dummy1991 * \tilde{T}_t + + e_t^N \qquad \text{(eq.37)}$$

where $\tilde{T}_t$ denotes deviations of temperature from its trend, and 'dummy1990' and 'dummy1991' are standard dummies being composed of zeros and ones. $\beta_n^{temp1990}$ captures the impact of a temperature shock on non-agriculture's performance until 1990, and $\beta_n^{tem\ \ 1990}$ captures it after 1991. Unlike the exercise done for the impacts of temperature shocks on agriculture, the all-year average temperature shocks rather than June-to-September temperature shock will be basic case to match the purpose of the exercise as well as to avoid multicollinearity arising from the negative correlation between rainfall deviation and temperature in the Monsoon season. Furthermore, to address the serial correlation issue, the specification with MA1 is also included. The estimation is done by OLS for the with-MA1 specification and by GLS for the without-MA1 specification using data from the entire period, 1952 to 2013.

The estimation results are shown in **Table 11** and residual test results are shown in **Table 12**. The residual shock tests and the abovementioned multicollinearity issue suggests that the **T-1** specification with the all-year average temperature and MA1 term is the most reliable result. As expected from the figure, it shows that temperature shock and non-agricultural performance had a negative relationship until 1990, which is consistent with the hypothesis of the negative shock of high temperature represented by a decrease in labor productivity, although it should be noted that this was statistically insignificant. On the contrary, after 1991, the relationship between the two becomes positive and significant at the 5% level. A 1 Celsius degree positive deviation leads to an increase of 2.7%. In fact, the magnitude is almost double the negative impact of temperature shocks on annual aggregate growth that was demonstrated by Dell et al. (2012) at -1.3%. Combined with the exercise in subsection 4.2, a high temperature shock has asymmetric impacts on agriculture and non-agriculture, i.e. a negative impact on agriculture and a positive impact on non-agriculture.

Examining the underlying mechanisms of the emerging positive relationship between temperature shocks and non-agriculture is beyond the scope of the present paper. The relationship will need to be fully examined in future research. Here, two notes are made. First, one of the possible factors is a positive correlation between a higher temperature and higher heat-related consumption, such as energy consumption for electric fans and air conditioners and the sales of these commodities. This phenomenon has been empirically identified in the case of Japan, especially among investors, and sometimes government officials attribute a low performance in the summer season to a lower-than-trend temperature. It is worth recalling that the average summer temperature in Japan is approximately the same as the all-year average temperature in India, and more than 90% of households in Japan have air conditioners. Of course, the distribution rate for air conditioners and electric fans in India is much lower than is the case in Japan, but nonetheless there emerges the possibility that India has started to have a more Japan type industrialized temperature–economy structure. Second, this demonstrates that the assessment of the positive impacts of a low temperature shock on productivity becomes more and more difficult from the macro-data analysis in the case of India, masked by the negative impacts of a low temperature on the economy through energy and other temperature-related consumption.

4.4.3 The Structural Change as Source of Persistent Increase

Finally, the results suggest that the country's structural change into a non-agrarian economy could be a major source of the persistent increase seen in the Indian economy. Firstly, the time-varying estimation shows that persistence remains at a similar level, in the range of 0.64 to 0.74 over the past six decades (**Figure 3**). On the other hand, the GLS estimation results show that the persistence of agriculture is not significant. This is consistent with Ghate et al.'s (2013) demonstration that the persistence measured as the first order correlation of GDP increased from 0.045 during 1950 to 1991 to 0.716 during 1992 to 2010. Namely, the persistence of aggregate output increased from the level of agricultural sector's persistence to the level of non-agricultural sector's persistence. Thus, the majority of the persistence increase in India can be explained by the increase of non-agriculture's share in aggregate output.

This demonstrates the necessity to revisit the view of Rand and Tarp (2002), one of the cornerstone studies on developing countries' business cycles, that the shorter business cycle of developing countries reflects their 'insufficient capacity to counteract exogenous influences'. The results of the current paper instead suggest that the shorter cycles seen in developing economies are simply due to the larger share of agriculture in the economy and how susceptive that particular sector is to weather shocks. A room which can be explained by limited capacity can be more limited in case of India and can be similar to some extent in other developing economies.

5. Concluding Remarks

Understanding the weather and climate's impact on the economy in the context of macroeconomic dynamism is necessary in terms of our future ability to properly design and use our limited resources to implement adaptation and mitigation efforts and to enhance the functional form in the integrated assessment model for weather-economy relationship. The present paper has developed an empirical framework composed of two-stage estimations (the first for agriculture, and the second for non-agriculture) and that is applicable to macro-level data to distinguish the impact of weather shocks on agriculture, the direct impacts of weather shocks on non-agricultural production, and the indirect impact on non-agricultural production through the weather shock's influence on agricultural production. The results can be aggregated to assess the impact of weather shocks on aggregate output. This is a crucial methodological advancement in the climate–economy literature, helping us to better understand the underlying mechanism of weather's impact on the economy and enhances our understanding of the weather shock's impact in changing developing countries transitioning into non-agrarian economic structures.

The present paper applied the developed framework to assess the impact of rainfall variability on the macroeconomic performance of India during the period 1952–2013, employing GLS to estimate the average impacts and the Kalman filter technique to estimate the time-varying impacts during these years. In addition to the impact of rainfall impacts on agriculture, the GLS estimation demonstrates that the majority of the impact on non-agriculture is rooted in rainfall's impact on agriculture, suggesting that adaptation measures supporting agriculture can also help non-agriculture. The Kalman filter estimation vividly depicted the changing relationship between the weather and the economy, underlining the decline of the agriculture-rooted impact of weather shocks on the economy over time and the changes in the direct impacts on non-agriculture from negative to positive values. Although the present paper measured the magnitude of direct impact on non-agriculture, distinguishing it from the indirect impact, exploring the specific mechanisms by which weather shocks directly affect non-agricultural sectors' economic performance remains a key issue for future research. Explaining how and why temperature shocks have a positive relationship with recent non-agricultural economic performance in India is also an issue for future research.

As a byproduct, the present paper found that a major part of the persistence increase seen in the Indian economy over the past six decades can be associated with the structural change into a non-agrarian economy, which highlights the need to revisit the established view that the shorter business cycles of developing economies are largely due to their insufficient capacity.

In conclusion, the present paper has contributed to the advancement of the weather–economy literature in terms of our understanding of the underlying mechanism of weather shock's impact in a macro-dynamic context by enabling a distinction to be made between the direct and indirect impacts of weather shocks on non-agriculture, laying the groundwork for important further research.

(fin.)

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Table 1: Characteristics of the Calculated Deviations from Trends during 1952-2013

	Rainfall	GDP	Agriculture	Non-Agriculture	Temp	Temp69
Mean	-0.0004	0.0006	(0.0000)	0.0012	-0.0005	-0.0019
Median	0.0180	(0.0005)	0.0019	(0.0005)	-0.0362	-0.0239
Maximum	0.2245	0.0497	0.0707	0.0469	0.7629	0.6341
Minimum	-0.2008	(0.0455)	(0.1043)	(0.0489)	-0.4957	-0.5037
Std. Deviation	0.0933	0.0227	0.0371	0.0211	0.2219	0.2135
ADF test statistic (t value)	-5.42***	-5.53***	-8.49***	-2.97***	-6.66***	-9.86***

Note1: The series except temperature is deviation from trend normalized by its trend level. Temperature series are raw deviation from trend in Celosias Degree.

Note2: () implies negative value; 'ADF test' implies Augmented Dickey-Fuller test; *** implies significant at 1%.

Table 2: Correlation of Economic Indicators and Weather Shocks in Deviations from Trends between 1952-2013

	Rainfall	Temp (All year)	Temp (Jun-to-Sep)	GDP	Agriculture	Non-Agriculture
Rainfall	1.000 -					
Temperature (all year average)	-0.076 (t=-0.59)	1.000 -				
Temperature (June-to-September)	-0.29** (t=-2.36)	0.642*** (t=6.50)	1.000 -			
GDP	0.570*** (t=5.38)	-0.061 (t=-0.47)	-0.27** (t=-2.20)	1.000 -		
Agriculture	0.770*** (t=9.35)	-0.164 (t=-1.29)	-0.39*** (t=-3.30)	0.797*** (t=10.21)	1.000 -	
Non-Agriculture	0.189 (t=1.49)	0.014 (t=0.11)	-0.118 (t=-0.92)	0.804*** (t=10.48)	0.311** (t=2.54)	1.000 -

Note: 't' implies t-statitics; *** Significant at 1%; * *Significant at 5%.

Table 3: The Results of the First Equation on Impact of Weather on Agricultural Cycle

	Rainfall		Agr	Temp69	Temp all	Adj-R2
	T	t-1	t-1	t	t	
A-1	0.309*** (z=9.43)					0.593
A-2	0.323*** (z=9.87)	0.065** (z=2.01)				0.619
A-3			-0.095 (z=-0.74)			0.009
A-4	0.318*** (z=9.33)		0.107 (z=1.25)			0.593
A-5				-0.068*** (z=-3.33)		0.153
A-6	0.286*** (z=8.66)			-0.032** (z=-2.21)		0.624
A-7					-0.028 (z=-1.31)	0.027
A-8	0.306*** (z=9.36)				-0.017 (z=-1.31)	0.604

Note1: Rain implies rainfall deviation from trend, agr implies agriculture's deviation from trend.
Note2: 'z' implies z-statitics; *** Significant at 1%; * *Significant at 5%.

Table 4: The characteristic of agricultural own shocks

	Mean	Stdev	Jaque-Bera	LM Test* (lag=1)	White -Test	Correl. with rain
A-1	-0.0003	0.023	0.293 (p=0.86)	0.117 (p=0.73)	0.866 (p=0.36)	-0.130 (t=-1.02)
A-2	-0.0001	0.023	0.537 (p=0.76)	0.331 (p=0.57)	0.936 (p=0.43)	0.000 (t=0.00)
A-3	0.0005	0.037	5.87 (p=0.05)	0.172 (p=0.68)	1.289 (p=0.26)	0.75*** (t=8.61)
A-4	0.0001	0.024	0.344 (p=0.84)	2.589 (p=0.11)	1.051 (t=0.37)	0.000 (t=0.00)
A-5	-0.0001	0.034	1.876 (p=0.39)	0.152 (p=0.70)	0.025 (t=0.87)	0.71 (t=7.87)
A-6	0.0003	0.023	0.087 (p=0.95)	0.082 (p=0.78)	0.801 (p=0.50)	0.000 (t=0.00)

Note: 'p' implies p-value.

Table 5: The Results of the Second Equation on Impact of Weather on Non-Agricultural Cycle and Implied Impacts (GLS)

	The First Estimation Results		The Second Estimation Results					Implied Impact by First and Second Estimate		
	β_A	β_A^{T-1}	β_N^{total} (total)	α	α'	ρ_N	adjusted R-square	β_N^{direct} (direct)	$\beta_N^{indirect}$ (indirect, t)	$\beta_{N,t-1}^{indirect}$ (indirect, t-1)
N-1	0.309*** (z=9.43)		0.065*** (z=3.48)	0.189*** (z=2.61)		0.684*** (z=8.37)	0.603	0.007	0.058	
N-2	0.309*** (z=9.43)		0.061*** (z=3.29)	【0.178】	0.330*** (z=2.65)	0.715*** (z=8.79)	0.604	0.007	0.055	
N-3	0.323*** (z=9.87)	0.065** (z=2.01)	0.067*** (z=3.62)	0.189*** (z=2.60)		0.684*** (z=8.37)	0.603	0.007	0.061	0.012
N-4	0.323*** (z=9.87)	0.065** (z=2.01)	0.071*** (z=3.78)	【0.180】	0.334*** (z=2.82)	0.709*** (z=8.79)	0.610	0.006	0.058	0.012

Note1: 'β_A' implies the impact of rainfall variability to agricultural cycle. 'β_N^{total}' implies the overall impact of rainfall variability on non-agriculture. 'α' implies the transmission parameters capturing how far the agricultural performance affects non-agriculture. 'ρ_N' implies the persistence of non-agricluture.

Note2 : 'z' implies z-statitics; *** Significant at 1%; * *Significant at 5%.

Table 6: The statistical Characteristics of Residuals in the Second Stage Equation

	Mean	Stdev	Jaque-Bera	LM Test (lag=1)	White -Test	Correl. with rain	Correl. with NAGR(-1)	Correl. Res_agr
N-1	-0.00029	0.0131	0.582 (p=0.74)	9.605 (p=0.003)	0.292 (p=0.94)	0.00049 (t=0.00)	0.00131 (t=0.01)	-0.00012 (t=-0.00)
N-2	-0.00029	0.0131	1.242 (p=0.53)	7.752 (p=0.01)	0.227 (p=0.97)	0.00049 (t=0.00)	0.00131 (t=0.01)	-0.00028 (t=-0.00)
N-3	-0.00029	0.0131	0.582 (p=0.74)	9.605 (p=0.00)	0.292 (p=0.94)	0.00049 (t=0.00)	0.00131 (t=0.01)	-0.00014 (t=-0.00)
N-4	-0.00031	0.0130	1.309 (p=0.52)	7.316 (p=0.01)	0.388 (t=0.88)	0.00052 (t=0.00)	0.00139 (t=0.01)	-0.00019 (t=-0.00)

Note: 'p' implies p-value.

Table 7: The Results of the Second Equation on Impact of Weather on Non-Agricultural Cycle and Implied Impacts

	The First Estimation Results		The Second Estimation Results						Implied Impact by First and Second Estimate		
	β_A	β_A^{T-1}	β_N^{total}	α	α'	ρ_N	MA(1)	Adjusted R-square	β_N^{direct}	$\beta_N^{indirect}$	$\beta_{N,t-1}^{indirect}$
N-1	0.309*** (z=9.43)		0.051*** (z=3.12)	0.179*** (z=2.81)		0.573*** (z=4.93)	0.365** (z=2.42)	0.644	-0.005	0.055	
N-2	0.309*** (z=9.43)		0.046*** (z=2.89)	【0.151】	0.279*** (z=2.75)	0.602*** (z=5.12)	0.369** (z=2.47)	0.643	-0.000	0.047	
N-3	0.323*** (z=9.87)	0.065** (z=2.01)	0.053*** (z=3.24)	0.179*** (z=2.81)		0.573*** (z=4.92)	0.365** (z=2.42)	0.644	-0.005	0.058	0.011
N-4	0.323*** (z=9.87)	0.065** (z=2.01)	0.051*** (z=3.17)	【0.151】	0.279*** (z=2.84)	0.598*** (z=5.13)	0.361** (z=2.39)	0.646	0.002	0.049	0.010

Note1: 'β_A' implies the impact of rainfall variability to agricultural cycle. 'β_N^{total}' implies the overall impact of rainfall variability on non-agriculture. 'α' implies the transmission parameters capturing how far the agricultural performance affects non-agriculture. 'ρ_N' implies the persistence of non-agricluture.

Note2 : 'z' implies z-statitics; *** Significant at 1%; * *Significant at 5%.

Table 8: The statistical Characteristics of Residuals in the Second Stage Equation

	Mean	Stdev	Jaque-Bera	LM Test (lag=1)	White -Test	Correl with rain	Correl with NAGR(-1)	Correl Res_agr
N-1	-0.00012	0.0124	0.825 (p=0.66)	1.414 (p=0.23)	0.292 (p=0.94)	0.04 (t=0.27)	-0.03 (t=-0.23)	0.03 (t=0.26)
N-2	-0.00012	0.0125	1.767 (p=0.41)	0.785 (p=0.37)	0.227 (p=0.97)	0.06 (t=0.44)	-0.04 (t=-0.28)	0.05 (t=-0.38)
N-3	-0.00012	0.0124	0.825 (p=0.66)	1.414 (p=0.23)	0.292 (p=0.94)	0.04 (t=0.27)	-0.03 (t=0.27)	0.03 (t=-0.25)
N-4	-0.00014	0.0124	1.613 (p=0.44)	0.495 (p=0.48)	0.388 (t=0.88)	0.03 (t=0.25)	-0.03 (t=-0.23)	0.05 (t=-0.41)

Note: 'p' implies p-value.

Table 9: The Results of Kalman Filter Estimation

	$\beta_{A,t}$ () is root MSE		$\beta^{total}_{N,t}$ () is root MSE		α_t () is root MSE		$\rho_{N,t}$ () is root MSE	
1952	0.4268	(0.3181)						
1953	0.3106	(0.2173)	0.1200	(405.79)	−0.0122	(995.67)	0.0518	(918.68)
1954	0.2840	(0.2159)	0.0877	(379.44)	0.1750	(540.84)	0.1704	(750.67)
1955	0.2497	(0.2109)	−0.5764	(1.5235)	−0.7717	(1.9383)	1.4844	(2.9919)
1956	0.2759	(0.1987)	0.1290	(0.3773)	0.1168	(0.5482)	0.1183	(0.8841)
1957	0.3800**	(0.1764)	0.2594*	(0.1516)	0.2770	(0.3470)	−0.1699	(0.4459)
1958	0.3962**	(0.1637)	0.0361	(0.1124)	0.3773	(0.3440)	0.5432*	(0.3054)
1959	0.2946**	(0.1437)	0.0173	(0.0939)	0.4366	(0.2834)	0.5950**	(0.2536)
1960	0.2434*	(0.1417)	0.0202	(0.0938)	0.3045	(0.2075)	0.6721***	(0.2271)
1961	0.2204**	(0.1096)	0.0223	(0.0699)	0.3053	(0.2062)	0.6715***	(0.2265)
1962	0.2224**	(0.1072)	0.0159	(0.0675)	0.2964	(0.2047)	0.6599***	(0.2242)
1963	0.2234**	(0.1070)	0.0068	(0.0673)	0.2693	(0.2041)	0.6474***	(0.2240)
1964	0.2953***	(0.0916)	0.0385	(0.0545)	0.3461*	(0.1802)	0.7215***	(0.2041)
1965	0.3265***	(0.0757)	0.0423	(0.0455)	0.3476**	(0.1798)	0.7098***	(0.1828)
1966	0.3926***	(0.0707)	0.0346	(0.0441)	0.2819**	(0.1525)	0.7099***	(0.1828)
1967	0.3931***	(0.0707)	0.0347	(0.0441)	0.2761*	(0.1521)	0.7113***	(0.1828)
1968	0.3763***	(0.0681)	0.0343	(0.0413)	0.2770*	(0.1468)	0.7108***	(0.1816)
1969	0.3789***	(0.0680)	0.0356	(0.0413)	0.3084**	(0.1449)	0.7148***	(0.1816)
1970	0.3944***	(0.0627)	0.0278	(0.0375)	0.3016**	(0.1441)	0.6855***	(0.1699)
1971	0.3968***	(0.0626)	0.0276	(0.0375)	0.2780**	(0.1402)	0.6555***	(0.1644)
1972	0.3605***	(0.0553)	0.0392	(0.0323)	0.2487*	(0.1315)	0.6466***	(0.1638)
1973	0.3441***	(0.0541)	0.0351	(0.0314)	0.2720**	(0.1248)	0.6497***	(0.1637)
1974	0.3473***	(0.0529)	0.0413	(0.0306)	0.2801**	(0.1244)	0.6785***	(0.1604)
1975	0.3537***	(0.0502)	0.0433	(0.0294)	0.2812**	(0.1243)	0.6691***	(0.1550)
1976	0.3506***	(0.0502)	0.0451	(0.0294)	0.2345**	(0.1194)	0.6510***	(0.1544)
1977	0.3567***	(0.0500)	0.0458	(0.0293)	0.2475**	(0.1128)	0.6569***	(0.1534)
1978	0.3635***	(0.0490)	0.0578**	(0.0285)	0.2715***	(0.1119)	0.7265***	(0.1483)
1979	0.3907***	(0.0461)	0.0673***	(0.0277)	0.3075***	(0.1091)	0.6423***	(0.1363)
1980	0.3857***	(0.0460)	0.0666***	(0.0276)	0.3149***	(0.1054)	0.6457***	(0.1357)
1981	0.3856***	(0.0460)	0.0666***	(0.0276)	0.3141***	(0.1053)	0.6404***	(0.1342)
1982	0.3766***	(0.0448)	0.0701***	(0.0266)	0.3053***	(0.1037)	0.6471***	(0.1334)
1983	0.3706***	(0.0431)	0.0698***	(0.0257)	0.3058***	(0.1029)	0.6474***	(0.1332)
1984	0.3687***	(0.0431)	0.0712***	(0.0256)	0.2773***	(0.0993)	0.6471***	(0.1332)
1985	0.3652***	(0.0429)	0.0715***	(0.0255)	0.2758***	(0.0982)	0.6480***	(0.1329)
1986	0.3593***	(0.0418)	0.0669***	(0.0247)	0.2834***	(0.0976)	0.6405***	(0.1325)
1987	0.3708***	(0.0408)	0.0607***	(0.0241)	0.2610***	(0.0957)	0.6334***	(0.1324)
1988	0.3425***	(0.0381)	0.0694***	(0.0224)	0.2350***	(0.0918)	0.6425***	(0.1320)
1989	0.3428***	(0.0380)	0.0727***	(0.0223)	0.2457***	(0.0916)	0.6889***	(0.1296)
1990	0.3416***	(0.0378)	0.0741***	(0.0219)	0.2461***	(0.0916)	0.7049***	(0.1202)
1991	0.3422***	(0.0374)	0.0762***	(0.0218)	0.2442***	(0.0916)	0.6667***	(0.1152)
1992	0.3363***	(0.0371)	0.0788***	(0.0217)	0.2269***	(0.0901)	0.6638***	(0.1151)
1993	0.3363***	(0.0371)	0.0789***	(0.0217)	0.2269***	(0.0901)	0.6671***	(0.1146)
1994	0.3319***	(0.0366)	0.0778***	(0.0215)	0.2312***	(0.0895)	0.6709***	(0.1142)
1995	0.3322***	(0.0366)	0.0758***	(0.0214)	0.2026**	(0.0887)	0.6446***	(0.1137)
1996	0.3351***	(0.0366)	0.0756***	(0.0213)	0.2014**	(0.0862)	0.6431***	(0.1111)
1997	0.3333***	(0.0365)	0.0761***	(0.0212)	0.1989**	(0.0856)	0.6482***	(0.1092)
1998	0.3340***	(0.0363)	0.0747***	(0.0211)	0.1967**	(0.0855)	0.6395***	(0.1079)
1999	0.3328***	(0.0363)	0.0747***	(0.0211)	0.2173***	(0.0838)	0.6508***	(0.1075)
2000	0.3316***	(0.0363)	0.0752***	(0.0211)	0.2092***	(0.0835)	0.6263***	(0.1051)
2001	0.3267***	(0.0362)	0.0772***	(0.0211)	0.1534*	(0.0802)	0.6197***	(0.1051)
2002	0.3315***	(0.0354)	0.0812***	(0.0204)	0.1605**	(0.0797)	0.6381***	(0.1023)
2003	0.3262***	(0.0352)	0.0787***	(0.0204)	0.1835**	(0.0786)	0.6872***	(0.0984)
2004	0.3265***	(0.0349)	0.0808***	(0.0201)	0.1840**	(0.0786)	0.7069***	(0.0923)
2005	0.3253***	(0.0348)	0.0808***	(0.0201)	0.1833**	(0.0781)	0.7043***	(0.0877)
2006	0.3237***	(0.0348)	0.0811***	(0.0200)	0.1802**	(0.0779)	0.6951***	(0.0858)
2007	0.3207***	(0.0344)	0.0815***	(0.0199)	0.1795**	(0.0778)	0.6940***	(0.0854)
2008	0.3196***	(0.0343)	0.0815***	(0.0199)	0.1805**	(0.0773)	0.6941***	(0.0854)
2009	0.3118***	(0.0331)	0.0704***	(0.0192)	0.1947***	(0.0770)	0.6798***	(0.0852)
2010	0.3109***	(0.0330)	0.0723***	(0.0191)	0.1903***	(0.0769)	0.6900***	(0.0848)
2011	0.3117***	(0.0330)	0.0727***	(0.0191)	0.1916***	(0.0767)	0.6940***	(0.0835)
2012	0.3092***	(0.0329)	0.0731***	(0.0190)	0.1881***	(0.0764)	0.6881***	(0.0825)
2013	0.3089***	(0.0328)	0.0714***	(0.0190)	0.1888***	(0.0764)	0.6810***	(0.0822)

Note 1: *** implies 1% significance; ** implies 5% significance; * implies 10% significance.

Table 10: The Results of Kalman Filter Estimation

	$\beta_{A,t}$ () is root MSE		$\beta^{R,t-1}_{A,}$ () is root MSE		$\beta^{total}_{N,t}$ () is root MSE		α_t () is root MSE		$\rho_{N,t}$ () is root MSE	
1952	0.0876	(891.45)	0.1724	(453.11)						
1953	0.2791	(0.2208)	0.0751	(0.1465)	0.1210	(396.72)	0.0000	(1000.0)	0.0523	(917.94)
1954	0.2431	(0.2149)	0.1241	(0.1292)	0.0370	(269.57)	0.1960	(733.67)	0.2466	(623.74)
1955	0.2109	(0.2091)	0.1335	(0.1284)	−0.2446	(0.7488)	−0.5706	(1.4601)	0.8983	(1.6474)
1956	0.2316	(0.1983)	0.1361	(0.1281)	0.0912	(0.3521)	0.0574	(0.7780)	0.1920	(0.8848)
1957	0.3699**	(0.1728)	0.0846	(0.1228)	0.2222	(0.1748)	0.3288	(0.4519)	−0.1277	(0.4756)
1958	0.4000***	(0.1599)	0.0666	(0.1164)	−0.0189	(0.1291)	0.5429	(0.4396)	0.5929*	(0.3198)
1959	0.2917**	(0.1408)	0.0250	(0.1127)	−0.0066	(0.0941)	0.4986	(0.3022)	0.5671**	(0.2605)
1960	0.2400*	(0.1384)	0.1061	(0.1049)	0.0045	(0.0928)	0.3580	(0.2284)	0.6569***	(0.2279)
1961	0.2271**	(0.1072)	0.1079	(0.1042)	0.0115	(0.0693)	0.3593	(0.2281)	0.6544***	(0.2268)
1962	0.2367**	(0.1060)	0.0759	(0.0897)	0.0014	(0.0668)	0.3293	(0.2214)	0.6343***	(0.2238)
1963	0.2368**	(0.1056)	0.0760	(0.0882)	−0.0051	(0.0666)	0.3252	(0.2214)	0.6293***	(0.2238)
1964	0.3076***	(0.0904)	0.0802	(0.0881)	0.0258	(0.0560)	0.4014**	(0.2027)	0.7016***	(0.2072)
1965	0.3458***	(0.0793)	0.0555	(0.0835)	0.0283	(0.0473)	0.4028**	(0.2019)	0.6937***	(0.1852)
1966	0.4084***	(0.0695)	0.1363**	(0.0673)	0.0260	(0.0458)	0.3921**	(0.1938)	0.6957***	(0.1849)
1967	0.4073***	(0.0694)	0.1155*	(0.0636)	0.0291	(0.0457)	0.3417*	(0.1865)	0.6949***	(0.1849)
1968	0.3901***	(0.0669)	0.1149*	(0.0636)	0.0310	(0.0424)	0.3347*	(0.1764)	0.6975***	(0.1836)
1969	0.3920***	(0.0669)	0.0976*	(0.0617)	0.0306	(0.0424)	0.3868**	(0.1687)	0.7033***	(0.1835)
1970	0.4039***	(0.0614)	0.1002*	(0.0614)	0.0240	(0.0384)	0.3831**	(0.1684)	0.6799***	(0.1722)
1971	0.4049***	(0.0613)	0.1051*	(0.0572)	0.0234	(0.0384)	0.3781**	(0.1679)	0.6646***	(0.1677)
1972	0.3687***	(0.0541)	0.1053*	(0.0572)	0.0391	(0.0328)	0.3271**	(0.1548)	0.6518***	(0.1669)
1973	0.3643***	(0.0535)	0.1179**	(0.0518)	0.0326	(0.0320)	0.3461**	(0.1534)	0.6542***	(0.1669)
1974	0.3704***	(0.0527)	0.1121**	(0.0511)	0.0370	(0.0313)	0.3625***	(0.1512)	0.6762***	(0.1633)
1975	0.3803***	(0.0506)	0.1079**	(0.0507)	0.0376	(0.0301)	0.3635***	(0.1505)	0.6732***	(0.1580)
1976	0.3683***	(0.0502)	0.0766*	(0.0480)	0.0419	(0.0300)	0.2536*	(0.1359)	0.6466***	(0.1572)
1977	0.3751***	(0.0500)	0.0814*	(0.0479)	0.0424	(0.0300)	0.2685**	(0.1279)	0.6523***	(0.1563)
1978	0.3805***	(0.0488)	0.0841*	(0.0476)	0.0550*	(0.0292)	0.2873**	(0.1275)	0.7254***	(0.1511)
1979	0.4085***	(0.0465)	0.0732*	(0.0472)	0.0631**	(0.0285)	0.3325***	(0.1228)	0.6478***	(0.1392)
1980	0.4086***	(0.0465)	0.0846*	(0.0448)	0.0616**	(0.0284)	0.3437***	(0.1209)	0.6542***	(0.1387)
1981	0.4080***	(0.0464)	0.0836*	(0.0447)	0.0617**	(0.0284)	0.3404***	(0.1206)	0.6461***	(0.1369)
1982	0.3980***	(0.0452)	0.0824*	(0.0446)	0.0663***	(0.0272)	0.3255***	(0.1177)	0.6536***	(0.1363)
1983	0.3958***	(0.0441)	0.0839*	(0.0441)	0.0654***	(0.0263)	0.3269***	(0.1172)	0.6547***	(0.1361)
1984	0.3980***	(0.0440)	0.0953**	(0.0426)	0.0666***	(0.0263)	0.3097***	(0.1151)	0.6549***	(0.1361)
1985	0.3932***	(0.0438)	0.0928**	(0.0425)	0.0673***	(0.0260)	0.3045***	(0.1128)	0.6566***	(0.1358)
1986	0.3825***	(0.0424)	0.0864**	(0.0420)	0.0640***	(0.0252)	0.3152***	(0.1108)	0.6524***	(0.1356)
1987	0.3903***	(0.0407)	0.0941**	(0.0404)	0.0593***	(0.0246)	0.3054***	(0.1103)	0.6479***	(0.1355)
1988	0.3686***	(0.0385)	0.1027***	(0.0401)	0.0681***	(0.0228)	0.2769***	(0.1060)	0.6560***	(0.1352)
1989	0.3649***	(0.0382)	0.0917***	(0.0372)	0.0718***	(0.0227)	0.2565***	(0.1056)	0.7049***	(0.1334)
1990	0.3627***	(0.0378)	0.0906***	(0.0371)	0.0733***	(0.0223)	0.2567***	(0.1056)	0.7223***	(0.1239)
1991	0.3640***	(0.0376)	0.0895***	(0.0370)	0.0753***	(0.0222)	0.2563***	(0.1056)	0.6859***	(0.1190)
1992	0.3540***	(0.0371)	0.0796**	(0.0365)	0.0782***	(0.0221)	0.2230**	(0.1018)	0.6779***	(0.1188)
1993	0.3535***	(0.0371)	0.0778**	(0.0361)	0.0784***	(0.0221)	0.2214**	(0.1017)	0.6819***	(0.1183)
1994	0.3486***	(0.0366)	0.0769**	(0.0361)	0.0773***	(0.0219)	0.2268**	(0.1006)	0.6861***	(0.1178)
1995	0.3476***	(0.0366)	0.0707**	(0.0357)	0.0749***	(0.0219)	0.1775*	(0.0986)	0.6522***	(0.1170)
1996	0.3506***	(0.0365)	0.0708**	(0.0357)	0.0749***	(0.0217)	0.1772*	(0.0951)	0.6520***	(0.1139)
1997	0.3480***	(0.0364)	0.0682*	(0.0356)	0.0753***	(0.0216)	0.1742*	(0.0942)	0.6567***	(0.1122)
1998	0.3481***	(0.0362)	0.0683*	(0.0355)	0.0740***	(0.0215)	0.1726*	(0.0942)	0.6486***	(0.1108)
1999	0.3479***	(0.0362)	0.0721**	(0.0353)	0.0740***	(0.0215)	0.1957**	(0.0925)	0.6626***	(0.1103)
2000	0.3464***	(0.0361)	0.0713**	(0.0353)	0.0744***	(0.0215)	0.1836**	(0.0918)	0.6363***	(0.1076)
2001	0.3400***	(0.0360)	0.0656*	(0.0352)	0.0762***	(0.0215)	0.1169*	(0.0870)	0.6248***	(0.1075)
2002	0.3436***	(0.0351)	0.0673*	(0.0350)	0.0806***	(0.0208)	0.1243	(0.0866)	0.6456***	(0.1046)
2003	0.3410***	(0.0350)	0.0732**	(0.0344)	0.0779***	(0.0208)	0.1468*	(0.0857)	0.7001***	(0.1004)
2004	0.3420***	(0.0348)	0.0724**	(0.0343)	0.0797***	(0.0204)	0.1493*	(0.0856)	0.7172***	(0.0940)
2005	0.3417***	(0.0348)	0.0751**	(0.0340)	0.0797***	(0.0204)	0.1492*	(0.0852)	0.7168***	(0.0892)
2006	0.3395***	(0.0347)	0.0735**	(0.0340)	0.0800***	(0.0204)	0.1442*	(0.0846)	0.7071***	(0.0871)
2007	0.3350***	(0.0342)	0.0710**	(0.0338)	0.0805***	(0.0202)	0.1427*	(0.0842)	0.7057***	(0.0868)
2008	0.3323***	(0.0342)	0.0645*	(0.0334)	0.0805***	(0.0202)	0.1439*	(0.0831)	0.7058***	(0.0868)
2009	0.3240***	(0.0330)	0.0639*	(0.0334)	0.0693***	(0.0195)	0.1605*	(0.0827)	0.6920***	(0.0865)
2010	0.3241***	(0.0329)	0.0630*	(0.0324)	0.0711***	(0.0195)	0.1625**	(0.0827)	0.7005***	(0.0862)
2011	0.3249***	(0.0329)	0.0639**	(0.0322)	0.0715***	(0.0194)	0.1637**	(0.0826)	0.7054***	(0.0848)
2012	0.3227***	(0.0328)	0.0648**	(0.0322)	0.0720***	(0.0194)	0.1601*	(0.0821)	0.6998***	(0.0838)
2013	0.3228***	(0.0327)	0.0647**	(0.0322)	0.0701***	(0.0193)	0.1592*	(0.0821)	0.6924***	(0.0835)

Note1: *** implies 1% significance; ** implies 5% significance; * implies 10% significance.

Table 11: Estimation Results on the Temperature Shocks and Non-Agricultural Performance

	1st Est Results	The Second Estimation Results									Implied Impact by First and Second Estimate	
	β_A	*Temp 1990 All*	*Temp 1991 All*	*Temp 1990 Temp 69*	Temp 1991 Temp 69	β_N^{total}	α	ρ_N	MA(1)	Adj. R-square	β_N^{direct}	$\beta_N^{indirect}$
T-1	0.309*** (z=9.43)	-0.009 (z=-0.91)	0.027** (z=2.56)			0.059*** (z=3.60)	0.185*** (z=2.92)	0.634*** (z=5.85)	0.302* (z=1.91)	0.658	0.001	0.057
T-2	0.309*** (z=9.43)	-0.012 (z=-1.12)	0.031*** (z=2.84)			0.069*** (z=3.91)	0.180** (z=2.58)	0.720*** (z=9.27)		0.636	0.014	0.055
T-3	0.309*** (z=9.43)			-0.008 (z=-0.84)	0.027*** (z=2.73)	0.051*** (z=3.07)	0.186*** (z=3.04)	0.595*** (z=5.31)	0.424*** (z=2.89)	0.664	-0.007	0.057
T-4	0.309*** (z=9.43)			-0.008 (z=-0.81)	0.031** (z=2.42)	0.066*** (z=3.48)	0.198*** (z=2.73)	0.705*** (z=8.92)		0.621	0.005	0.061

Note1: 'β_A' implies the impact of rainfall variability to agricultural cycle. 'β_N^{total}' implies the overall impact of rainfall variability on non-agriculture. 'α' implies the transmission parameters capturing how far the agricultural performance affects non-agriculture. 'ρ_N' implies the persistence of non-agricluture.

Note2 : 'z' implies z-statitics; *** Significant at 1%; **Significant at 5%; *Significant at 10%.

Table 12: The statistical Characteristics of Residuals in the Second Stage Equation for Temperature Shocks

	Mean	Stdev	Jaque-Bera	LM Test (lag=1)	Breusch-Pagan-Godfrey Test	Correl with rain	Correl with NAGR(-1)	Correl Res_agr
T-1	-0.00023	0.0117	0.177 (p=0.92)	1.468 (p=0.20)	0.877 (p=0.50)	-0.00 (t=-0.10)	-0.00 (t=-0.19)	0.00 (t=0.16)
T-2	-0.00039	0.0121	0.142 (p=0.93)	7.00 (p=0.01)	0.481 (p=0.79)	0.00 (t=0.00)	0.00 (t=0.01)	-0.00 (t=-0.00)
T-3	-0.00008	0.0116	0.000 (p=0.99)	0.29 (p=0.59)	0.845 (p=0.52)	0.00 (t=0.17)	-0.00 (t=-0.31)	0.00 (t=0.39)
T-4	-0.00028	0.0124	0.255 (p=0.88)	11.15 (p=0.00)	0.745 (p=0.59)	0.00 (t=0.00)	0.00 (t=0.01)	-0.00 (t=-0.00)

Note: 'p' implies p-value.

Figure 1: The time-varying Impact of Rainfall on Agriculture (by Kalman Filter)

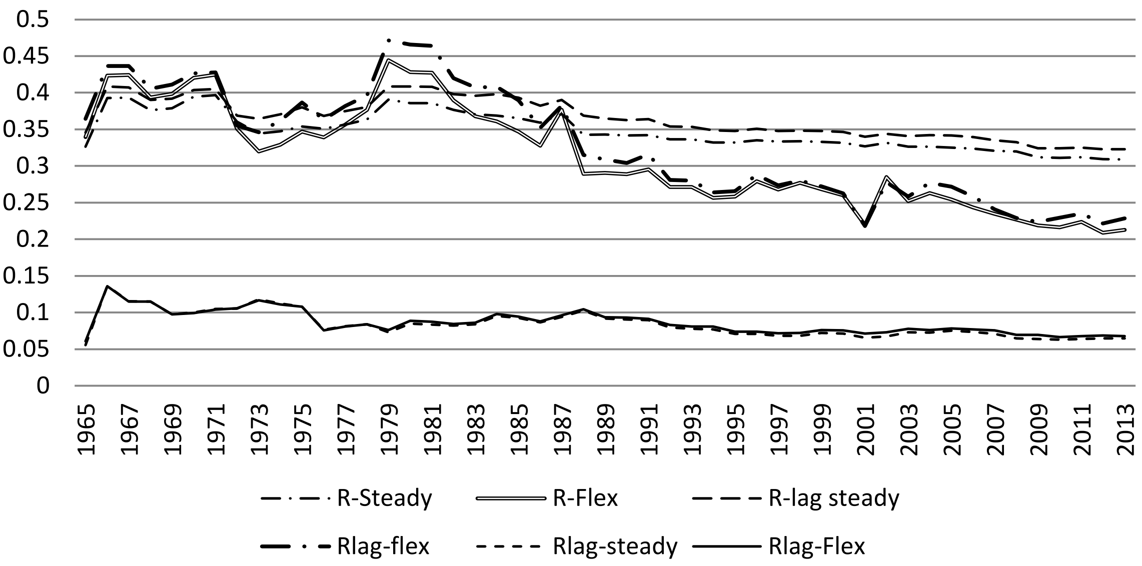


Figure 2: Transmission Parameters from Agriculture to Non-Agriculture (by Kalman Filter)

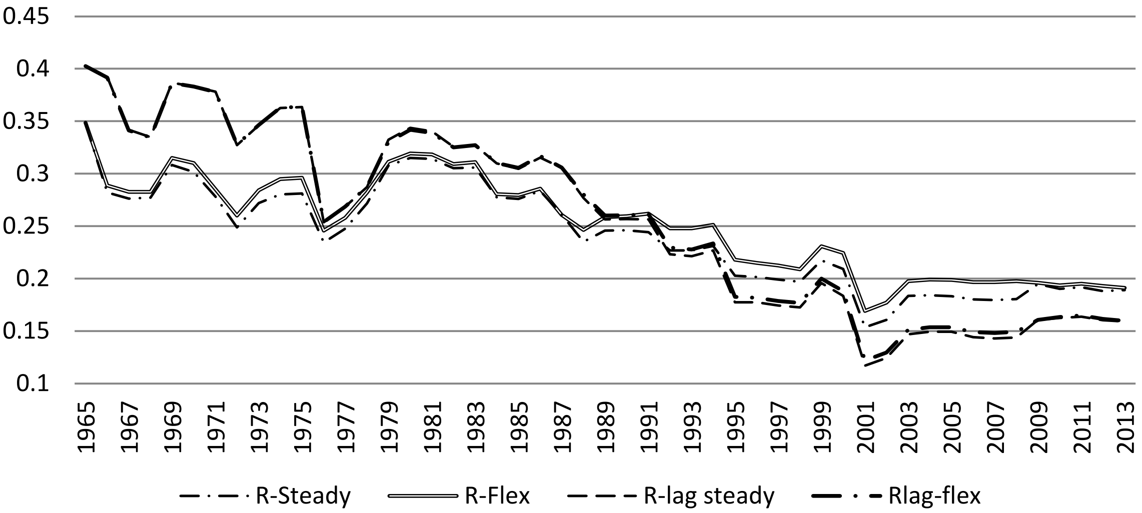


Figure 3: Persistence of Non-Agriculture (by Kalman Filter)

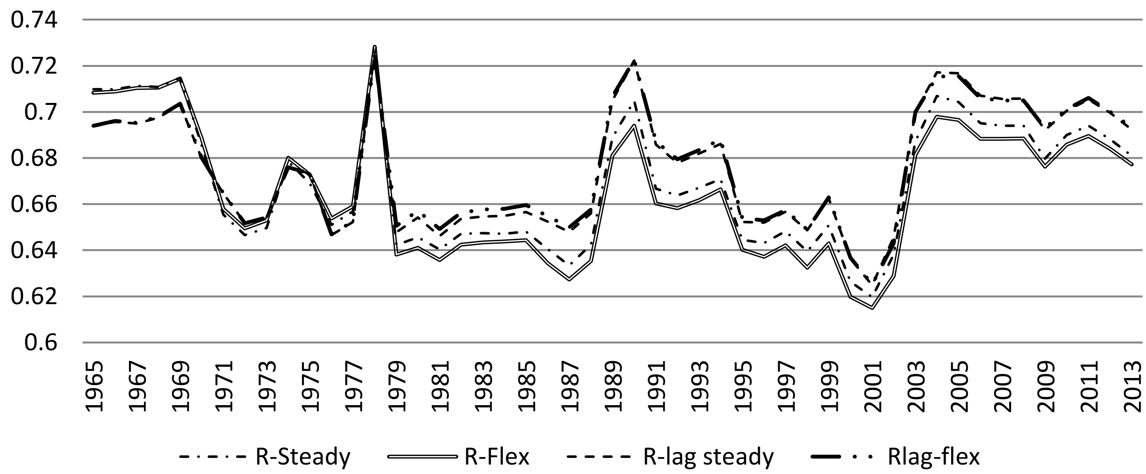


Figure 4: The Overall Impact of Rainfall on Non-Agriculture (by Kalman Filter)

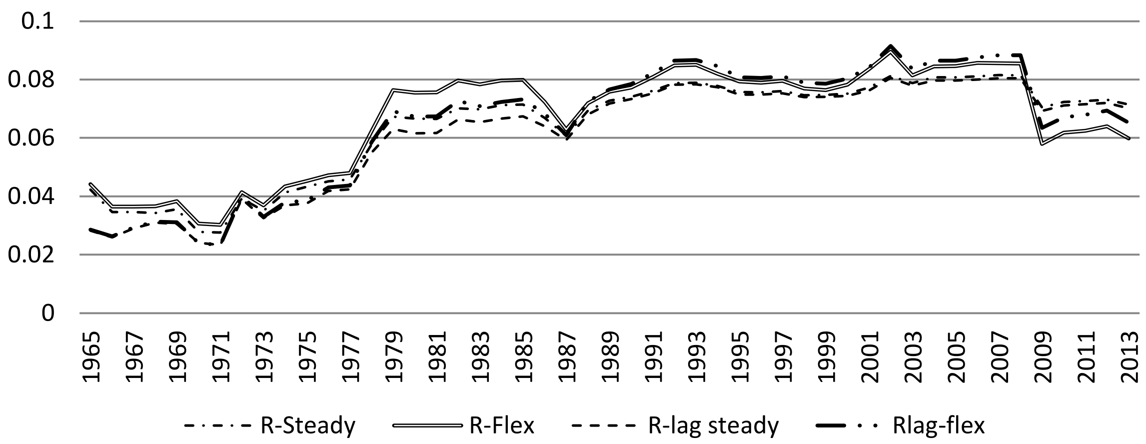


Figure 5: The Indirect Impact of Rainfall on Non-Agriculture (by Kalman Filter)

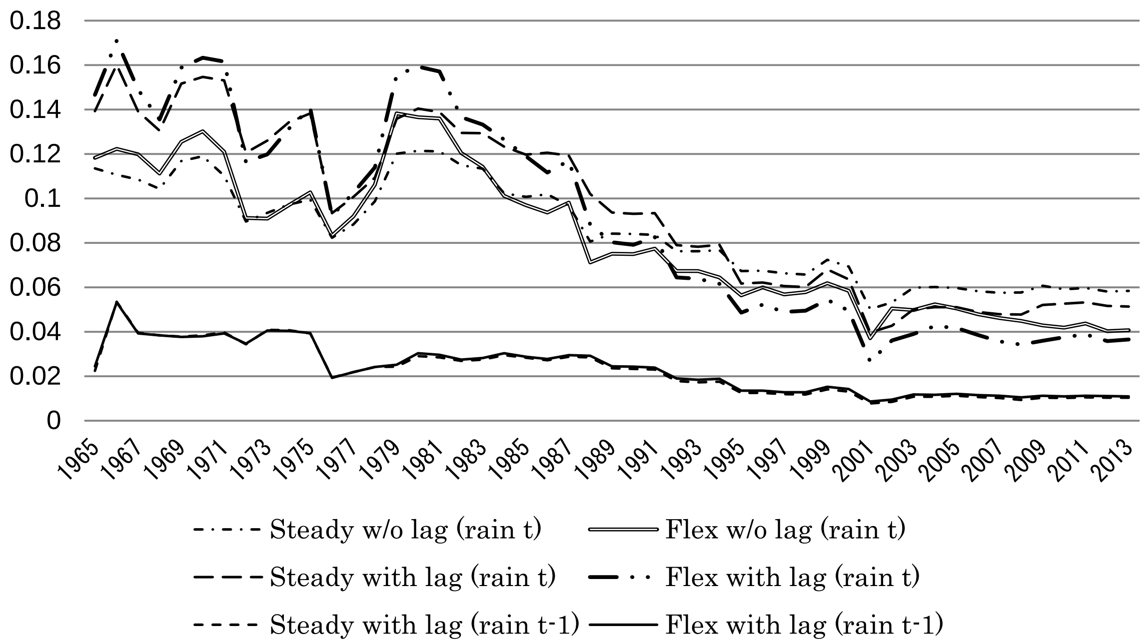


Figure 6: The Direct Impact of Rainfall on Non-Agriculture (by Kalman Filter)

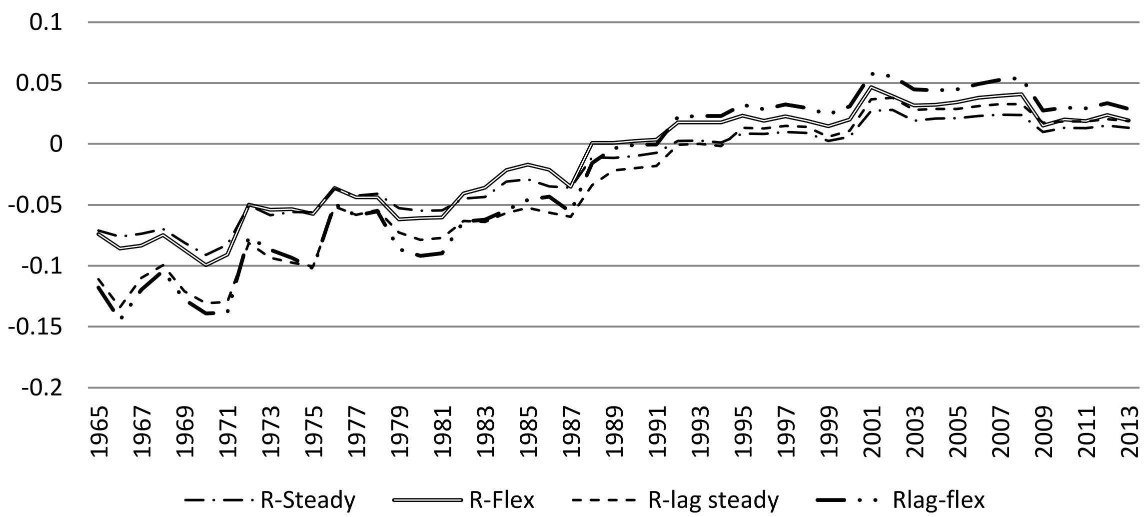


Figure 7: Impact of Rainfall on GDP (without lag specification)

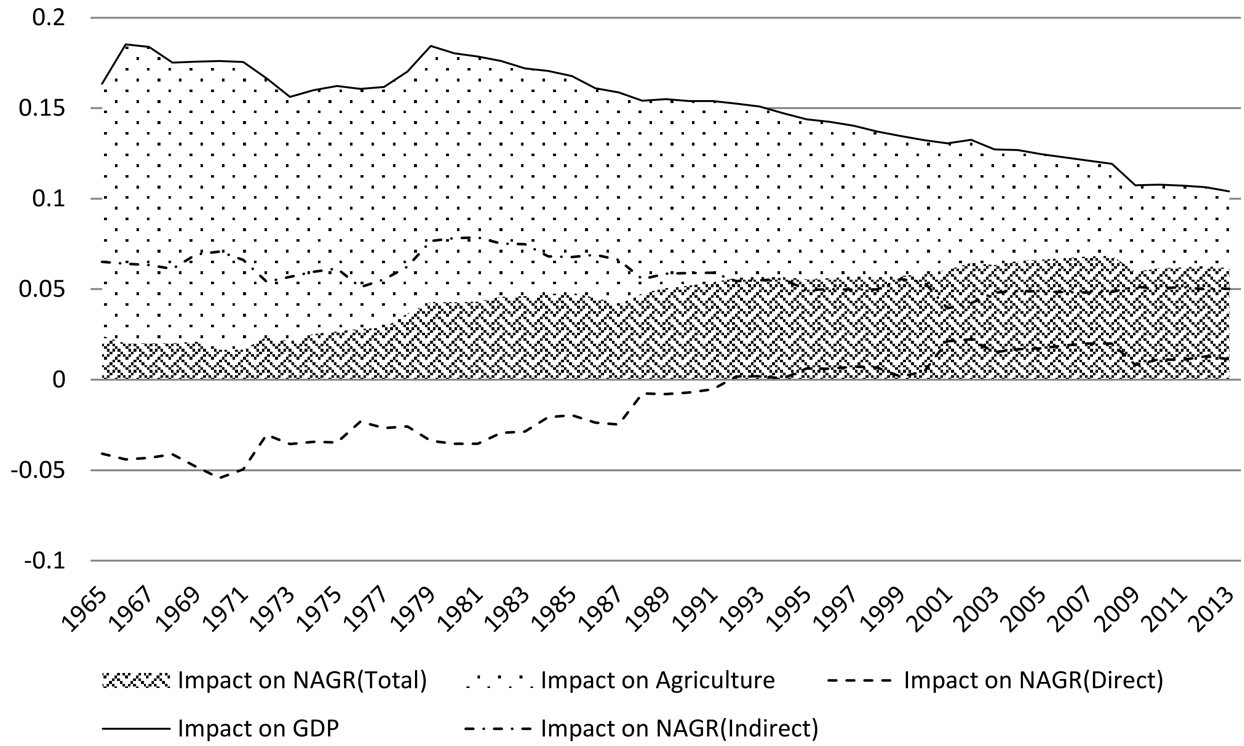


Figure 8: Impact of Rainfall on GDP (with lag specification)

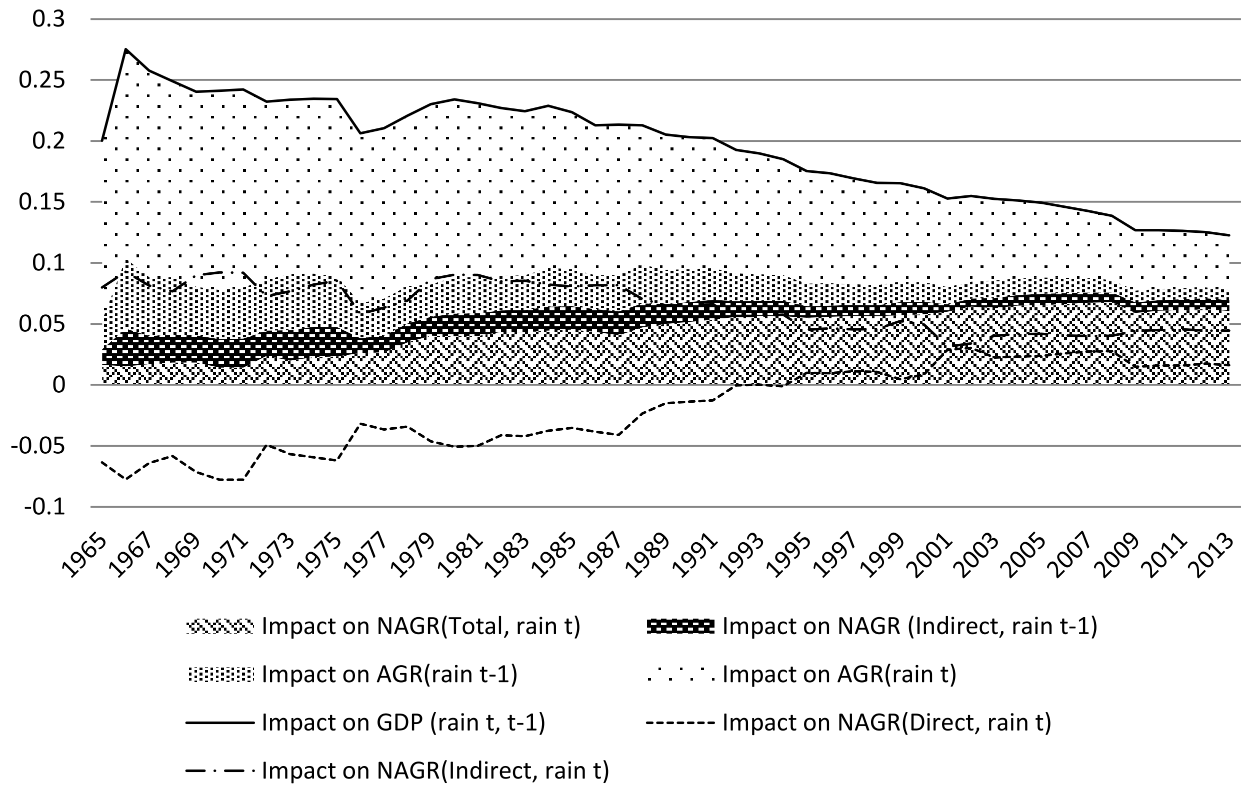
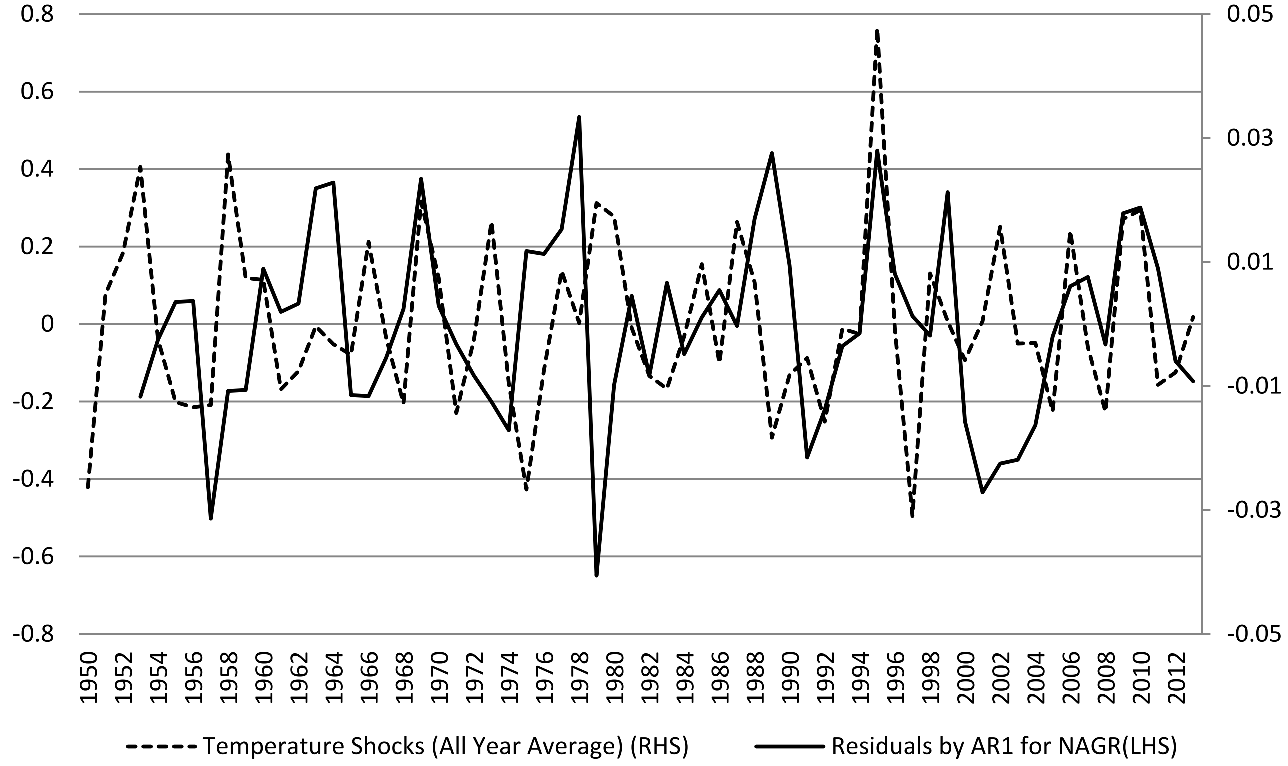


Figure 9: Temperature Shocks and Residuals of AR1 Estimation for Non-Agricultural Performance



Appendix:

A test of the validity of two stage estimation empirical framework by simulation

To test the validity of the two stage estimation empirical framework developed in the present paper, the empirical framework is applied to the one thousand sets of hypothetical series of rainfall, agriculture, and non-agriculture, which is produced by the following equation using the random functions of econometric software and therefore the true values are known to us, to see if the estimation can obtain the true values.

$$\tilde{R}_t = e_t^R \, (i.i.d) \quad \text{(eq.A1)}$$

$$\tilde{A}_t = 0.30 * \tilde{R}_t + e_t^A (i.i.d) \quad \text{(eq.A2)}$$

$$\tilde{N}_t = 0.07 * \tilde{R}_t + 0.20 * \tilde{A}_t + 0.70 * \tilde{N}_{t-1} + e_t^N \, (i.i.d) \quad \text{(eq.A3)}$$

The values of parameter are set by approximating the results of the GLS estimation shown in **Table 3** and **Table 5**, and the standard deviations of the three shocks, e_t^R, e_t^A, and e_t^N above are set to match the **Table 1**. Time t takes from 1to 61, which is similar to the India sample during 1952-2013. Note that the above equation implies direct impact is 0.01 by the following calculation.

$$\beta_N^{direct} = \beta_N^{total} - \alpha \ \ \beta_A = 0.07 - 0.20 * 0.30 = 0.01.$$

The average estimated and calculated values by applying the empirical framework is shown in **Table A1**. It shows that the true value can be obtained by the developed empirical framework. Furthermore, **Table A2** demonstrates the average fitness of the estimated shocks of agriculture and non-agriculture to the true shocks measured by R-squares of regression of estimated shocks on true shocks. It shows that estimation can identify the almost true shocks with very high R-squares at 0.98 for agricultural shocks, and 0.93 for non-agricultural shocks.

Table A1: Comparison of True Value and Estimated Values by Two Stage Estimation

	β_A	β_N^{total}	β_N^{direct}	α	ρ_N
True value	0.300	0.070	0.010	0.200	0.700
Average estimated value	0.3009	0.0703	0.0099	0.2014	0.6856

Table A2: Average R-squares of the Below Regressions.

Regression of true e_t^R on estimated $\hat{e}_t^R$	0.984
Regression of true e_t^N on estimated $\hat{e}_t^N$	0.932