

Weather Risk and Cropping Intensity: A Non-Stationary and Dynamic Panel Modeling Approach

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Abstract

Climatic conditions and weather play an important role in production agriculture. Using district level panels for 42 years from India and dynamic panel estimation procedure we estimate the impact of weather risk on cropping intensity. Our non-stationary and dynamic panel model results suggest that the impact of weather risk on cropping intensity, in rural India, is negative on short run, while it is positive on long run. Additionally, we found a negative effect of education on cropping intensity. Finally, in the long run, our results indicate positive effects of high yielding variety production and share of irrigated land on cropping intensity.

Introduction

Climatic variation influences agricultural production and hence it affects crop productivity and land use pattern. With population growth and increased challenges for food security, there has been increased human encroachment on uncultivated fallow and forestlands and shifting agriculture in developing countries—where majority of the population resides. Weather risk (also referred to weather variability) not only impacts human settlement but also puts a greater pressure on agricultural lands and agricultural production. Variability in weather may lead to variability in agricultural output and subsistence farming in developing countries in particular, as many rural households cultivate smaller holdings and mostly engage in farming to raise crops for households' income and food consumption.

Farmers in developing countries are classified as risk-averse agents (Rosenzweig and Binswanger 1992; Lamb 2002). In the absence of insurance and credit markets, farmers undertake ex-ante or ex-post activities to self-insure or to smoothen consumption. There is a

growing consensus among policymakers and scientists that weather variability influences the performance of agriculture and farmers need to adopt strategies to minimize their losses (Whinston et al., 1981; Rosenzweig and Perry 1994; Seo and Mendelson 2008; Taraz 2012). This is particularly true for rural farmers in developing countries where agricultural production is highly dependent on rainfall and sensitive to weather and adaptive capacities are low.

Similarly, farmer's behavior is affected by weather outcome and affecting cropping decisions. Farmers in most of the semi-arid regions solely rely on rainfall as a source of irrigation or moisture for crops; annual and seasonal rainfall patterns influence food crop choice among farmers in developing countries (Bezabih, Falco, and Yesuf, 2011; Bezabih and Falco 2012). For example, subject to the expectation of high or low rainfall, farmers may alter types of crops or the area under cultivation. One prospect of weather risk or rainfall variability could be that it pushes farmers away from farming, inducing occupational shifts or migration to other areas. However, having fewer opportunities for other alternative income generating opportunities in the area, as may be the case in most of the rural villages, it is plausible that variability in rainfall induces farmers to allocate even more land area for different crop portfolio with the objective of loss minimization. In other words, subject to a higher variation in rainfall, farmers may diversify crops by bringing in more area under different crops such that the income risk is minimized by overall returns from non-sensitive crops while compensating for losses in sensitive crops.

Land use, climatic variability and changes in agricultural productivity have been studied widely in developing countries (Masvaya, Mupangwa and Twomlow, 2008; Graef and Heigis, 2001). However, literature falls short on assessing the impact of weather risk on cropping intensity. Additionally, the literature has failed to account for the spatial or temporal nature of

risk. It should be of paramount importance that both spatial and temporal phenomena (for example: climate changes over time, population growth, rural literacy, irrigation availability, availability of improved varieties etc.) to analyze weather risk in the short and long run.

Utilization of the information in terms of both cross-sectional variation and time variation leads to better insights; panel data modeling approaches offer such better inferences. Moreover, policymakers may be interested in methods that mitigate farmer's sensitivities towards reduction in weather risk, assessing the impact of climate change, stabilization of food supply, and to enhance agricultural production and income of farm families under weather adversities.

Therefore, the objective of this study is to assess the impact of weather risk¹ on cropping intensity. We use different class of non-stationary and panel data modeling techniques to examine the short-term and long-term relationships between weather risk and cropping intensity. To examine this relationship, we use district-level data compiled by the International Crops Research Institute for the Semi-Arid-Tropics (ICRISAT²) based on agricultural production and climatic information, 1966-2007, in rural villages of India.

This paper contributes to the literature in several ways. First, the study uses data that is long (1966-2007) and has several significant changes in production agriculture, policies, and weather. Our short- and long- term analysis enables researchers to infer about the impact of weather risk on cropping intensity in short- and long- runs. For example, inferences from

¹Weather risk in this study is measured by variability in rainfall, a major source of weather risk.

²The International Crops Research Institute for the Semi-Arid-Tropics (ICRISAT) is a non-profit agricultural research organization headquartered in [Patancheru \(Hyderabad, Andhra Pradesh, India\)](#) with several regional centers ([Niamey \(Niger\)](#), [Nairobi \(Kenya\)](#)) and research stations [Bamako \(Mali\)](#), [Bulawayo \(Zimbabwe\)](#). It was founded in 1972 by a consortium of organizations convened by the [Ford](#) and the [Rockefeller](#) Foundations. Its charter was signed by the [FAO](#) and the [UNDP](#).

short-run analysis may serve as a base for further studies in food crop-portfolio choices, and income management by farming households not only in developing countries but also in developed countries. Inferences from long-run behavior contribute to the literature by adding further insights in farmers' adaptation to mitigate climate change, an issue that gets wide attention in recent literature (Rosenberg and Perry 1994; Mendelsohn and Dinar 1999; Macous, Premand and Vakis, 2012). Second, the paper embraces a comprehensive procedure in empirical analysis by applying static and dynamic panel data models. The paper proceeds as follows. Section 2 presents a review of literature related to climate, weather, and rainfall variability in relation to agriculture and also discusses review of methodological perspectives. Section 3 discusses about data and methodology. Section 4 provides results and discussion. Section 5 concludes.

2. Literature Review

A wide variety of literature in crop sciences and agronomy, development economics, and agricultural economics have discussed the issue of weather and climatic conditions and its impact on production agriculture (for example, Rosenzweig and Parry 1994; Seo and Mendelsohn 2008; Taraz 2012; Bezabih and Falco 2012; Traore et al. 2013; Graef and Haigis 2001). For example, Traore et al. (2013) investigated the effect of climate and weather on production of cotton, soybean and groundnut using long-term experimental data from 1965-2005 in Southern Mali. They found a negative effect of maximum temperature and total seasonal rainfall in cotton yield, while corn yield was positively correlated with rainfall in relatively drier locations. In another agronomic study Graef and Haigis (2001) found that the rainfall variability resulted in yield loss for millet in semi-arid areas in Niger. They reported two major strategies at the farm level that farmers practice—firstly, cultivate fields in different locations within the village district and

secondly, sow as much as area as possible. Both of these strategies result in increased cultivated area over total cultivable area—in other words, higher cropping intensity or higher land use intensity for crops.

Form a global perspective, Rosenzweig and Parry (1994) sought to understand the potential impact of climate change on world food supply. They conclude that vulnerability to changes in weather and climate is different between developed and developing countries. They suggest an interdisciplinary research on biophysical and socio-economic aspects to explore the sensitivity and mitigation towards climate change. Additionally, weather and climatic factors influence crop choices. For example, Lamb (2002) investigated the impact of weather risk on crop choices in some of the villages in India and found that crop choices were indeed influenced by weather risks³. It should be pointed out that land allocation across different crops is an important decision under weather risk because crops differ widely in terms of yield variability arising from fluctuation in weather (Lamb 2002).

Recall that variability in rainfall is an important source of uncertainty in agricultural production decisions. Bezabie, Falco, and Yesuf (2011) used household and plot-specific longitudinal data from Ethiopia to analyze riskiness of crops and household's decision on crop choices. They found that level of riskiness of crop portfolios are partly motivated by both annual and seasonal rainfall variability and moisture sensitive crops. Household behavior suggested that they chose less moisture-sensitive crops in times of rainfall shortages and combine risky and less-risky crops in case of greater variability in rainfall. Therefore, once can conclude that in response to rainfall variability, farmers are more likely to select less risky crops with less return; crop selection and crop management practices are ex-ante practices towards mitigating rainfall

³ Weather risk in measured by variability in the start date of monsoon season, with at least 20 mm of rainfall, after June 1st.

risk (Bezabih, Falco, and Yesuf, 2011; Bezabih and Falco, 2012). Finally, Seo and Mendelsohn (2008) investigated South American farmers' adaptation to climate change. Analyzing the crop choice among seven most popular crops under different environmental conditions across the landscape, they concluded that the farmers adjust crop choice and hence area under those crops to fit their local climate conditions. They also indicated a possibility of crop switching. However, cross-sectional data did not capture switching over time.

While crop choices, crop mix, production diversifications are ex-ante risk management; income diversification through off-farm labor supply is explained as major ex-post adjustment. These studies relate crop production and weather risk with household specific behavior, human capital, and household's economic conditions. For example, Dercon (1996, 2000) examined poor households' use of risk-management and risk-coping strategies and crop choices in Tanzania. Choosing a less risky crop portfolio, mostly likely behavior of poor households, leads to substantial low income—resulting from low returns from the crop portfolio. Even with low returns, households choose low risk crops because they are not able to find jobs in nonfarm sectors (Dercon, 1996).

Broadly, the major investigations in these studies and a common literature on climatic conditions and production agriculture can be explained under three major aspects. First, crop production and yield are affected by weather conditions; second, weather and climatic factors influence crop choice in general; third, farmers tend to adjust/adapt towards weather risk through management practices in production (such as crop portfolio choice) or through ex-post income diversification activities. While adapting towards risk, factors shaping farmers' behavior such as household economic conditions, human capital etc. also play an important role.

Though the aspects of weather risk, climate change, agricultural production and adaptation has been discussed in variety of disciplines, concrete evidences based on responses through farming behavior requires careful attention. However, most of the studies mentioned above use cross-sectional or aggregate level data. Note that cross-sectional studies and/or aggregate level time-series studies focused on specific regions may lack generalization. Solid evidences to back-up theory or strong empirical study to provide a different perspective on weather risk, crop choice, and cropping intensity is lacking in the literature. Secondly, above studies have not investigated cropping intensity (cropped area/total cultivable area). Third, to better understand about farmer's adjustment behavior in response to weather risk, it is important to consider short- medium- and long- term effects of weather risk on cropping intensity. Thus, the literature falls short of concrete empirical evidences that can be generalized. Moreover, due to possibilities of multi-dimensional factors such as agricultural system, behavioral responses, and constraints due to weather and other dimensions of risk, the adjustments to weather risk is more an empirical question that requires careful attention. Our study aims to fill this gap in empirical literature by providing an evidence of short- and long-run responses to weather risk and farmer's behavior using a panel data set, that account for temporal and spatial aspects, from 1966-2007, in 115 district in India.

Conceptual Model

We consider a model of land allocation for cropping decision (acreage decision) of a farm household. Consider a simple income-leisure utility function of a farm household. The farm household maximizes the utility function subject to production and time constraints, where utility is a function of farming household's income (π) and leisure (l).

$$U = U(\pi(F, O(e)), l) \quad (1)$$

We simplify the model with only two potential sources of income, farm income (F) and/or the income from off-farm jobs (O). We further assume that education is the major determinant of off-farm earning decisions, $O = O(e)$ and $\frac{\partial O(\cdot)}{\partial e} > 0$; *i.e.*, farm households with more educated members in the households are more likely to chose off-farm works in rural areas over farming. Farm household's profit function from agriculture is considered as:

$$F = P * Q(A, L^F, K, \phi) - C(Q, r) \quad (2)$$

where $C(\cdot)$ represents cost function and $Q(\cdot)$ represent concave production function of a farm household. P is price of farm output and r is the vector of input prices. Labor and capital inputs for production are represented as L^F , and K , respectively. L^F is allocated on the basis of total time by: $T = L^F + L^o + l$, where T represents total time, L^F is labor provided for farm production, L^o and l represent off-farm labor supply from household and leisure, respectively. Land acreage allocation for the agricultural production is represented by A , with possibility of acreage allocations for $i = 1, 2, \dots, j$ crops such that $A = \sum_i A_i$. ϕ represents the vector of other exogenous variables influencing production. For fixed capital and labor inputs (usually in short-run), land allocation is a major input for total crop production. However, in long run there could be adjustment in factors.

Now we introduce weather variability and some exogenous factors that influence total land allocation decisions for crops. Assuming that the total cultivable (total available land for use) as G , a measure $S_A = \frac{A(A_i)}{G}$, represents the cropping intensity or share of cropped area (total cropped area over total cultivable area). Let C_v represent weather risk or variability in weather. Now we represent the weather risk augmented model in equation 3:

$$F = P * Q(S_A(C_v), L^F(C_v), K, \phi) - C(Q, r) \quad (3)$$

Cropping intensity decisions can represent two scenarios of farmer behavior. First, more intensity of cropping, *i.e.*, allocate more total acreage under crop as a response towards weather variability—diversifying the crop portfolio towards response of risk perhaps including more acreages under less risky crops. $\frac{\partial(S_A(C_v))}{\partial C_v} > 0$ implies such behavior. Second, lower intensity of cropping, *i.e.*, allocate less acreage under agricultural crops when weather variability is increased. $\frac{\partial(S_A(C_v))}{\partial C_v} < 0$ may imply that the farmer moves away from cropping. In the nutshell, we can assume that the households with potential higher off-farm opportunities may move away from farming when weather variability is higher—perhaps households with more educated members, *i.e.*, we expect $\frac{\partial L^F(C_v)}{\partial C_v} < 0$ in equation 3 and $\frac{\partial \pi(O)}{\partial C_v} > 0$ in utility function in equation 1.

Econometric Method

Equation 3 can be transformed to derive the empirical model. Empirically, we estimate the short-term and long-term sensitivity of cropping intensity to rainfall variability as follows.

$$S_{A_{i,t}} = \Gamma C_{v_{i,t}} + \beta X_{it} + \alpha_i + \varepsilon_{it} \quad (4)$$

$S_{A_{i,t}}$ represents cropping intensity in the district i in year t . Our main variable of interest, rainfall variability in district i in year t is represented as $C_{v_{i,t}}$. X_{it} includes exogenous control variables that may affect cropping intensity, such as share of rural literates in the district, share of cultivators in total population, productivity of high yielding variety, availability of agricultural labor, net irrigated area over total cultivable area etc. α_i is useful in controlling district-level fixed effects.

In our study, equation 4 is estimated using panel data. Broadly, two types of panel data models have been discussed in literature—firstly, the models with large cross-sectional units but

small time-span (large N, smaller (or fixed) T), and secondly, models with larger time span as well as larger cross-sectional units (larger N, larger T). The former types of panel model require pooling individual groups and allowing only the intercepts to differ across the groups. On this extreme, we can estimate the fixed effects model in which the time series data for each group are pooled and only the intercepts are allowed to differ across the groups⁴. However, if the slope coefficients are not identical, these estimators could result in misleading inferences. Previous studies have found that the assumption of homogeneity of parameters across group is often inappropriate (Phillips and Moon, 2000; Baltagi 2005; Pesaran, Shin, and Smith, 1999).

In recent years, there has been a growing interest in cases, such as sets of countries, regions or industries, where there are fairly long time-series for a large N. The second approach can be utilized in estimation of non-stationary or co-integrated panel models where heterogeneity in parameters is allowed across groups. Econometric methods for non-stationary panels are applied in many empirical studies. Some recent studies, for example, include—Narayan et al. (2010); Mark and Sul (2003); Costantini and Martini (2009); Onel (2012).

Pesaran, Shin, and Smith (1997, 1999) present techniques to estimate non-stationary dynamic panels in which the parameters are heterogeneous across groups—the mean-group (MG) and pooled mean group (PMG) estimators. With MG estimator, the intercepts, slope coefficients, and error variances are all allowed to differ across groups. The PMG estimator, on the other hand, combines both pooling and averaging. This allows the intercept, short run coefficients, and error variances to differ across the groups but constraints the long run coefficients to be equal across group. Pesaran, Shin, and Smith (1999) have developed maximum likelihood methods to estimate these parameters (Blackburne III and Frank, 2007).

⁴For detail description of panel data models, we refer to Baltagi (2005).

Bangake and Eggo (2010) estimated long run relationships using MG, PMG, and dynamic OLS models to study international capital mobility in African countries using 37 African countries from 1970 to 2006. Frank (2005) used MG and PMG models to study income inequality and economic growth relations in the long-term.

In this paper, we presented the results of both classes of panel data models (first, models for fixed T and large N and second, models for large T and large N). Assuming fixed T and large N, we presented results of static fixed effect (FE) models, static random effect (RE) models, and first difference (FD) models. For the second-class or co-integrated models, we presented regressions applying dynamic OLS (DOLS) regression, dynamic fixed effects (DFE) regression, and MG and PMG model estimations. MG and PMG models (Pesaran, Shin, and Smith (1997, 1999)) are estimated to assess the long run and short run effects of rainfall variability in cropping intensity.

Data

This study uses data set collected by International Crop Research Institute for Semi-arid Tropics (ICRISAT) in India. Our sample includes data for 115 districts from 1966 to 2007 for 5 states *Andra Pradesh (AP)*, *Madhya Pradesh (MP)*, *Maharashtra (MH)*, *Karnataka (KT)*, and *Haryana (HR)*. Figure 1 shows five States and their location on Indian map. Meso dataset of ICRISAT has compiled district-level information on different climatic and land-use variables such as annual and June-July rainfall, soil-type, irrigated acreage, high yielding varieties production area. Additionally, information on rural and urban population, farming population, rural and urban agricultural labors, and number of literates in rural population are available through different modules of ICRISAT meso dataset.

Table 1 presents variable definitions and summary statistics in raw form (*i.e.*, summary of district-time data points). In total we have 4,782 district and time observations were used in our analysis. We calculated district-level cropping intensity as the ratio of total cropped area to total available area for cultivation (excluding area for non-agricultural uses, buildings, etc.). Average cropping intensity is 0.627 with standard deviations of 0.267. This indicates that around 63% of the total cultivable area has been allocated for agricultural production of the crops in a district. The cropping intensity pattern for each district is represented in figure 2. Overall, figures suggest a slightly increasing trend in most of the districts over time. Rainfall variability, indicator of weather risk is measured by the coefficient of variation of the annual rainfall. Coefficient of variation is a unit-less measure and has been used in other studies as a measure of variability or risk (see, Mishra and Goodwin 1997; Bezabih et al., 2011). Average rainfall variability was 0.537 with standard deviation of 0.051. Rainfall variability is measured on a yearly basis. Figure 3 represents rainfall variability plots in each district and over time.

Cultivator share is the share of total cultivators (farmers) in total district population. In another perspective, this measure indicates the number of many famers that are available to cultivate in the district population. Surprisingly, this is only about 16% compared to the total district population. Agricultural labor availability is calculated as the ratio of total agricultural labor available in the district to total cultivators. Labor availability variable with mean of 0.865 indicates that agricultural labor availability per cultivator was around 86%. However, relatively higher standard deviation of 0.623 indicates that the district-time labor availability has higher variation across time and space. Another variable of interest is the literacy rate in the rural areas. Our rural literate share variable is the ratio of rural literate population to total literate (rural and

urban) population in the district. On an average, rural literate population is around 66% of the total literate population in the district.

Indicator of irrigation facility and production of high yielding varieties (HYV) are captured by two variables— share of irrigated cropped area over total cropped area and total HYV production per total cultivated area total cropped area and net irrigated area in the district over total cropped area. Irrigation variable suggests that only 19% of the area in the district is irrigated and HYV production per cultivable area in district is around 0.23.

Results and Discussion

Panel regressions for fixed T and Large N

Table 2 presents panel regressions commonly used for models with *smaller T* component and *large N* component. Typically, household panel data with large cross-section but small time span are commonly estimated through these models. *Small T* panel models usually rely on fixed or random effect models or combinations. These models assume fixed T, and $N \rightarrow \infty$, asymptotically. First column in table 2 reports for pooled ordinary least squares (POLS) regression. Second and third columns show fixed effects and random effects regression estimations, respectively. Serial correlation test suggests a presence of serial correlation in both POLS and fixed effects models. This finding leads us to estimate a generalized estimating equation (GEE) model. GEE population average model allows for unrestricted system heteroskedasticity. In the fourth column, we estimated first difference (FD) model. In all models, rainfall variability and share of HYV production significantly impact cropping intensity. Share of irrigation area is significant in all but GEE regression. Coefficient estimates from GEE regression suggest that a 10% increase in rainfall variability decreases cropping intensity by 0.5%. A plausible explanation could be that subject to higher rainfall variability, farmers intend

to move away from agriculture and perhaps choose to diversify income through other sources, perhaps with off-farm and non-agricultural works.

Unlike rest of the estimates presented in Table 2, FD regression relates a change (first difference) in cropping intensity variable with changes (first difference) in independent variables. Results show that a 1% increase in change in rainfall variability from previous year results a decrease in change in cropping intensity by 1.6%. Taking results from the GEE and FD models together, our results show that risk has a negative effect on cropping intensity and is decreasing over time. The positive effect of share of HYV production on cropping intensity, on the other hand, is increasing over time. For example, 10% increase in the share of HYV crop, changes cropping intensity by 0.1%.

However, one must be cautious in inferring relationships from our aggregate district level data using *large N and small T* panel models presented in Table 2. *Large N and small T* panel models require pooling individual groups and allow only the intercepts to differ across groups. By the nature of our data, we have much longer time span (T) along with substantial cross-sectional groups. As indicated in previous studies, homogeneity of slope parameters, the assumption of *large N and small T*, is often inappropriate for case where we have *large T and large N* (Pesaran and Smith 1995; Phillips and Moon 2000; Baltagi 2005). Asymptotic of *large T and large N* dynamic panel models is different from traditional *large N and small T* dynamic panels (Baltagi, 2005). With increase in time observations inherent in *large N and large T* dynamic panels is non-stationarity that needs to be addressed. Therefore one needs to test for non-stationarity using stationary, unit root, and cointegration tests. Next, we proceed to panel non-stationary and unit root, and co-integration tests.

Panel Unit Root and Stationarity Tests

There are many options for panel stationary and unit root tests. Hardi (2000) has developed several residual-based Lagrange multiplier tests for heteroscedastic and serially dependent error processes with a null hypothesis of trend stationary. Table 3 presents results of stationarity tests for each variable. Test provides the evidence that variables of our interest are non-stationary in level form but stationary in the first difference form.

With respect to a null hypothesis, no cointegration, both Pedroni (1995, 2004) and Kao (1999) tests for panel data are commonly used in literature. The Pedroni (1995, 2004) test is based on pooled type tests, while Kao (1999) test is based on augmented Dickey-Fuller (ADF) type test applicable to panel data. Based on these test results, results show a rejection of null hypothesis in majority of test results based on Pedroni (1995, 2000) and rejection of null hypothesis using Kao (1999) test. Therefore, we conclude the variables of interest are cointegrated and the variables of the interest are cointegrated implying that one should use non-stationarity dynamic panel modeling approach. Next, we estimate non-stationary, cointegrated dynamic panel models appropriate for *large T and large N*.

Non-stationary and dynamic panel models for large N and large T

We estimated short-term and long-term associations of cropping intensity with rainfall variability and other variables of interest using cointegrating regressions suitable for non-stationary dynamic panel models. These estimates assume both N and T approach infinity asymptotically. Table 4 presents results of these models. First column, table 4, of the table presents dynamic OLS (DOLS) regression results suggesting that there is a long term association of cropping intensity with rainfall variability, share of cultivators, share of HYV crop production, and share of irrigated area. The effects of all these variables are positive and significantly

different from zero at the 5% level of significance or higher. The DOLS has a remarkably high R-square 0.972 suggesting that the model explains cropping intensity very well in long run. DOLS results suggest that 10% change in rainfall variability increases cropping intensity by 3%. The long-term effect of a 10% change in share of cultivator, share of HYV crop production, and share of irrigated areas increase change in cropping intensity by 0.7%, 0.1%, and 0.9%, respectively.

Column 2 of table 4 shows the results of dynamic fixed effects (DFE) model. DFE has similar coefficient estimates as DOLS except that it suggests one additional variable affecting cropping intensity. Results show that share of rural literates is negatively cropping intensity in long-term. A 10% increase in change in share of rural literate results in a 1.6% reductions in cropping intensity in the long-term.

Allowing for the heterogeneity of parameters across groups, Pesaran, Shin, and Smith (1997, 1999) have developed two important techniques to estimate non-stationary dynamic panel models: The mean group (MG) and pooled mean group (PMG) estimators. The MG estimator relies on estimating N-time series regressions and averaging the coefficients, whereas the PMG estimator relies on a combination of pooling and averaging the coefficients (Pesaran and Smith 1995; Pesaran, Shin, and Smith 1999). These estimation techniques have been applied to empirical studies (Freeman 2000; Frank 2005). Column 3 and column 4 of our results in table 4 present mean-groups (MG) and pooled mean groups (PMG) regression, respectively. MG results suggest a positive 0.5% growth in cropping intensity as a result of 1% increase in change in weather variability while PMG estimator suggests a positive effect of around 0.2%. Additionally, PMG result suggest a negative long term effect of share of rural literates and a positive effect of

share of irrigated area on cropping intensity. A 10% growth in share of rural literates is associated with a 1.8% reduction in change in cropping intensity.

We conducted a Hausman test to compare which model is more suitable among DFE, MG, and PMG. Test results are presented in table 5. Our two sets of Hausman test suggest that DFE model is preferred over MG model and PMG model is preferred over MG model. Overall, DFE and PMG model estimates suggest a positive long-term effect of growth in rainfall variability, a negative long-term effect of growth in share of rural literates, and a positive effect of a growth in share of irrigated area. A positive effect of rainfall variability suggests for the portfolio or crop mix diversification behavior of farmers that we have discussed as one of the possibilities in our conceptual model—i.e., increase in cropped area (perhaps with higher allocated areas for less risky crops) when subjected to higher variability in rainfall. This may seem dubious at first glance because one assumes that there is a more likely chance of moving away from farming and diversify income through alternative off-farm jobs when farming becomes riskier—resulting a lower cropping intensity due to weather risk. However, the scenario of peasant farmers in rural areas may be different from this assumption because they may have less opportunity for alternative practices and continue farming. A positive relation is plausible. Farmers with low or no outside opportunities, the response towards weather risk is to crop more areas in different locations and with different crops (crop mix).

A negative effect of share of rural literate share variable in the district could be explained through education and off-farm labor supply relations established in farm household literature. Increased education in rural area increases off-farm work opportunities for the educated; this may induce farmers to move away from farming and towards off-farm work that is often less variable and parameters. Increase in share of HYV to total cropped area is an indication of

adoption of improved varieties and progressive farming. Higher HYV production pattern increases cropping intensity as more people are attracted by higher yield in crops and increased returns and thus aim to expand farming or attracted towards farming. A positive effect of a growth in share of irrigated area on growth in cropping intensity is as expected. With irrigation facilities, farmers are better able to reduce the impact of rainfall variability and thus able to stabilize production and income from farming. This enables existing farmers to expand cropping areas, increasing economies of scale.

Finally, we also examined the long-term effect of rainfall variability and cropping intensity using DFE, MG, and PMG estimators in state-wise regression for 3-states. Results are shown in table 6. A positive effect of rainfall variability is also confirmed in state-wise regression indicating robustness of our findings.

Summary and Conclusion

Weather and climatic conditions play an important role in agricultural production. Variability and risks associated with climate and weather in an area not only influence farmer's decision on cropping intensity and pattern but may also influence the decision to farm in the first place. This paper presents empirical evidence on a relationship between cropping intensity and weather variability using a panel of 115 districts in India over the 1966 to 2007 period. We presented results using different panel data methods used in the literature. Rather than 115 cross-sections with 5 or 6 time periods, as is common in most of the prior panel data studies, we are able to compile a sample that is large in both cross-sections and time-periods ($N=115$, $T=42$) and enables us to implement a more suitable non-stationary cointegrated dynamic panel model for large T and large N .

Results indicate a positive long-term association between rainfall variability on cropping intensity. The positive relation is quite strong and robust among all different panel data models—dynamic OLS, dynamic FE, mean group, and pooled mean group estimation techniques. The findings are significant and consistent even with the inclusion of numerous additional regressors. Additionally, our results suggest that the indicator of higher education in the district is negatively associated with cropping intensity while indicators of irrigation facilities and share of high yielding variety production positively influence cropping intensity.

With an opportunity to choose alternative income generating activities such as off-farm jobs, a positive effect of weather risk on cropping intensity may seem dubious because when farming is risky, people may move away from farming. However, the scenario of peasant households in rural areas and subsistence farming could be different in that they have fewer off-farm alternatives. Instead, in this case a response towards weather risk would be to diversify crop mix and increase the allocated areas for less risky crops, that will intend to have stabilized quantity of food produced and income generated. This latter behavior results in increase in cropping intensity. However, we have not tested for crop specific area allocations in this study and warrants for further extension. Other limitations of this study may come from a district-level aggregate data. A micro-level crop-specific data on cropping intensity and pattern will be more helpful to verify this behavior. Further, land quality and land type variables may also help in providing better insights.

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Table 1: Descriptive Statistics of the variables in raw form, 1966 to 2007, India

Variable definition	Mean	Standard Deviation
Cropping intensity (Total cropped area over total available cultivable area)	0.627	0.267
Rainfall variability (Coefficient of variation of total annual rainfall)	0.537	0.051
Cultivator share (Share of total cultivators (farmers) in total population)	0.159	0.059
Agricultural labor availability (Total agricultural labor population over total cultivators population)	0.865	0.623
Rural literate share (Share of rural literate population over total literates)	0.664	0.160
HYV production (High yielding variety production over gross cropped area)	0.228	0.181
Irrigated area share (Net irrigated area over total cropped area)	0.190	0.145
Total observations	4782	

Table 2: Panel models for fixed T, Large N (dependent variable: cropping intensity, in log)

	Pooled OLS	Random effects GLS	Fixed effects (within) estimation	Generalized Estimating Equation (GEE)	First Difference (FD) model
Rainfall variability ^a	0.091 (1.47)	0.105** (4.00)	0.105** (3.93)	-0.048** (-2.55)	-0.158** (-8.58)
Cultivator share ^a	-0.100 (-0.48)	0.025 (0.76)	0.025 (0.75)	0.007 (0.34)	0.015 (0.51)
Ag. Labor availability ^a	-0.012 (-0.12)	0.0014 (0.08)	0.002 (0.07)	0.012 (1.08)	0.021 (1.02)
Rural literate share ^a	0.023 (0.13)	-0.003 (-0.09)	-0.003 (-0.09)	0.015 (0.82)	-0.003 (-0.10)
HYV production ^a	0.032* (1.79)	0.016** (2.70)	0.015** (2.61)	0.006** (2.18)	0.013** (4.16)
Irrigated area share ^a	0.043 (0.97)	0.090** (5.96)	0.090** (5.81)	0.013 (1.43)	-0.043* (-1.71)
Constant	-0.542	-0.240**	-0.237**	-0.506**	
<i>N</i>	4025	4025	4025		3785
<i>Serial Correlation Test (H₀: no serial correlation)</i>	Reject null t= 262.10 (p<0.000)		Reject null t= 17.65 (p< 0.000)		Reject null t = -10.33 (p< 0.000)
<i>Fraction of individual-specific variation (ρ)</i>		0.935	0.933		

^a Variables are in log; t statistics in parentheses; * $p < 0.1$, ** $p < 0.05$

Table 3: Stationary, unit root and Co-integration tests for panel data

Hardi (2000) Stationary Tests for Panel Data	Hardi z-statistic	Heteroskedastic consistent z-statistic
<i>Stationary test on variables in level form</i>		
H ₀ : log of rainfall variability is stationary	30.14**	29.36**
H ₀ : log of cropping intensity is stationary	30.93**	28.13**
H ₀ : log of rural literate share is stationary	19.17**	14.87**
H ₀ : log of rural cultivators share is stationary	19.21**	15.99**
H ₀ : log of high yielding variety production per cultivable area is stationary	33.74**	32.84**
H ₀ : log of availability of agricultural rural labor is stationary	12.08**	12.06**
H ₀ : log of share of irrigated area is stationary	42.16**	37.08**
<i>Stationary test on variables in first difference form</i>		
H ₀ : first difference of rainfall variability is stationary	-7.25 (p=0.99)	-7.21 (p=0.99)
H ₀ : first difference of cropping intensity is stationary	-2.73 (p=0.97)	5.13**
Co-integration Tests		
	Pedroni (1995)	Kao (1999)
H ₀ : No integration, H _a : Common AR coefficient (within dimension)		
Panel v-statistic	-34.82 (p=1.00)	
Panel rho-statistic	-0.16 (p=0.43)	
Panel PP statistic	-14.06** (p<0.00)	
Panel ADF statistic	-8.09** (p<0.00)	-1.98** (p=0.02)
H ₀ : No integration, H _a : Individual AR coefficient (between dimension)		
Group rho statistic	3.12 (p=0.99)	
Group PP-statistic	-19.95** (p<0.00)	
Group ADF statistic	-7.34** (p<0.00)	

Table 4: Long run effects, non-stationary panel models for large N and large T (dependent variable: cropping intensity, in log)

	Dynamic OLS	Dynamic FE	Mean Group (MG) regression	Pooled Mean Group (PMG) regression
<i>Long-run coefficients</i>				
Rainfall variability ^a	0.301** (6.25)	0.316** (5.64)	0.509** (2.83)	0.182** (5.74)
Ag. Labor availability ^a	-0.011 (-0.72)	0.024 (0.71)	-2.577 (-1.28)	0.014 (0.80)
Rural literate share ^a	-0.04 (-1.28)	-0.156** (-3.75)	-2.708 (-0.73)	-0.178** (-6.84)
Cultivator share ^a	0.065** (2.89)	0.106* (1.84)	-3.463 (-1.15)	0.043* (1.77)
HYV production ^a	0.012** (2.28)	-0.010 (-1.21)	0.936 (1.02)	0.003 (0.85)
Irrigated area share ^a	0.089** (8.89)	0.074** (2.81)	-0.145 (-0.77)	0.108** (20.07)
Adjustment factor (ϕ)		0.375** (8.70)	0.636** (15.63)	0.358** (10.27)
Adjusted R ²	0.972			
<i>Short-run coefficients</i>				
D.Rainfall variability ^a		-0.041** (-2.78)	0.017 (0.69)	-0.053** (-3.07)
D.Ag.Labor availability ^a		-0.017 (-1.02)	-0.343 (-1.47)	-0.282 (-1.20)
D.Rural literate share ^a		0.035 (1.17)	-0.395 (-1.50)	-0.440* (-1.68)
D.Cultivator share ^a		-0.033 (-1.11)	-0.699 (-1.59)	-0.640 (-1.54)
D.HYV production ^a		0.002 (0.45)	0.003 (0.39)	-0.003 (-0.33)
D.Irrigated area share ^a		-0.057* (-1.71)	-0.073* (-1.87)	-0.071** (-2.12)
Constant		0.016 (0.37)	1.586 (0.89)	0.082** (2.60)
N			1812	1812

^a Variables are in log; D. refers to first difference; t statistics in parentheses; * $p < 0.1$, ** $p < 0.05$

Table 5: Hausman test results for model choice between FE, MG, PMG models

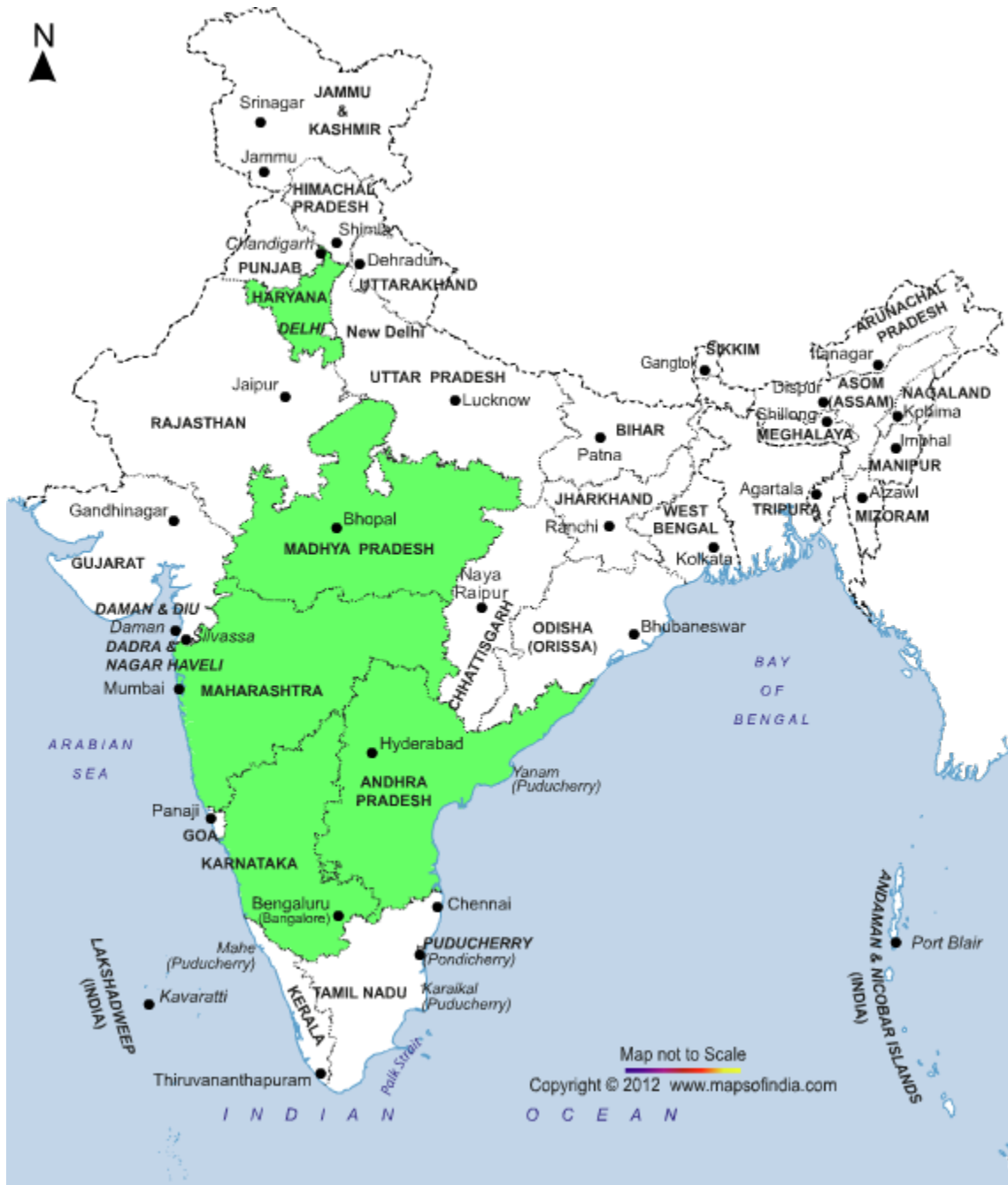
Hausman test	Hypothesis	Chi-square Statistics	Conclusion
Comparison between MG and Dynamic FE	MG estimator is consistent under null and alternative FE is inconsistent under alternative, efficient under null	2.59 ($p > \chi^2 = 0.86$)	FE model, efficient under null, is preferred over MG model
Comparison between MG and PMG regression	MG estimator is consistent under null and alternative PMG estimator is inconsistent under alternative, efficient under null	0.00 ($p > \chi^2 = 1.00$)	PMG estimator, the efficient estimator under the null hypothesis, is preferred

Table 6: Long run effects using non-stationary panel models, state-wise regressions

	Dynamic FE	Mean Group (MG)	Pooled Mean Group (PMG)
<i>State: Andhra Pradesh (AP)</i>			
Rainfall variability ^a	0.388** (4.47)	1.045** (2.48)	0.289** (3.94)
Ag. Labor availability ^a	0.043 (0.48)	-1.370 (-0.65)	0.025 (0.46)
Rural literate share ^a	-0.130** (-2.02)	1.390 (1.29)	-0.083 (-1.37)
Cultivator share ^a	0.172* (1.70)	-1.144 (-0.39)	0.178** (2.46)
HYV production ^a	-0.006 (-0.51)	-0.011 (-1.01)	0.018** (2.78)
Irrigated area share ^a	-0.125** (-2.58)	-0.032 (-0.23)	-0.128** (-5.70)
Adjustment factor (\emptyset)	0.402** (8.03)	0.712** (11.17)	0.397** (7.65)
N		658	658
<i>State: Hariyana (HP)</i>			
Rainfall variability ^a	0.314** (2.78)	0.234** (2.86)	0.288** (3.03)
Ag. Labor availability ^a	0.134 (1.46)	-13.49 (-1.00)	-0.019 (-0.38)
Rural literate share ^a	-0.002 (-0.01)	-25.80 (-0.94)	-0.045 (-0.54)
Cultivator share ^a	0.0742 (1.22)	-20.54 (-0.99)	-0.108** (-2.16)
HYV production ^a	0.124* (1.85)	6.856 (1.01)	0.028 (0.92)
Irrigated area share ^a	-0.020 (-0.46)	-1.364 (-1.04)	0.087** (2.28)
Adjustment factor (\emptyset)	0.463** (3.72)	0.622** (4.85)	0.293** (2.12)
N		259	259
<i>State: Maharastra (MH)</i>			
Rainfall variability ^a	0.271** (2.92)	0.158 (1.32)	0.140** (4.17)
Ag. Labor availability ^a	0.035 (0.77)	-0.488 (-0.71)	0.021 (0.98)
Rural literate share ^a	-0.272** (-3.89)	0.479 (0.52)	-0.237** (-6.68)
Cultivator share ^a	0.163** (2.38)	-0.538 (-0.57)	0.068** (2.00)
HYV production ^a	0.005 (0.51)	0.0358** (2.68)	0.001 (0.14)
Irrigated area share ^a	0.111** (4.46)	0.106** (2.55)	0.114** (21.23)
Adjustment factor (\emptyset)	0.349** (5.25)	0.580** (10.13)	0.383** (7.50)
N		895	895

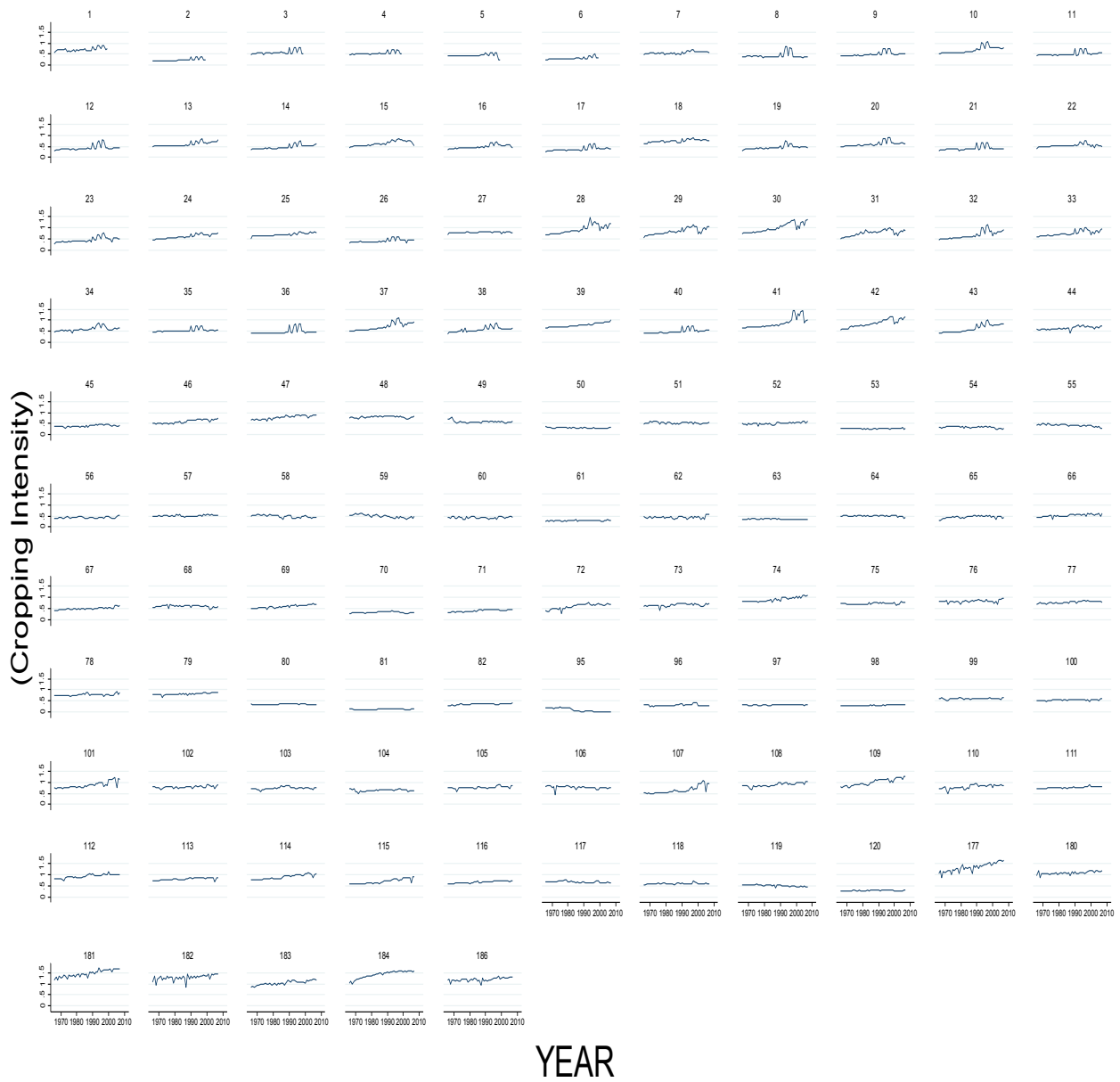
^a Variables are in log; *t* statistics in parentheses; * $p < 0.1$, ** $p < 0.0$

Figure 1: India map showing study area



Note: Study area is denoted by green color

Figure 2: Cropping intensity pattern over years in different districts, 1966 to 2007, India



Graphs by District

Figure 3: Rainfall variability over years in different districts, 1966-2007, India

