Impact of COVID-19 on Agricultural Productivity (2017-2022) and Female Labor Force Participation (1992-2021) in India: "An Analysis"

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DECLARATION BY STUDENT

I hereby declare that the data presented in this Dissertation report entitle, "Impact of COVID-19 on Agricultural Productivity (2017-2022) and Female Labor Force Participation (1992-2021) in India: "An Analysis" is based on the results of investigation carried out by me in Economics at the Goa Business School, Goa University under the Supervision of Ms. Sumita Datta and the same has not been submitted elsewhere for the ward of degree or diploma by me. Further, I understand that Goa University or its authorities will be not be responsible for the correctness of observations / experimental or other findings given the dissertation.

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COMPLETION CERTIFICATE

This is to certify that the dissertation report "Impact of COVID-19 on Agricultural Productivity (2017-2022) and Female Labor Force Participation (1992-2021) in India: An Analysis" is a bonafide work carried out by Ms. Farheen Khan under my supervision in partial fulfilment of the requirements for the award of the degree of Masters of Arts in the Discipline Economics at the Goa Business School, Goa University.

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PREFACE

Undertaking this research on "Impact of COVID-19 on Agricultural Productivity (2017-2022) and Female Labor Force Participation (1992-2021) in India: “An Analysis”” has been a profound journey of inquiry, analysis, and discovery. This dissertation represents the culmination of my academic pursuits, driven by a deep-seated passion for understanding the intricate dynamics between pre-covid and post-covid. The genesis of this study can be traced back to a desire to unravel the complexities of agriculture sector and its impact on covid-19 in agriculture sector and female labour participation in agriculture and non-agriculture. India, with its unique socio-economic and demographic profile, emerged as an ideal setting to explore these dynamics. Through meticulous research, data collection, and analysis, I have endeavoured to shed light on the Impact of COVID-19 on Agricultural Productivity (2017-2022) and Female Labor Force Participation (1992-2021) in India: “An Analysis”

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I take great pleasure in presenting this project report on ‘The Impact of COVID-19 on Agricultural Productivity (2017-2022) and Female Labor Force Participation (1992-2021) in India: An Analysis’.

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ABSTRACT

Agriculture has historically been the backbone of the Indian economy, employing a significant portion of the population and contributing substantially to the country's GDP. The aim of this paper was to study the impact of Covid 19 on agricultural crops such as rice, wheat, maize, pulses and cereals in India and to examine the role of female labourer participation rate in the agriculture and non-agricultural sector in India. The data was collected from the Ministry of Agriculture and Farmer's Welfare, Economic Survey, Periodic Labour Force Survey ,India Stat the Census of India and from the Global Data Lab. I have analysed by using Analysis of Covariance (ANCOVA) and by using line graph in order to capture the scenario of pre-covid and post-covid. In conclusion, I found that COVID-19 in India had a significant impact on agriculture productivity and female labour participation rate in agriculture and non- agriculture.

KEYWORDS

COVID-19	Impact
Agriculture Sector	
Non- Agriculture Sector	
Pandemic	
ANCOVA	
Female Labour Force Participation	
Crops	
Significant	

CHAPTER 1: INTRODUCTION

1.1 Background

In developing countries a large proportion of population live in rural areas with the majority among of them depending on agriculture. Rural economy constitutes the most predominant section of Indian economy in terms of its share in employment. Among the total rural workforce ‘rural labour’, in particular, constitutes the largest segment. The shift out of agriculture and into other more “modern” sectors (e.g., manufacturing) has long been viewed as central to economic development.**(Hicks et al., n.d.)**

India’s economy experienced dramatic changes, the magnitude of which differed across states **(Deininger et al., 2018)**. Agriculture has historically been the backbone of the Indian economy, employing a significant portion of the population and contributing substantially to the country’s GDP. Agriculture has long been the cornerstone of India's economy, employing a significant portion of its workforce and sustaining livelihoods across rural communities. The sector's journey reflects a centuries-old tradition of subsistence farming intertwined with cultural practices and agrarian traditions. However, the latter half of the 20th century witnessed a seismic shift in India's economic landscape, spurred by policies aimed at liberalization, industrialization, and modernization.

Indian agriculture began around 11000 years ago. Agriculture not only provides food security for the nation but also serves as a source of livelihoods for millions of rural households worldwide. In ancient India farmer’s used to plough, sow, reap and harvest during auspicious day because it was linked to some religious customs. Agriculture had made a significant progress since the beginning of civilisation, but during civilisation food shortage made a serious impact on Indian agriculture as it was monsoon-dependent, and unfavourable rains and natural calamities resulted in droughts and crop failures. Such droughts, sometimes in consecutive years, led to famines. Famines in India resulted in more than 30 million deaths over the course of the 18th, 19th, and early 20th centuries. The famous quote of India's first prime minister Pandit Jawaharlal Nehru and Mahatma Gandhi is that " everything can wait but agriculture" and " there are people in the world so hungry, that God cannot appear to them except in the form of bread" which signifies prioritizing agricultural development and food security initiatives. After India got its independence, India has witnessed a remarkable transformation from a food importing to a food surplus nation during seven and a half decades of its independence. The journey of this transition is marked by the inauguration of 'The Green Revolution' in the mid-1960s, 'The Yellow Revolution' in the early 2000s, and 'The Pulse Revolution' in the 2010s. **(H Pathak, 2022)**

The food production in India particularly in the pre-green revolution (1951-52 to 1966-67), India heavily relied on food imports. The Green Revolution, heralded as a turning point in India's agricultural history, catalyzed unprecedented growth in agricultural productivity through the adoption of high-yielding crop varieties, irrigation infrastructure, and chemical fertilizers. This period marked a departure from traditional farming methods, ushering in an era of commercialized agriculture and increased mechanization. While the Green Revolution succeeded in alleviating food scarcity and bolstering agricultural output, it also introduced new challenges, including environmental degradation, water scarcity, and socio-economic disparities. However, after the initiation of the green revolution in 1966-68 there was a significant acceleration in food grain production, leading to a doubling of production from 74.2 MT to 150 MT by 1985-86. Despite a subsequent slowdown of in agricultural productivity from 1997-98 onwards, production doubled again to 314.51 MT by 2021-22. Alongside the green revolution, India also witnessed other agricultural revolutions such as the yellow revolution which focused on increasing oilseed production, the sugar revolution aimed at enhancing the sugarcane cultivation and it's processing, the gene revolution wherein they introduced genetically modified crops for improved yield and resistance, and the pulse revolution was for promoting the cultivation of pulses for protein security. These revolutions have played a pivotal roles in diversifying crop production, improving technology adoption and enhancing overall agricultural productivity in India. The green revolution not only revolutionised food production but also strengthened the National Agricultural Research System (NARS). Many research institutes, co-ordinated projects, and universities were initiated under the Indian Council of Agricultural research (ICAR). Overtime, NARS was expanded and research centres were established to foster multidisciplinary research. Technological developments and policies have increased productivity and expanded crops into non-traditional areas. **(H Pathak, 2022)**

Indeed, labour also played an important role in India's development journey. Its contribution can be seen in all sectors of the economy, including the primary, secondary, and tertiary sectors. Labour plays a crucial role in driving economic activities across various industries, contributing to production, innovation, and growth. In ancient India, labour was mostly engaged in agriculture, as the majority of the population relied heavily on agriculture. The labour sector in India has been significantly impacted by rapid structural transformation in the economy. The rapid structural transformation in India has led to a gradual shift of labour from agriculture to the industry and service sectors. This shift has been driven by urbanisation, industrialisation and the expansion of the service sector, resulting in changes in employment patterns and opportunities.

Despite the growth of the industrial and service sector, a large portion of the labour force in India remains employed in the informal economy. Informal employment is characterised by low wages, lack of social security benefits, and limited stability, posing challenges for worker's rights and welfare. Rapid urbanisation has also led to the labour migration from rural to urban areas in search of better employment opportunities.

However, the influx of migrants has also resulted in challenges such as urban poverty, informal settlements, and pressure on infrastructure and services. In response to the labour market, the government has introduced various labour market reforms aimed at promoting formal employment, improving working conditions, and enhancing social protection for workers. These reforms include changes to labour laws, initiatives to promote skill development, and schemes that provide social security benefits. The labour sector in India is also influenced by technological advancement and automation, which leads to changes in job roles, skill requirements, and employment opportunities. The rapid pace of structural transformation has often exceeded the developments in skills and education levels among the workforce.

This study presents the outbreak of the coronavirus, COVID-19, in late 2019 sent shockwaves across the globe, affecting nearly each and every aspect of human life. Among the many sectors, agriculture emerged as a critical point, with its consequences worldwide. The pandemic's disruptive force on agricultural productivity has complicated revealing vulnerabilities in supply chains, labour markets, and food security systems.

As COVID-19 spread rapidly, governments worldwide implemented strict restriction measures, including lockdowns and social distancing protocols, to prevent transmission rates. These measures, while necessary for public health, have significantly disrupted agricultural activities, posing unusual challenges to farmers and food producers. One of the most immediate impacts of these measures was labour shortages, as restrictions on movement and the closure of borders led to a scarcity of migrant workers, who are the backbone of agricultural labour in many regions. From harvesting crops to tending livestock, the absence of sufficient labour has hindered agricultural operations, harming crop yields and livestock production.

The imposition of lockdowns and travel restrictions led to a significant shortage of agricultural labour, particularly in regions heavily reliant on migrant workers. Some Farmers faced challenges in hiring and retaining workers for critical tasks such as planting, harvesting, and processing crops and Disruptions in transportation hindered the timely delivery of agricultural inputs and the distribution of produce to markets, which disrupts the flow of goods and services, resulting in delays and inefficiencies.

Furthermore, disruptions in transportation and logistics have impeded the timely delivery of agricultural inputs, such as seeds, fertilizers, and pesticides, as well as the distribution of produce to markets. Supply chain bottlenecks have left farmers to struggle with surplus produce and mounting losses, worsening financial strains and threatening livelihoods. Meanwhile, restrictions on the movement of goods have led to food shortages in some regions, intensifying food insecurity and heightening concerns about access to nutritious food, particularly for vulnerable population.

The closure of restaurants, schools, and other food service establishments in response to the pandemic had also reshaped demand patterns, which lead to shifts in consumption preferences and distribution channels. With a significant portion of agricultural produce traditionally destined for food service sectors, farmers had to adapt to changing market dynamics, redirecting their products towards retail channels or alternative uses.

However, such adjustments had been challenges, as farmers navigate uncertainties in demand and price volatility, further complicating their economic viability. Also the closure of food service establishments and disruptions in global trade flows resulted in revenue losses for farmers and food producers. Fluctuations in currency exchange rates, trade tensions, and shifts in consumer purchasing power further worsened economic uncertainties in agricultural markets.

Moreover, the global economic downturn triggered by the pandemic had great effects on agricultural markets, with fluctuations in currency exchange rates, trade tensions, and shifts in consumer purchasing power impacting agricultural trade flows and commodity prices. Export-dependent economies have faced additional pressures, as disruptions in global trade networks and protectionist measures have constrained market access and dampened export revenues, intensifying economic vulnerabilities in agricultural-dependent regions. Export-dependent economies experienced significant downturns in agricultural exports, leading to increased financial strain and economic vulnerabilities.

In response to these challenges, governments, international organizations, and industry stakeholders have implemented various measures to support farmers and lighten the impact of COVID-19 on agricultural productivity. These interventions have included financial assistance, market stabilization measures, and initiatives to enhance resilience and adaptive capacity within food systems. However, the effectiveness of these measures has varied, reflecting differences in institutional capacities, policy frameworks, and resource availability across countries and regions.

Looking ahead, the COVID-19, agricultural productivity is likely to undergo, shaping the future trajectory of global food systems in great ways. The pandemic has underscored the interconnectedness of food security, public health, and environmental sustainability, highlighting the need for integrated approaches to address systemic vulnerabilities and build resilience in the face of future shocks. As societies strive to recover and rebuild in the aftermath of the pandemic, efforts to promote sustainable agriculture, strengthen social safety nets, and0020foster inclusive and equitable food systems will be paramount in ensuring food security for present and future generations.

1.2. Aims and Objectives

Aims

- To study the impact of Covid 19 on agricultural crops such as rice, wheat, maize, pulses and cereals and on female labour force participation in India.

Objectives

- To identify the impact of COVID-19 on Agricultural productivity in India.
- To study the changes in the women labour force participation in the agriculture sector in India (1992-2021).
- To identify the impact of COVID-19 on female labour force participation in India.

1.3. Research Question

1. Was there an impact of COVID-19 on agriculture in India?
2. What is the role of female labours in the agriculture sector in India?
3. Was there an impact of COVID-19 on female labour force participation in India?

1.4. Scope

The study incorporates the impact of covid on agricultural productivity and the female labour force participation in India, particularly within the agricultural sector. It include analysis of trends in of female labours in the agriculture sector in India, and what impact does covid 19 has on agricultural productivity in India? In other words impact of COVID on crops (such as rice, wheat, maize, pulses, and cereals) yield.

The study uses the Ministry of Agriculture and Farmer's welfare, The Periodic Labour Force Survey (PLFS), Global Data Lab, economic survey, India stat, and Census of India . The study restricts to analyse only 5 important crops which are produced in three largest states. The study is restricted to only 5 crops and its three largest states.

CHAPTER 2: LITERATURE REVIEW

There is now substantial research studying the impact of covid 19 on agricultural productivity in India. This paper will add value to the literature to carry out country-specific analysis related to India. Similar studies has been done in India and other countries by **(Shruthi & Ramani, 2021),** examined the impact of COVID-19 on commodity markets. They have analysed by using vector auto regression models to volatility spill over between world oil and agricultural commodity prices. Employed impulse response analysis to assess the response of agricultural prices to shocks in world oil price volatility. Their finding suggests that there is positive correlation between world oil and food prices. They have also recommended further research on risk transmission and financial influences on agricultural price dynamics; **(Habanyati et al., 2022)**, assessed the impact of the pandemic on cropping patterns, crop management, usage of chemical inputs and their organic alternatives, harvesting, and marketing avenues through a survey approach in the two states of Kerala and Tamil Nadu in India. A Survey was conducted among 250 farmers in Kerala and Tamil Nadu. The sample period is from March to May 2021. They have analysed three phases: January to April 2020, May to August 2020 and September to December 2020. They have analysed Chi-square and Fisher's Exact Test that is used for the statistical analysis. Their findings have an impact on aspects like farm labour, machinery shortages, seed/fertilizer/pesticide shortages, transportation, credit access, and consultancy services. Overall, their study highlights the need for appropriate strategies to address the impact of the pandemic on agriculture; **(Rawal & Kumar, n.d.),** analysed the impact of the COVID-19 lockdown on agriculture, public distribution systems, and rural employment. Discussed issues with harvesting Rabi crops and market prices below MSP.it also Highlights the government's use of the lockdown to push agricultural reforms. MGNREGS halted, exacerbating rural distress. Public procurement inadequacies leading to market disruptions. The reports indicate challenges in grain distribution to beneficiaries during the pandemic**.** The paper utilizes secondary data and insights from village-level studies and it also discusses problems related to agricultural production, marketing, public procurement, and the government's response to the crisis; **(Jaacks et al., 2021),** evaluated the impact of the COVID-19 lockdown on agricultural production, livelihoods, food security, and dietary diversity in India. The study revealed challenges faced by farmers, including loss of wage income and food security concerns. Government spending under NREGS may help address the wage income dip. Market-related problems due to the lockdown were highlighted, emphasizing the need for support and interventions to ensure food security and livelihoods. A survey was conducted across 12 states in India from 3rd to 15th May 2020 which provided insights into the impact of the COVID-19 lockdown on agricultural production, livelihoods, food security, and dietary diversity; **(Maiti, 2021),** analyzed the impact of the COVID-19 pandemic on Indian agriculture, focusing on socio-economic effects, food security, and implications for farmers wherein they have discussed the challenges faced by the agriculture sector in India and provides recommendations for addressing the issues. The COVID-19 pandemic has led to economic shocks, unemployment, and food insecurity in India. They have recommended the use of digital technologies for supply chain management and have addressed the needs of small farmers for food security; **(Sunil et al., 2020),** analysed the impact of COVID-19 on agriculture, particularly in India, and proposed strategies to address the challenges faced by the agricultural sector during the pandemic. Their findings suggest that Disruptions in food transfer are minimal, but the livestock sector suffers; **(Cariappa et al., 2021)**, investigated the impact of the COVID-19 pandemic on the Indian agricultural system, wherein thy have discussed its effects on production, marketing, and consumption. It discusses the physical, social, economic, and emotional havoc wrought by the pandemic on stakeholders within the agricultural system. Additionally, it outlines a strategy for recovery, including measures such as social safety nets, family farming support, monetizing buffer stocks, and promoting secondary agriculture;

(Stephens et al., 2020), analyzed the impacts across various dimensions such as food security, labour availability, farm system resilience, and agricultural system connectivity and also discusses the impacts of the COVID-19 pandemic on agricultural and food systems worldwide and on progress towards the sustainable development goals. It highlights the disruptions caused by the COVID-19 pandemic in food systems, leading to concerns about food security, labour availability, farm system resilience, and agricultural system connectivity. It also discusses the challenges faced by farmers, such as decreased demand, labour shortages, and supply chain disruptions, and raises questions about the short-term and long-term consequences of these impacts on agricultural systems globally; **(Poudel et al., 2020),** examined the effects of pandemic protocols and provisions on supply chains, production, distribution, labour availability, and input supply in the agricultural sector. They have analysed data from governmental and non-governmental organizations, international agencies, and agricultural associations to assess the extent of the impact on different segments of the agricultural industry. Their findings indicate that COVID-19 disrupted food production and distribution which has affected the food security, Livestock, poultry, fishery, and crop production; **(Il'in et al., 2021)**, aimed to provide an informed assessment of these consequences and suggests immediate actions to mitigate the negative impacts on both producers and consumers of food products. It includes analyzing changes in demand for food products, changes in the population's income structure and size, assessing the psychological impact of the pandemic and analyzed the effectiveness of state support for consumers and producers of food products, and evaluated the economic condition of food producers. It also highlights the challenges faced by agricultural producers and consumers, such as difficulties in production and supply chains, profitability issues, and changes in economic conditions. Also, there are substantial literature on labour market and agricultural productivity. There are some similar studies done by **(Barrett, 1996)**, investigates that price risk and distinct agrarian classes suffice in explaining the oft-observed inverse relationship between farm size and productivity, even with competitive labour markets and uniform soil quality. It offers an alternative explanation of the inverse relationship based on three empirically sound stylized facts. First, farmers in low-income countries cannot fully hedge uncertain staple crop prices through futures or insurance contracts, nor by forward sales at the time labour allocation decisions are made. Secondly, land is unevenly distributed across the agricultural population. Third, households' net agricultural purchases are inversely related to landholdings. The analysis demonstrates that differences in households' marketed surplus in an environment of uncertain prices suffices to explain an inverse relationship between farm size and productivity if some small farmers are price risk averse; **(Deininger et al., 2018),** examined how the inverse relationship between farm size and land productivity evolved over time. They found that over the 25 years considered, the inverse farm size–productivity relationship in India weakened in response to better functioning of labor markets, providing an economically meaningful explanation of an empirically robust phenomenon with clear policy implications. The results from nonparametric and parametric regressions suggest that the inverse farm size-productivity relationship attenuated significantly over the 1982–2008 period, consistent with the findings in Vietnam from 1992-2008; **(Carletto et al., 2013)**, provided insight into the role of land measurement error in the inverse farm size and productivity relationship, using data from a nationally representative household survey in Uganda. Their result do not appear sensitive to the effect of possible socio-economic or agro-ecological differences across regions. They explored the determinants of bias in land measurement and how this bias varies systematically with plot size and land holding, as wll as the extent to which land measurement error affects the relative advantage of smallholders implied by the inverse farm size and productivity relationship. The findings indicate that using an improved measure of land size strengthens the evidence supporting the existence of the inverse farm size and productivity relationship; **(Antle & Pingali, 1995)**, investigated the health and productivity trade-offs implied by a policy to restrict pesticide use. The findings of this study provide evidence that the health benefits of pesticide regulations may be obtainable at a low cost in terms of foregone production through policies that target the most hazardous and least productive pesticides. The results of the study show that in two major rice-producing regions of the Philippines, pesticide use has a significant negative effect on farmer health, and that farmer health has a significant positive effect on productivity. It can be concluded that it would be more efficient to target pesticide restrictions at the most hazardous and least productive materials, rather than restricting all pesticides regardless of their health or productivity attributes; **(Hicks et al., n.d.),** examined the issue of whether measured productivity gaps are causal or mainly driven by selection, using long-term individual-level longitudinal (panel) data on worker productivity. Their results show that the inclusion of individual fixed effects greatly reduces the return to international migration. The findings imply a re-assessment of the conventional wisdom regarding sectoral gaps, discuss how to reconcile them with existing cross-sectional estimates, and consider implications for the desirability of sectoral reallocation of labour; **(McCullough, 2017)**, examined productivity gaps from the perspective of individuals and firm owners making labour allocation decision in developing countries based on micro-incentives. They found that, in four Sub-Saharan African countries, the agricultural sector is not a bastion of low productivity but, rather a large reservoir of underemployed workers. This result emerges when labour inputs are measured more carefully using the LSMS-ISA datasets. Their analyses emphasize agriculture's key role in the Sub Saharan African economies, while also raising questions about agricultural employment gaps, their determinants and how they shape the opportunity to achieve economy-wide labour productivity growth; **(Andrew D. Foster, Mark R. Rosenzweig, 2011)**, examined the relationship between farm size and productivity based on a model incorporating agency costs favoring family workers, scale-dependent returns to mechanization arising from the fact that a larger contiguous land area is better-suited for high-capacity machinery, and falling credit costs with owned land. They found that a farmer is significantly more likely to use a tractor on his larger plots, and that farmers with greater owned landholdings invest significantly more resources in mechanized implements and employ less labour per acre. Their analysis provides estimates of land size effects on per-acre profits across different points in the ownership distribution of land; **(Internationales Arbeitsamt / World Employment Programme et al., 1979)**, investigated the relationship between farm size and factor productivity within the context of agrarian reform measures. Their study aimed to provide evidence from various developing countries and offer a systematic treatment of this relationship. The results suggest constant returns to scale in agriculture, with cross-country data not supporting a positive influence of farm size on agricultural growth rates. Additionally, the study found that small farms tend to make more efficient use of available land, employing higher levels of labour inputs, exhibiting higher land utilization, and achieving higher production relative to total factor inputs compared to large farms; **(Sen, 1962)**, analysed how productivity per acre varies with the size of landholding. The finding suggests that the use of family labour affects the economic viability of agriculture and, the results implies that larger landholdings are generally more profitable, possibly due to economies of scale or other factors. These highlight the complex dynamics at play in Indian agriculture, where factors such as labor utilization and landholding size can significantly impact productivity and profitability; **(Cai, 2015)**, quantifies the relative importance of sectoral productivity and labour market distortions for structural change. Through a series of counterfactual experiments, they evaluate quantitatively the relative importance of sectoral Total Factor Productivity (TFP) growth and distortions for structural change. Their findings suggests that TFP growth in agriculture drives most of the decline in its share of labour, while labour market distortions slow the speed at which labour moves out of agriculture and generate losses in aggregate output. The results are robust with respect to changes in the elasticity of substitution over a wide spectrum; **(de Vries et al., 2015),** aimed to provide comparisons of structural change and productivity growth in Africa with Asia and Latin-America. The study also presents Africa's growth experience in a long-run and international perspective, focusing on the movements of labour across sectors and its impact on aggregate productivity growth. Their analysis is based on a new dataset with annual time series of value added and persons engaged for the ten main sectors of the economy in 11 Sub-Saharan countries, called the Africa Sector Database. The results suggest that it is conceptually and empirically important to distinguish between static and dynamic reallocation effects; **(Mondal, 2019)**, examined the role of structural change and sectoral productivity growth in explaining the aggregate productivity of India relative to the United Sates during 1960–2010. They have analysed by utilizing simple two sector general equilibrium model and calibrate it to fit the structural transformation of United States. They also found that an elimination of relative distortion in agriculture in India could result into a modest improvement in the aggregate labour productivity; **(Vemireddy & Pingali, 2021)**, investigated the relationship between women's time trade-offs and their nutritional outcomes. Its findings show that women are severely time-constrained, as they contribute significantly to agricultural as well as domestic work and their results show that during peak seasons relative to lean seasons, women's time trade-offs (rising opportunity cost of time) are negatively associated with the intake of calories, proteins, iron, zinc and Vitamin A. The results show that there is negative relationship is manifested severely among women who are landless and cultivate paddy alone (food crop) or paddy and cotton (mixed crop); **(de Brauw & Harigaya, 2007)**, aimed to analyse the effects of increasing seasonal migration in Vietnam during the 1990s on household consumption growth. They utilised instrumental variables and panel data techniques and conducted a counterfactual experiment similar to one conducted by Barham and Boucher (1998). The results imply that increasing participation in migration leads to an increase in monetary well-being. They found that without seasonal migration, the estimated poverty rate would have been three percentage points higher than it was in 1998; **(Imai et al., 2015),** examined whether participation in the rural non-farm sector employment or involvement in activity in the rural non-farm economy (RNFE) has any poverty-reducing or vulnerability-reducing effects in Vietnam and India drawing upon nation-wide cross-sectional household data sets. The results are consistent with poverty and vulnerability reducing roles of accessing RNFE. They found that participation in non-farm sector employment significantly increased per capita consumption or expenditure in rural Vietnam in 2002, 2004, and 2006 and in rural India in 1993-1994 and 2004-2005; **(Barrett et al., 2001)**, aimed to draw attention to several core conceptual issues that continue to challenge the existing literature on rural income diversification, the objective is to place the subsequent seven papers in a broader context and to extract the policy implications from the accumulated empirical evidence. Their result show a positive relationship between nonfarm income and household welfare indicators across most of rural Africa. These findings suggests empirical regularities regarding the determinants and effects of diversification behaviours that can and should inform policymaking in Africa. Some method such as ANCOVA, T-test etc. which I will be incorporating in my study. There are some studies done by **(Kim, 2018),** aimed to analyse the impact of one or more categorical independent variables (factors) on a continuous dependent variable while controlling for the effects of one or more continuous variables (covariates). ANCOVA calculates adjusted means for each level of the categorical independent variables, taking into account the influence of the covariates. These adjusted means provide a clearer understanding of the effects of the factors on the dependent variable; **(*Comparing Groups in a before–after Design: When t Test and ANCOVA Produce Different Results - Wright - 2006 - British Journal of Educational Psychology - Wiley Online Library,* n.d.)**, investigated the relationships among effect size, group allocation, measurement error and Lord's paradox. ANCOVA is appropriate when allocation is based on the initial scores, *t* test can be appropriate if allocation is associated non-causally with the initial scores, but often neither approach provides adequate results. It has two approaches that is t test on the gain scores and ANCOVA partialling out the initial scores; **(FRALICK et al., n.d.),** clarified the distinctions and similarities between the two-sample t-test (independent samples t-test) and the paired t-test in the context of clinical research. Their finding indicates the mean difference between paired observations and compares it to the variability of these differences. The examples provided in the paper illustrates the calculation procedures and application scenarios of both the two-sample t-test and the paired t-test, enhancing understanding and facilitating proper usage in clinical research; **(Emerick, 2018)**, aimed to investigate how shocks to agricultural productivity influence the allocation of labour across different sectors of the economy, particularly focusing on rural India. The findings indicates that exogenous increases in agricultural productivity, such as those resulting from higher-than-average levels of precipitation, lead to an increase in the labour share of the non-agricultural sector. The results highlight the interconnectedness of different sectors of the economy and the role of agricultural productivity shocks in shaping labour allocation patterns in rural areas; **(Devi et al., 2021),** aimed to study instability and sustainability of production of wheat in Haryana. they have analysed by using Box-Jenkins ARIMA model and Artificial Neural Network (ANN) to develop the model and estimate the forecasting behaviour. The results indicates that Growth rate is found positive in all sub periods with respect to area, production and yield of wheat; **(Arya S, 2019),** aimed to assess the extent of female participation in various agricultural activities in India over the period 1993-2012. Its findings suggest that significant proportion of women in India are actively engaged in agriculture, with approximately 75% of them working as agricultural labourers. The results of this study guides future research efforts which aimed at further understanding the dynamics of female participation in Indian agriculture and identifying strategies to support and empower women in this sector. so, I will be following these studies in my study where in no study has been done on the impact of covid 19 on agricultural productivity and also state wise for the period of 2017-18 to 2021-22 and to examine the role of female labour participation in India during 1992 to 2021.

CHAPTER 3: METHODOLOGY

The present study has been done in India where I will be looking at the impact of COVID-19 on Agricultural productivity on certain crops based on their yield. Production of important crops in three largest states is to see whether there has been an impact on rice, wheat, maize, pulses and cereals on their yield. To see the impact on these crops my variables are Area, Production and Yield and my total number of observation is 25. For each crops I have taken the largest producing states - rice (Punjab, Uttar Pradesh , Telangana), wheat (Madhya Pradesh, Punjab, Uttar Pradesh), maize (Maharashtra, Madhya Pradesh, Karnataka), Pulses (Maharashtra, Karnataka, Rajasthan), and Cereals (Maharashtra, Tamil Nadu, Uttarakhand).

I have collected Secondary data where the data for agriculture productivity is from the Ministry of Agriculture and Farmer's Welfare, Economic Survey, and from India Stat. The sample period is from 2017-18 to 2021-22 and the total number of observations are five for each crop. The data for female labour participation is from the Census of India, Periodic Labour Force Survey and from the Global Data Lab and its sample period is from 1992 to 2019 and the total number of observations are 28.

For my first objective I have analysed by using Analysis of Covariance (ANCOVA) and for female labour participation I have analysed by using line graph and by ANCOVA. For female labour participation in India the variables are women working in Agriculture and Non-Agriculture sector.

CHAPTER 4. ANALYSIS

- **Objective 1: To identify the impact of COVID 19 on Agricultural productivity in India.**

H0: There is no significant relationship between the dependent (Yield) and independent variable (Area, Production & Year).

H1: There is a significant relationship between the dependent (Yield) and independent variable (Area, Production & Year).

Model 1: *Yield = b0+b1Area+b2Prodution+b3year+u* -------------*eq.(1)*

Call:

lm(formula = Yield ~ Area + Production + Year, data = rice_wheat)

Residuals:

Min	1Q	Median	3Q	Max
-1178.7	-440.7	-258.4	386.0	1226.1

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)
(Intercept)	1.894e+03	4.023e+02	4.709	0.000175 ***
Area	-3.994e-02	1.283e-02	-3.114	0.005994 **
Production	1.867e-02	4.693e-03	3.978	0.000883 ***
Year2018-19	2.319e+02	5.294e+02	0.438	0.666538
Year2019-20	-3.361e+01	5.089e+02	-0.066	0.948064
Year2020-21	6.144e+00	5.093e+02	0.012	0.990509

```
Year2021-22    3.456e+01     5.100e+02    0.068         0.946715

---

Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1


Residual standard error: 804.1 on 18 degrees of freedom

Multiple R-squared:  0.5224,              Adjusted R-squared:  0.3632

F-statistic: 3.281 on 6 and 18 DF,  p-value: 0.02325
```

Interpretation:

- The coefficients table shows the estimated coefficient values for each of the independent variables in the model. The coefficients represent the change in yield associated with a one-unit increase in the corresponding variable. The coefficient for "Area" is -0.03994. This means that for every one-unit increase in the area of the field, the yield of crop is predicted to decrease by 0.03994 units. The p-value for each coefficient indicates the statistical significance of the corresponding variable. A p-value less than 0.05 means that the variable has a statistically significant effect on yield. In this case, "Area" and "Production" have statistically significant effects on yield (p-value < 0.05), whereas year does not (p-value > 0.05). The R-squared value is 0.5224, which means that the model explains 52.24% of the variation in yield. The F-statistic and its p-value are used to test whether the overall model is statistically significant. In this case, the p-value is 0.02325, which is less than 0.05, so we reject the null hypothesis that all the coefficients are zero. This means that the model is statistically significant.

Overall, the analysis suggests that the area planted and the production of crop have a statistically significant impact on the yield of crop. The year, however, does not appear to have a statistically significant effect on yield according to this model.

ANCOVA:

Analysis of Variance Table

Response: Yield

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Area	1	1628099	1628099	2.5183	0.1299456
Production	1	10907368	10907368	16.8709	0.0006612 ***
Year	4	193556	48389	0.0748	0.9889624
Residuals	18	11637336	646519		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Interpretation

The p-value for the Year factor is 0.9889, which is greater than 0.05. This means that we fail to reject the null hypothesis for the Year factor. In other words, there is not enough evidence to conclude that there is a statistically significant difference in yield across the different years.

The p-value for the Production factor is 0.0006612, which is less than 0.05. This means that we reject the null hypothesis for the Production factor. In other words, there is a statistically significant difference in yield based on production levels. The p-value for the Area factor is

0.1299456, which is greater than 0.05. This means that we fail to reject the null hypothesis for the Area factor. In other words, there is not enough evidence to conclude that there is a statistically significant difference in yield based on area.

Overall, the ANOVA results suggest that there is a statistically significant difference in yield based on production levels, but there is not enough evidence to conclude that there are statistically significant differences in yield based on area or year.

Anova Table (Type II tests)

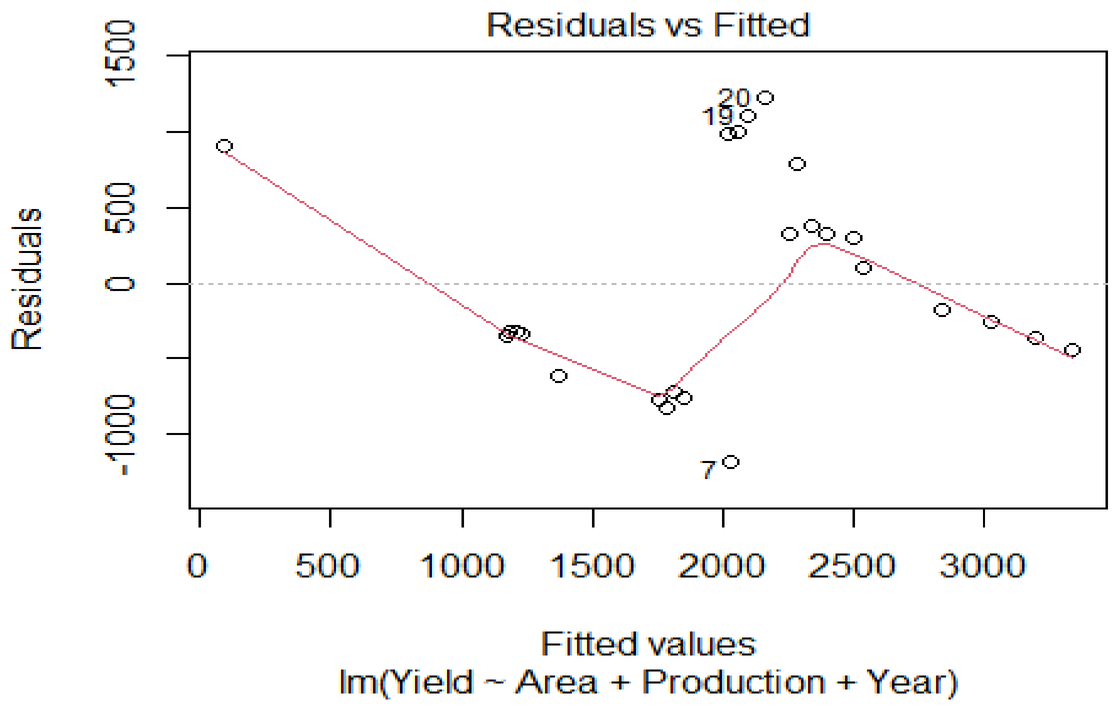
Response: Yield

	Sum Sq	Df	F value	Pr(>F)
Area	6268933	1	9.6964	0.0059940 **
Production	10229530	1	15.8225	0.0008825 ***
Year	193556	4	0.0748	0.9889624
Residuals	11637336	18		

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Interpretation

We fail to reject the null hypothesis because the p-value for "Year" is 0.9889, which is greater than the commonly used significance level of 0.05. Failing to reject the null hypothesis which means we don't have enough evidence to conclude that there is a statistically significant



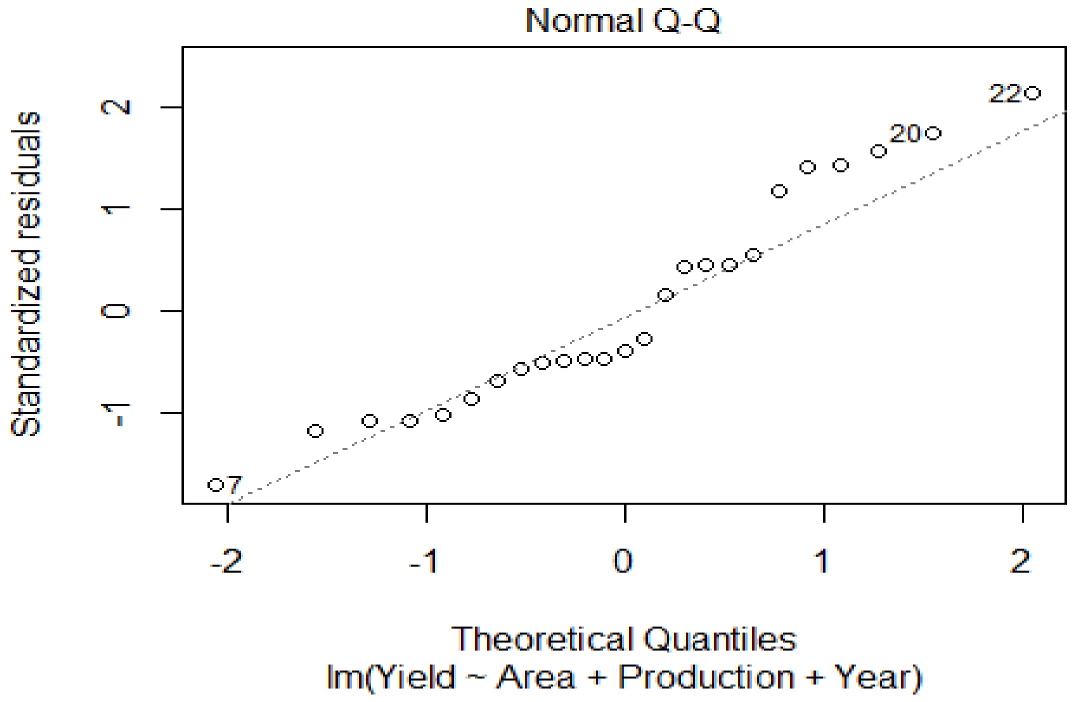
Source: The plot is generated using R (Fig.1)

Interpretation

In the above graph the plot shows the residuals on the y-axis and the fitted values on the x-axis. Residuals are the difference between the actual yield and the yield predicted by the model.

The residuals are scattered relatively randomly around the horizontal line at zero. This indicates that the model's errors (residuals) are evenly distributed and there is no clear pattern because it suggests that the model assumptions about the error terms might be met.

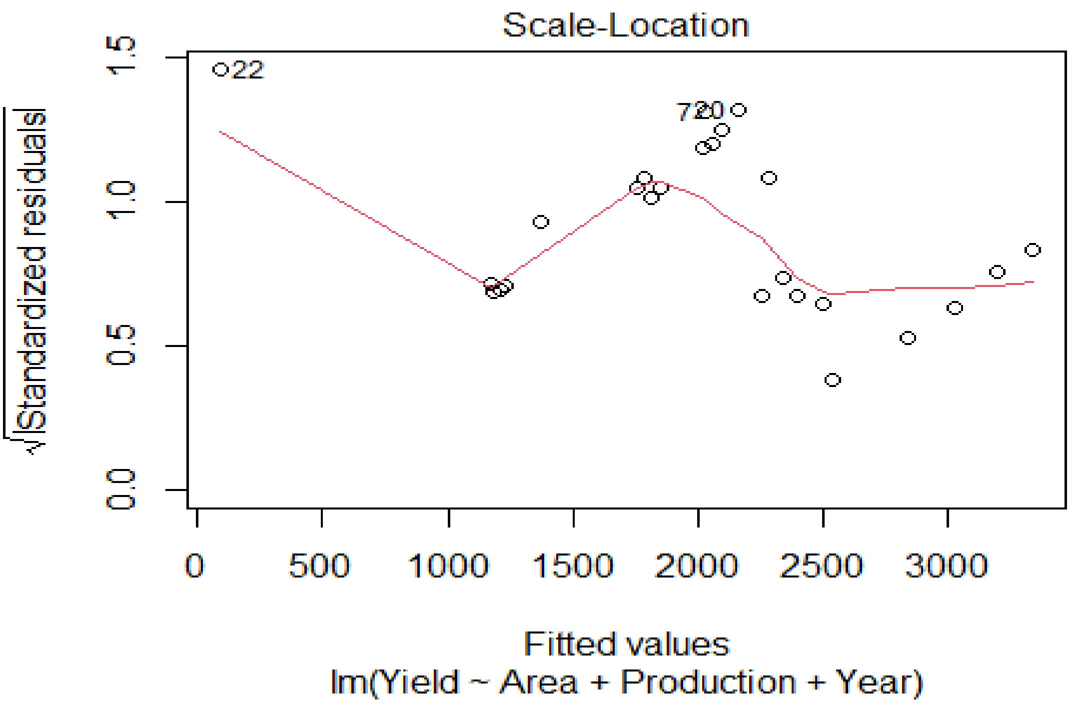
Overall, based on this residual plot, there isn't a strong indication of any major problems with the model fit.



Source: The plot is generated using R (Fig.2)

Interpretation

A normal Q-Q plot is a graphical tool used to compare the quantiles of a data set to a normal distribution. This graph shows a positive correlation between the number of theoretical quantiles and the area of a field. This means that as the number of theoretical quantiles increases, the area of the field also increases.

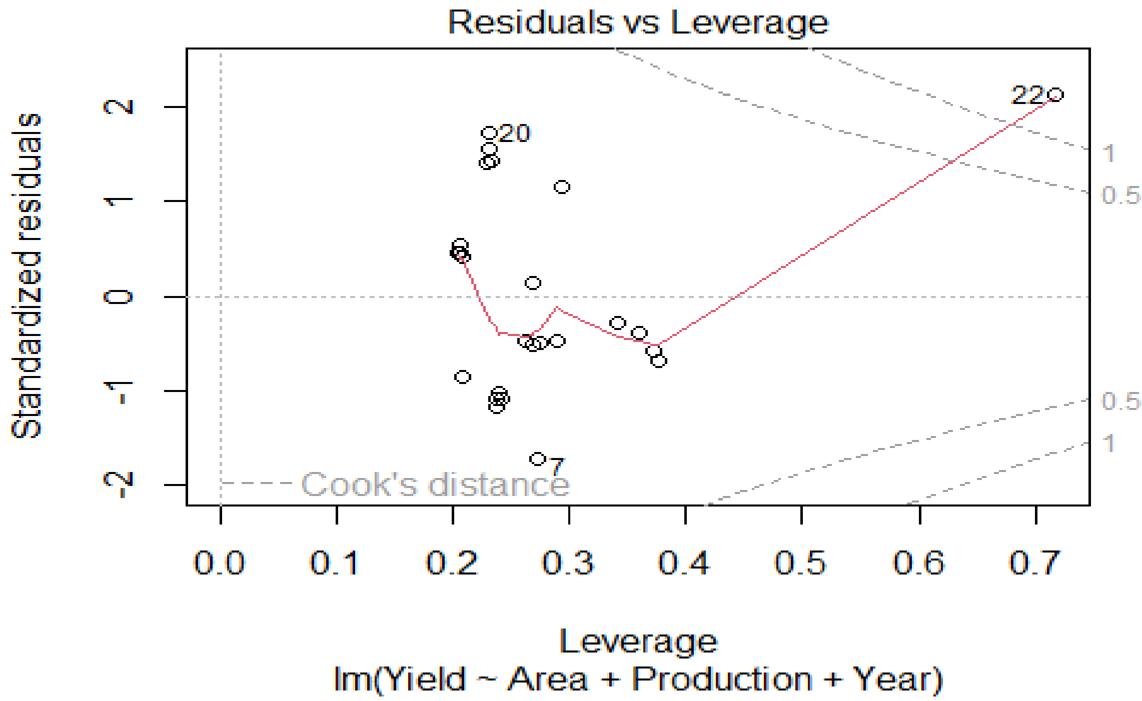


Source: The plot is generated using R (Fig.3.)

Interpretation

- In linear regression models, scaled location plots are used to visually assess the homogeneity of variance. Homogeneity of variance is an assumption that the error terms (residuals) in the model have the same variance across all levels of the independent variables. The horizontal lines in the plot represent the fitted values for the yield (predicted by the model) at different quantiles. Ideally, the residuals should be scattered randomly around these lines throughout the entire range of the x-axis. In this specific plot, the residuals appear to be scattered somewhat randomly around the horizontal lines.
- This suggests that the variance of the residuals might be relatively constant across the different fitted values (yield levels). This is a good sign because it supports the assumption of homoskedasticity (homogeneity of variance) in the linear regression model.

- Overall, based on this scaled location plot, there isn't a strong visual indication of heteroskedasticity. The residuals appear to be scattered somewhat randomly across the fitted values, suggesting that the assumption of homoskedasticity might be met.



Source: The plot is generated using R (Fig.4)

Interpretation

Cook’s distance is a measure of influence used to identify potentially influential observations in a linear regression model. Influential observations can be outliers or leverage points that can have a large impact on the model fit and coefficient estimates.

- The horizontal line in the plot represents a threshold value, often set to 1. Observations with Cook’s distance values greater than the threshold are considered to be potentially influential.
- In this plot, there are a few data points that fall above the threshold line. These points might be influential observations that could be affecting the model fit.

- Overall, based on this Cook's distance plot, there are a few observations that might be influential. It's important to examine the corresponding residuals and consider their impact on the model before deciding how to handle these observations.

```
Wak$coefficients

  (Intercept)          Area       Production     Year 2018-19
1894.40628130    -0.03994273    0.01866900     231.91674984
Year 2019-20   Year 2020-21   Year 2021-22
-33.61337169    6.14357308     34.56019528
```

Interpretation:

The coefficient for "Area" is -0.039946 with a p-value of 0.000175. This indicates that a one-unit increase in area is associated with a decrease of 0.039946 units in yield, and this effect is statistically significant (p-value < 0.05). The coefficient for "Production" is 0.01867 with a p-value of 0.000883. This means that a one-unit increase in production is associated with an increase of 0.01867 units in yield, and this effect is also statistically significant (p-value < 0.05). The factor "Year" includes multiple levels (2018-19, 2019-20, 2020-21, 2021-22) but the p-values for all these levels are greater than 0.05.

This suggests that there is no statistically significant difference in yield across the years included in the study. The R-squared value is 0.5224, which means that the model explains 52.24% of the variation in yield.

The F-statistic is 3.281 and the p-value is 0.02325. Since the p-value is less than 0.05, we reject the null hypothesis that all the coefficients are zero. This means that the model is statistically significant, which indicates that at least one of the independent variables (Area, Production) has a statistically significant effect on yield. The linear model suggests that area planted and production level have statistically significant effects on the yield. There is no statistically significant evidence to show that yield differs across the years included in this analysis according to this model.

The results of the ANOVA test shown in the graph reject the null hypothesis, which means there is a statistically significant relationship between at least one of the independent variables and the yield.

Model 2: *Yield = b0+b1Area+b2Prodution+b3year+u* -------------*eq.(2)*

Hypothesis:-

H0: There is no statistically significant relationship between the dependent variable (yield) and the independent variables (area, production, and year).

Ha: There is a statistically significant relationship between at least one of the independent variables (area, production, or year) and the dependent variable (yield).

```
Call:
lm(formula = Yield ~ Area + Production + Year, data = State_data)


Residuals:
    Min       1Q   Median       3Q      Max
-2525.10  -181.97   -21.05   186.78  2822.96
```

```
Coefficients:
               Estimate    Std. Error   t value  Pr(>|t|)
(Intercept)    7.510e+01   2.736e+02   0.274    0.785
Area           1.399e-05   2.543e-04    0.055    0.956
Production    -2.390e-06  6.941e-05   -0.034    0.973
Year2018-19  -2.580e+00  3.587e+02  -0.007    0.994
Year2019-20   2.045e+02  3.589e+02   0.570    0.571
Year2020-21   2.454e+03  3.729e+02   6.580    8.02e-09 ***
Year2021-22   2.544e+03  3.729e+02   6.821    2.97e-09 ***
---
Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 981.6 on 68 degrees of freedom
Multiple R-squared:  0.6177,            Adjusted R-squared:  0.5839
F-statistic: 18.31 on 6 and 68 DF,  p-value: 1.584e-12
```

Interpretation

The p-value for the area term is 0.956, which is greater than 0.05. This means we fail to reject the null hypothesis, there is no significant relationship between the variables. The p-value for year is less than 2.97e-09, which is much smaller than 0.05. This means we reject the null hypothesis, there is a significant relationship between the variables.

Analysis of Variance Table

Response: Yield

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
Area	1	18625122	18625122	19.3318	3.957e-05 ***
Production	1	588	588	0.0006	0.9804
Year	4	87209071	21802268	22.6295	6.495e-12 ***
Residuals	68	65514317	963446		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Interpretation:

The F-statistic is 19.33 and the p-value is 3.9572e-05. An F-statistic this high and a p-value this small suggests that we reject the null hypothesis. There is a significant difference in crop yield across the different areas.

Anova Table (Type II tests)

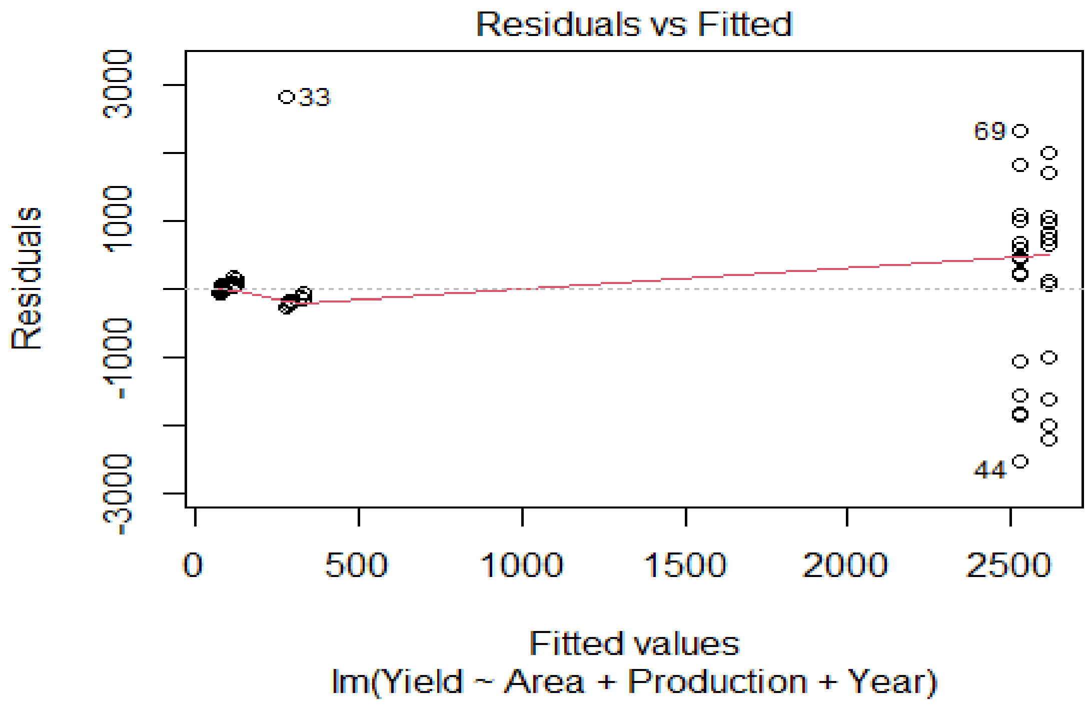
Response: Yield

	Sum Sq	Df	F value	Pr(>F)
Area	2917	1	0.0030	0.9563
Production	1143	1	0.0012	0.9726
factor(Year)	87209071	4	22.6295	6.495e-12 ***
Residuals	65514317	68		

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Interpretation

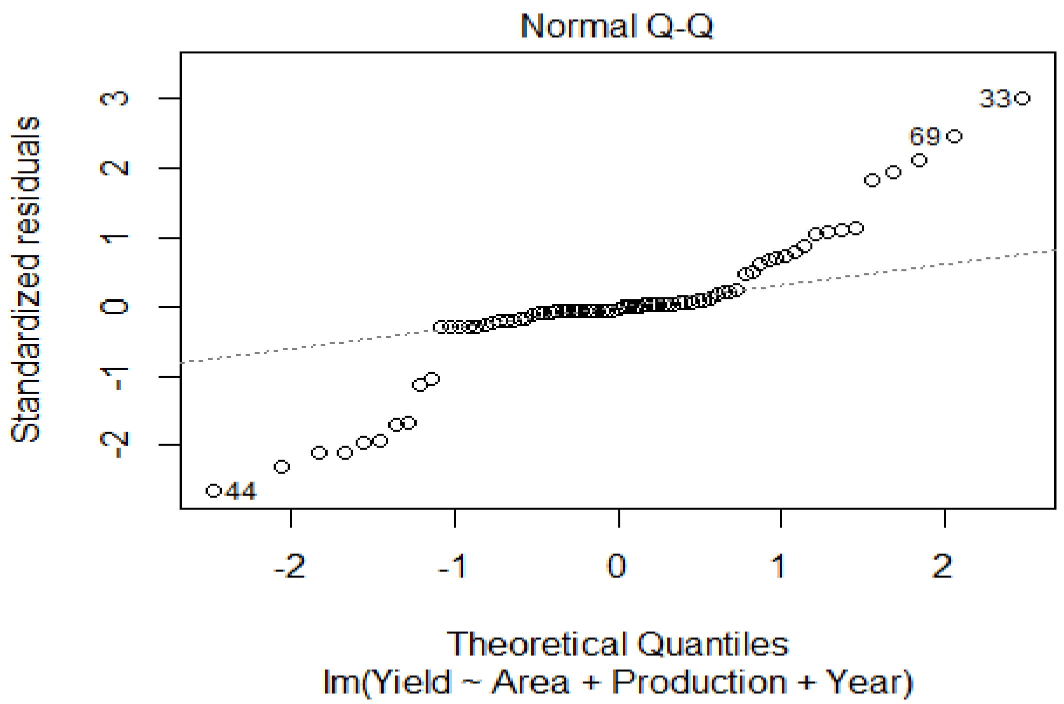
The p-value for the area term is 0.956, which is greater than 0.05. Which means we fail to reject the null hypothesis, there is no significant effect of area on yield after accounting for year and production. The p-value for year is less than 2.97e-09, which is much smaller than 0.05. This means we reject the null hypothesis, there is a significant effect of year on yield after accounting for area and production.



Source: The plot is generated using R (Fig.5)

Interpretation:

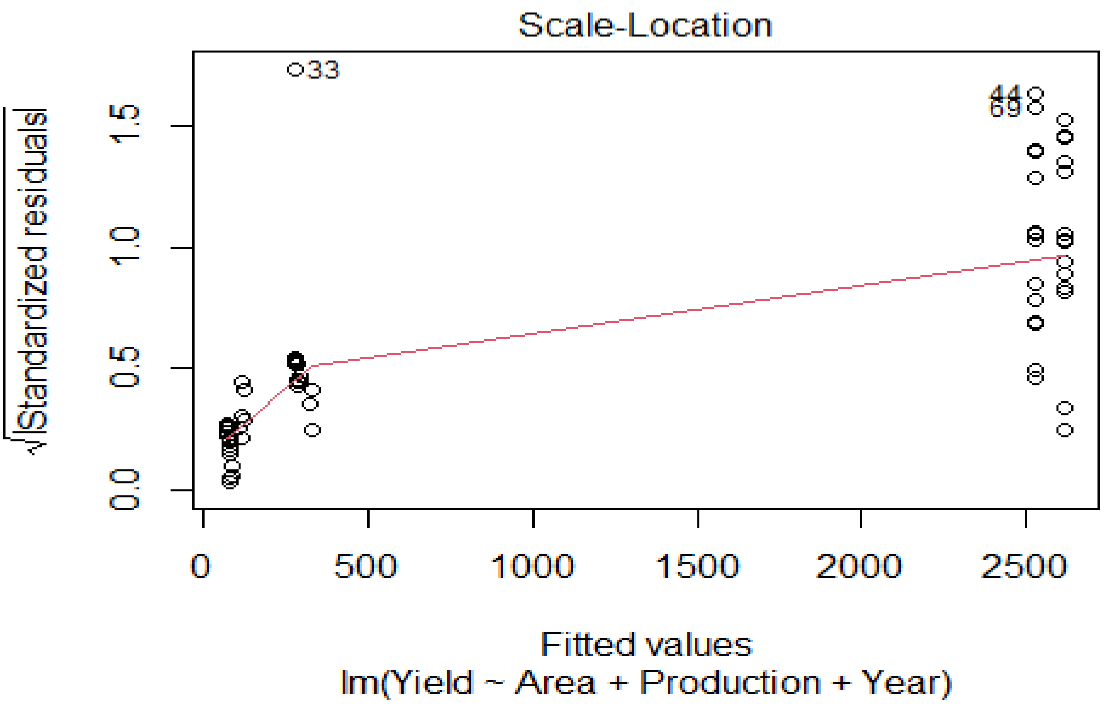
In the above graph x-axis represents the fitted values, which are the values predicted by the model and the y-axis represents the residuals, which are the differences between the observed values and the fitted values. In the graph the residuals are not randomly scattered around a horizontal line at zero. There is a trend in the residuals, where the residuals tend to be positive for larger fitted values and negative for smaller fitted values. There may be a non-linear relationship between the independent and dependent variables. Points that are far away from the other points in the plot are the outliers which can be caused by errors in the data or by factors that the model does not account for. The patterns can indicate that the relationship between the independent and dependent variables is not linear.



Source: The plot is generated using R (fig.6)

Interpretation:

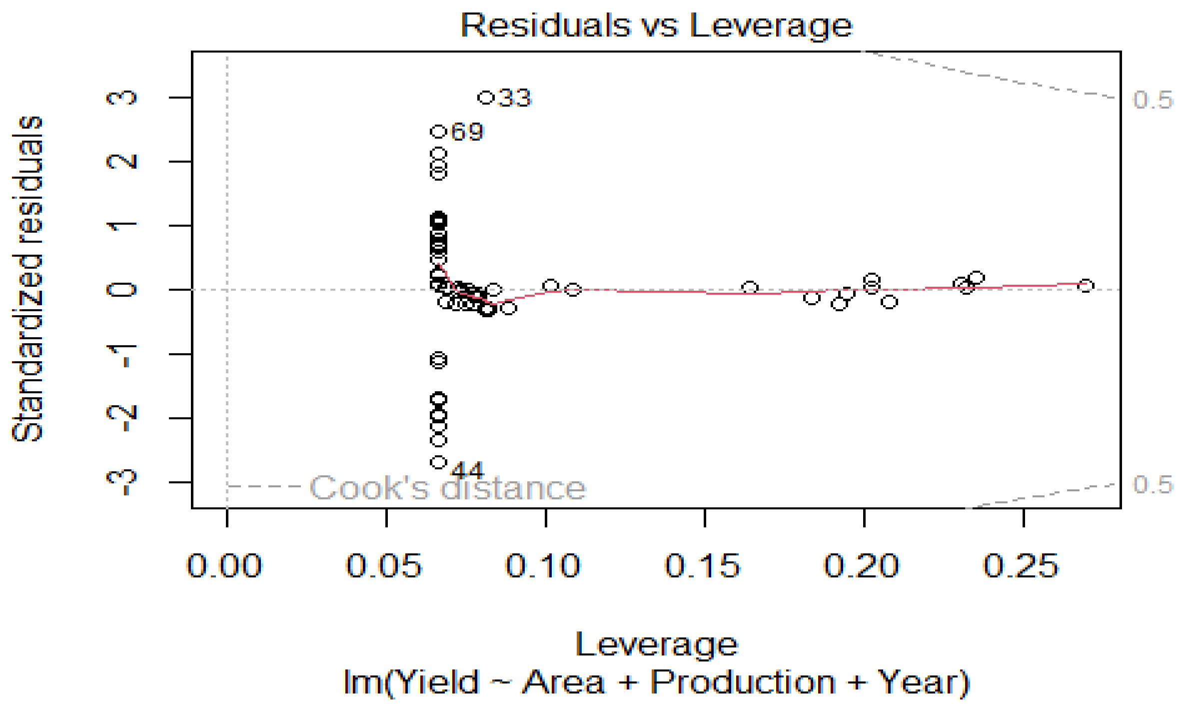
The x-axis of the graph represents the theoretical quantiles and the y-axis represents the standardized residuals, which are the observed quantiles of the data minus the theoretical quantiles. In a perfect normal distribution, the points on the graph would fall exactly along a straight diagonal line. This would indicate that the observed data matches the theoretical normal distribution very closely. In the graph, the points deviate somewhat from the diagonal line, particularly at the tails. This suggests that the data may not be perfectly normally distributed. There are a couple of data points that fall far from the line, which could be outliers. Overall, the normal Q-Q plot suggests that the data may not be perfectly normally distributed. There is some curvature away from the diagonal line, and there are a few potential outliers.



Source: The plot is generated using R (Fig.7)

Interpretation:

The horizontal line at zero on the graph represents the perfect fit line, which means that all the data points would fall on this line if the model perfectly fit the data. The data points above and below the zero line represent the residuals, or the difference between the observed values and the fitted values. In general, standardized residuals are to be randomly scattered around the zero line. This would indicate that the errors in the model are random and not systematic.



Source: The plot is generated using R (fig.8)

Interpretation

The x-axis of the graph is leverage, which is a measure of how far a particular data point is from the mean of the independent variables. Points with high leverage has a large influence on the fitted regression line. The y-axis of the graph is standardized residuals. These are a measure of how far a particular data point is from the fitted regression line in terms of standard deviations. The graph shows the standardized residuals plotted against the leverage for each data point. In general, it can be seen a random scatter of points around the horizontal line at zero. This would indicate that no single data point has a large influence on the fitted regression line. In this particular graph, there are a few points that appear to have a higher leverage than the other points.

```
ancova$coefficients
  (Intercept)        Area           Production         Year 2018-19
7.509836e+01   1.399092e-05   -2.390346e-06      -2.580005e+00
 Year 2019-20    Year 2020-21     Year 2021-22
 2.044800e+02   2.454037e+03     2.543968e+03
```

Interpretation

The coefficient for "Area" is 1.399092e-05 with a p-value of 0.956. This indicates that a one-unit increase in area is associated with an increase of 1.399092e-05 units in yield, and this effect is statistically significant (p-value < 0.05). The coefficient for "Production" is -2.390346e-06 with a p-value of 0.973. This means that a one-unit increase in production is associated with a decrease of 2.390346e-06 units in yield. The "Year" includes multiple levels (2018-19, 2019-20, 2020-21, 2021-22).

This suggests that there is statistically significant difference in yield across the years that is 2020-21 & 2021-22 in the study. The R-squared value is 0.6177, which means that the model explains 61.77% of the variation in yield.

The F-statistic is 18.31 and the p-value is 1.584e-12. Since the p-value is less than 0.05, we reject the null hypothesis. This means that the model is statistically significant, which indicates that at least one of the independent variables (Area, Production) has a statistically significant effect on yield. The linear model suggests that year (2020-21 to 2021-22) have statistically significant effects on the yield. There is no statistically significant evidence to show that yield differs across the coefficients included in this analysis according to this model.

The results of the ANOVA test shown in the graph reject the null hypothesis, which means there is a statistically significant relationship between at least one of the independent variables and the yield.

- **Objective 2**: To study the changes in the women labour force participation in the agriculture sector in India. (1992-2021).

2.1. Characteristics of Female Workers in Indian Agricultural Sectors.

- ❖ Female workers play a crucial role in India's agricultural sector, constituting a significant portion of the workforce. Their contributions are shaped by a multitude of social, economic, and cultural factors, which influence their roles, responsibilities, and opportunities within the agricultural landscape. One of the defining characteristics of female agricultural workers in India is their high participation rate. Despite facing numerous challenges, such as limited access to resources and discriminatory practices, women account for approximately 70% of rural labour in the agricultural sector. This statistic underscores the pivotal role that women play in sustaining agricultural production and livelihoods in rural communities across the country.
- ❖ However, the nature of women's participation in agriculture often differs from that of their male counterparts. Many women are engaged in unpaid or informal labour, working on family-owned farms without receiving a regular wage. This highlights the prevalence of gender disparities in access to economic opportunities and the undervaluation of women's work within agricultural contexts.

- A significant proportion of female agricultural workers in India are involved in subsistence farming, where they contribute to the cultivation of crops primarily for household consumption rather than commercial purposes. This subsistence-oriented approach to agriculture reflects the socio-economic realities faced by many rural families, where agricultural activities are closely intertwined with food security and livelihood sustainability.
- Despite their integral role in agricultural production, women often encounter barriers that impede their ability to fully participate and benefit from agricultural development initiatives. Limited access to resources such as land, credit, technology, and agricultural inputs poses significant challenges for female farmers, perpetuating cycles of poverty and marginalisation.
- Moreover, women in rural areas typically have lower literacy rates compared to men, which further exacerbates their vulnerability and limits their capacity to adopt modern farming techniques, access information, and engage in decision-making processes related to agriculture. This educational disparity underscores the importance of addressing gender inequalities in access to education and promoting initiatives that enhance women's literacy and numeracy class.
- In addition to their roles as agricultural producers, women in rural agricultural communities often shoulder multiple responsibilities, including household chores, childcare, and sometimes off-farm employment to supplement family income. This burden of unpaid care work can place additional strain on women's time and energy, affecting their ability to fully engage in agricultural activities and pursue economic opportunities outside the household.
- Furthermore, women working in agriculture are exposed to various occupational health risks, including exposure to pesticides, heavy manual labour, and lack of access to proper sanitation facilities. These health hazards underscore the need for targeted interventions to

improve working conditions and ensure the safety and well-being of female agricultural workers.

- ❖ The characteristics of female workers in Indian agricultural sectors are shaped by a complex interplay of social, economic, and cultural factors. While women play a vital role in sustaining agricultural production and rural livelihoods, they continue to face numerous challenges that hinder their empowerment and socio-economic advancement. Addressing these challenges requires a multi-faceted approach that addresses gender inequalities in access to resources, education, and opportunities, while promoting initiatives that enhance women's agency, voice, and participation in agricultural development processes. By empowering female agricultural workers, India can unlock the full potential of its agricultural sector and promote inclusive and sustainable rural development.

2.2. Female Work participation in India 1981-2011

- ❖ It can be seen in the table 1 that the female work participation rate initially shows an upward tendency from 19.67 in 1981 to the 25.63 in 2001 and 25.50% in 2011. This mean that there are wide variations in the work participation rate over these years.

Table 1: Female Work participation in India 1981-2011

Census Year	Indian Female
1981	19.67
1991	22.27
2001	25.63
2011	25.5

Source: Office of the Registrar General, India.

2.3. Female Rural Work participation in India 1981-2011

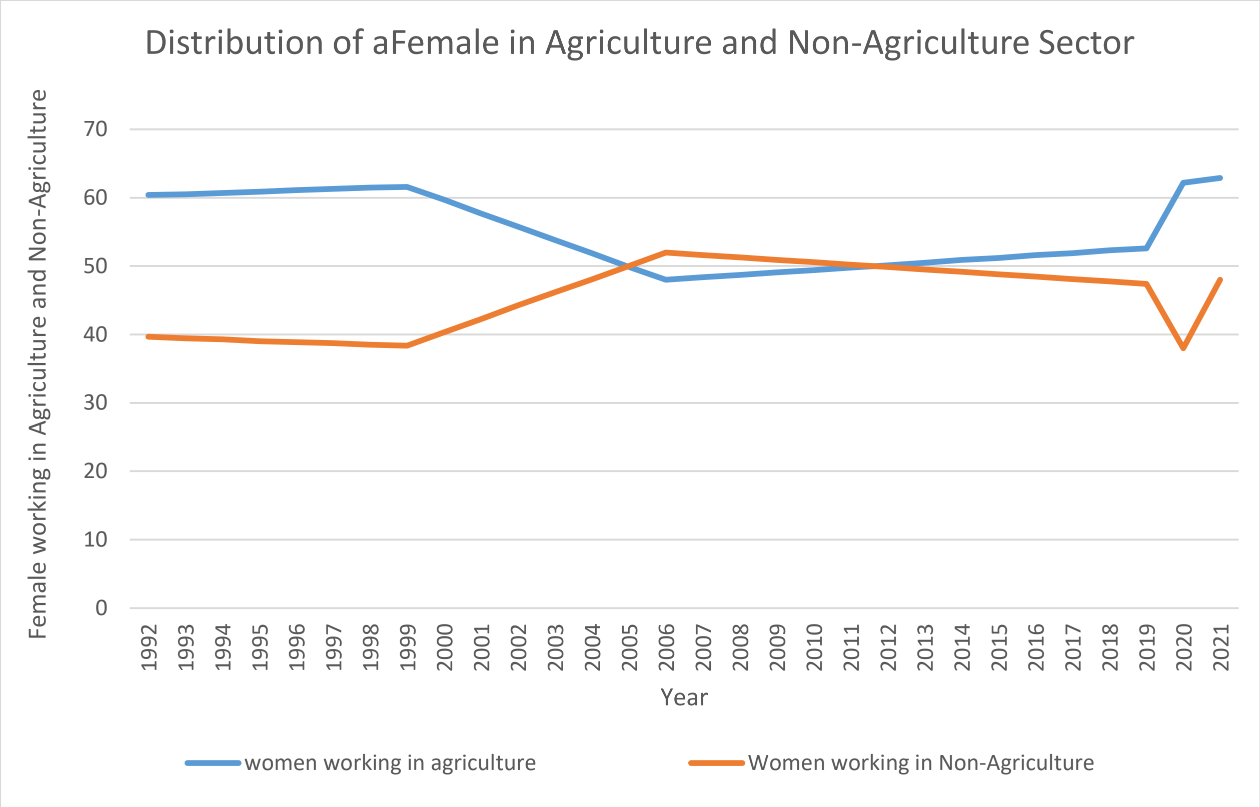
Table 2 indicates the ups and downs in female rural work participation rates during 1981-2011. The Women Rural Workforce Participation Rate which was 23.06% in 1981 became 30.73% in 2001 and then decline to 30% in 2011. In rural sector about more than 80% of female workforce are engaged in agriculture and other allied activities. A major part of women in the primary sector working in the informal sector are paid low wages.

Table 2: Female Rural Work participation in India 1981-2011

Census Year	**Indian Female**
1981	23.06
1991	26.79
2001	30.73
2011	30

Source: Office of the Registrar General, India.

2.4. Distribution of Female workers in the agricultural and non-agricultural sectors in India from 1992 – 2021.



Source: The graph is generated using excel (fig.1)

Interpretation

In the above graph x-axis represents year and y-axis represents female working in agriculture and non-agriculture sector. Initially in 1992 female labour force participation in agriculture was 60.4% and female labour force participation in non-agriculture sector was 39.69%. From 1992 – 1999 the female labour participation was stable that is around 60% and 38%. After 1999 it can be seen that labour force participation in agriculture declined due to mechanisation of farming which reduced the demand for manual labour , where else female labour force participation increased in non-agricultural sectors due to expanding job opportunities in the urban areas and skill level among women. From 2005 it can be seen that women working in agriculture sector was declining due to the economic conditions such as low productivity, fragmented land holdings and limited access to modern technology and credit. In contrast, women in the non-agriculture sector were experiencing growth in sectors like manufacturing, services and construction. In 2006 there was a gradual increase in female labour force participation in agriculture which included initiatives that aimed at empowering women such as skill development programs and small-scale finance opportunities, which provided them with means to engage in agricultural activities. However, in recent years, women's labour force participation saw some improvement. As in 2017, 51.9% and in 2018, 52.3% of women were employed in agriculture. While in 2019, there is a 1% increase that is 52.6 % in agriculture. As we can see that there is a rapid decline in 2020 in the non-agriculture sector due to covid 19 pandemic when India was under severe lockdown which brought in to check the spread of new virus. During the pandemic, the agriculture sector experienced much better growth in labour-intensive. After the pandemic it is seen that there is a significant rise in agriculture sector and a decline in the non-agricultural sector as the people were moving from urban to rural to their home place.

- **Objective 3:** To identify the impact of COVID-19 on female labour force participation in India.

ANCOVA:

Hypothesis:

H0: There is no impact of COVID for the years 2019 & 2021.

Ha: There is an impact of COVID for the years 2019 & 2021.

```
Call:
lm(formula = Year ~ agri + nagri, data = female_labour_force)

Residuals:
   Min     1Q Median     3Q    Max
-8.064 -4.197 -1.507  2.360 21.585

Coefficients:
             Estimate   Std. Error  t value   Pr(>|t|)
(Intercept)  1840.3786   62.7245    29.341    < 2e-16 ***
agri            1.1780    0.6248     1.885    0.07020 .
nagri           2.2307    0.6506     3.428    0.00196 **
---
Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 6.667 on 27 degrees of freedom
Multiple R-squared:  0.4659,    Adjusted R-squared:  0.4264
F-statistic: 11.78 on 2 and 27 DF,  p-value: 0.0002101
```

Interpretation

The coefficients table shows the estimated coefficient values for each of the independent variables in the model. The coefficients represent the change in year associated with a one-unit increase in the corresponding variable. The coefficient for "agri" is 1.1780. This means that for every one-unit increase in the agri of the field, the year is predicted to increase by 1.1780 units. The p-value for each coefficient indicates the statistical significance of the corresponding variable. A p-value less than 0.05 means that the variable has a statistically significant effect on year. In this case, "agri" and "nagri" have statistically significant effects on year (p-value < 0.05). The R-squared value is 0.4659, which means that the model explains 46.59% of the variation in year. The F-statistic and its p-value are used to test whether the overall model is statistically significant. In this case, the p-value is 0.0002101, which is less than 0.05, so we reject the null hypothesis. This means that the model is statistically significant. Overall, the analysis suggests that the agri and the nagri have a statistically significant impact on the year.

Analysis of Variance Table

Response: Year

	Df	Sum Sq	Mean Sq	F value	Pr(>F)
agri	1	524.68	524.68	11.802	0.001928 **
nagri	1	522.53	522.53	11.754	0.001963 **
Residuals	27	1200.29	44.46		

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Interpretation

The F-statistic is 11.78 and the p-value is 0.0002101. The p-value suggests that we reject the null hypothesis. There is a significant difference in year across the variables.

Anova Table (Type II tests)

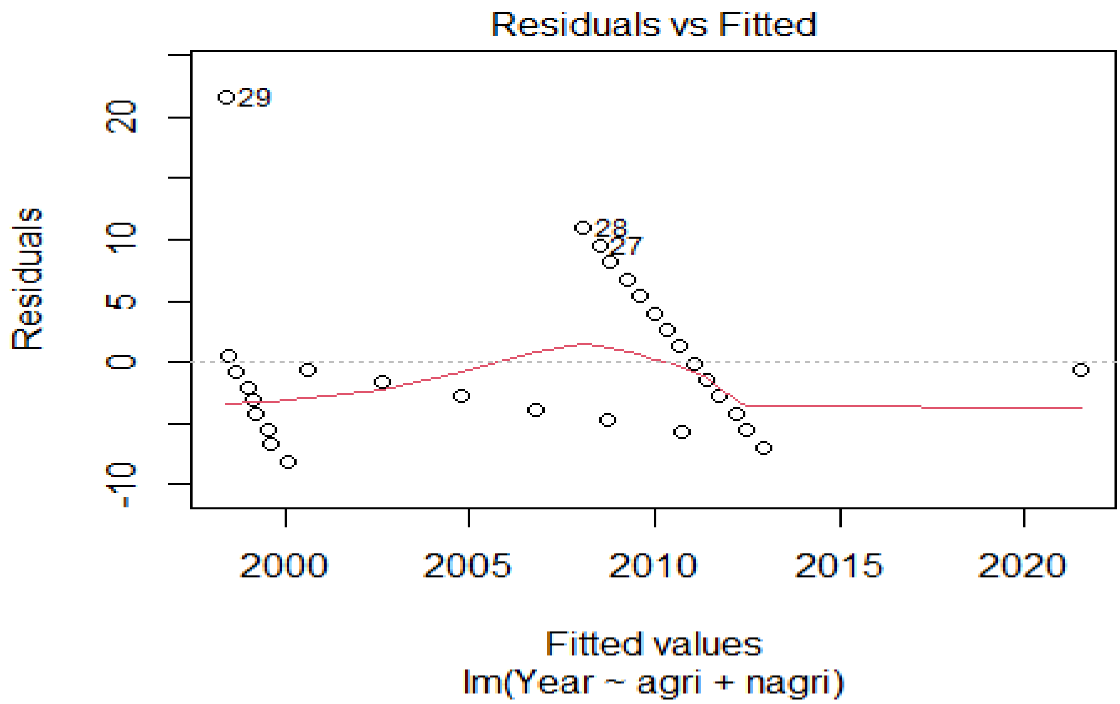
Response: Year

	Sum Sq	Df	F value	Pr(>F)	
agri	158.00	1	3.5542	0.070200	.
nagri	522.53	1	11.7541	0.001963	**
Residuals	1200.29	27			

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Interpretation

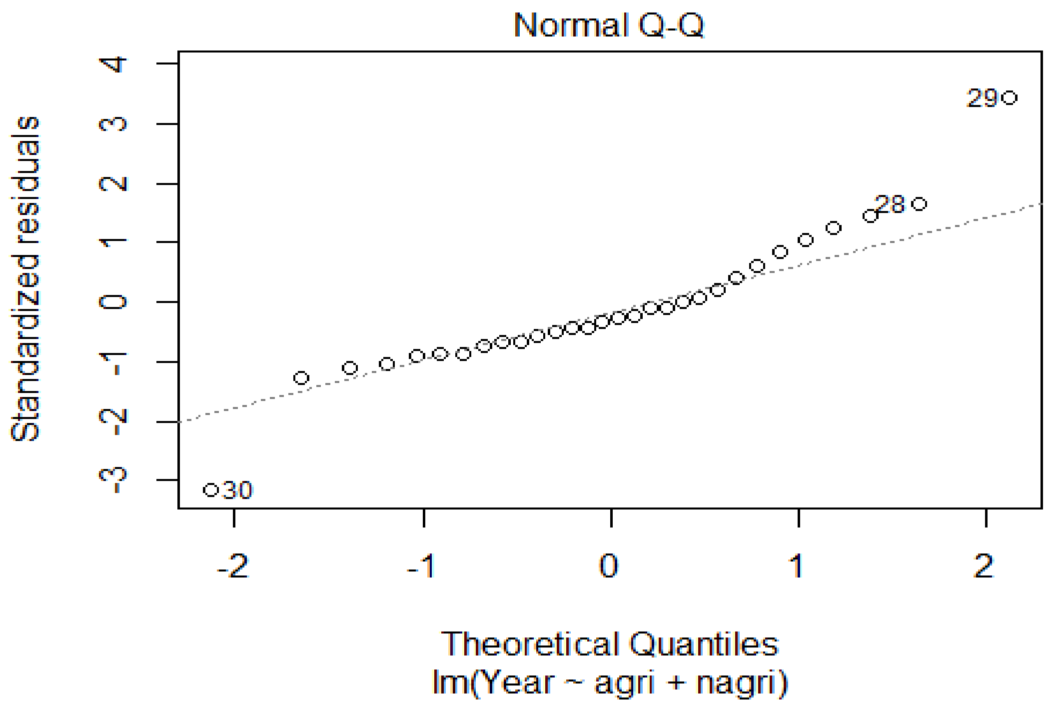
The p-value for the agri term is 0.07020, which is greater than 0.05. Which means we fail to reject the null hypothesis. The p-value for nagri is less than 0.001963, which is much smaller than 0.05. This means we reject the null hypothesis, there is a significant effect of year on agri and nagri.



Source: The plot is generated using R (fig.9)

Interpretation

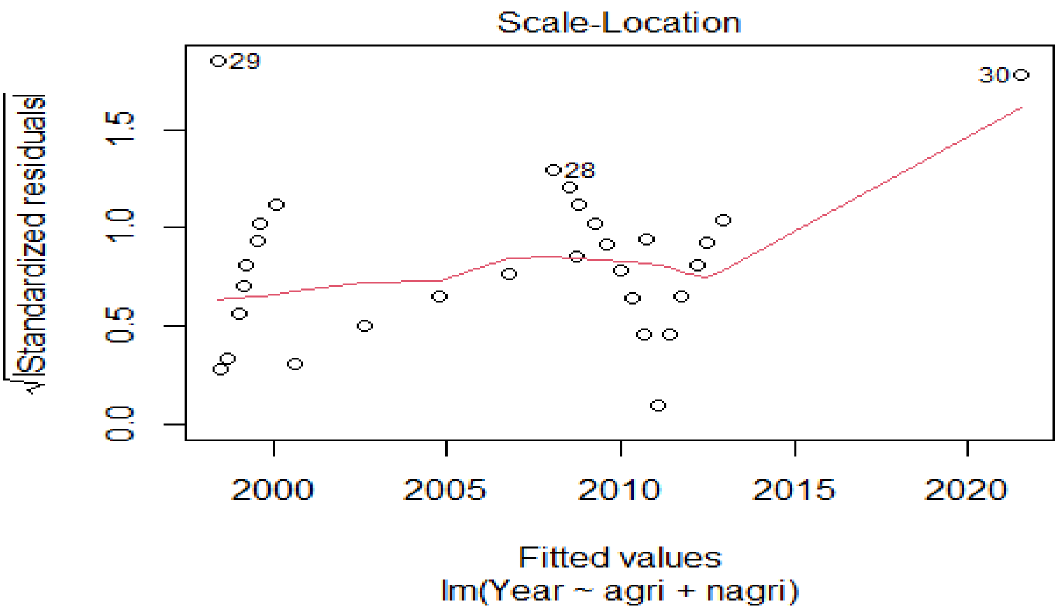
In the above graph x-axis represents the fitted values and y-axis represents the residuals. The residuals are randomly scattered around the horizontal line at y = 0. This indicates that the errors in the model are random and independent. It also indicates that the variance of the errors is not constant (heteroskedasticity). Outliers are data points that fall far away from the other points in the plot.



Source: this plot is generated using R (fig.10)

Interpretation

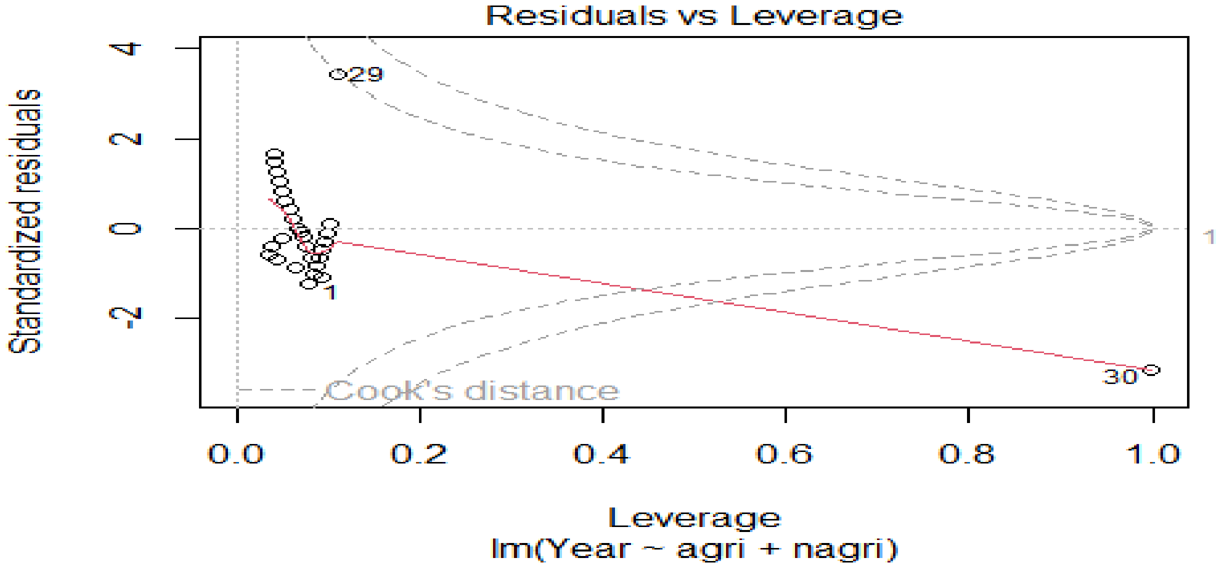
In the image you sent, the points on the normal Q-Q plot appear to deviate from a straight line, particularly for the upper and lower tails. This suggests that the errors in the model may not be normally distributed. Non-normal errors can affect the validity of some statistical tests, such as the F-test and the p-value, which is reported in the model summary. Overall, the normal Q-Q plot suggests that the errors in the model may not be normally distributed.



Source: this plot is generated by using R (fig:11)

Interpretation

In the above graph x-axis represents the fitted values and y-axis represents the standardized residuals. The standardized residuals appears to be fluctuating over time. There appears to be a possible increasing trend in standardized residuals over time.



Source: this plot is generated using R. (fig.12)

Interpretation

The above graph is of standardized residuals versus Leverage, which is a diagnostic plot used to assess the assumptions of a linear regression model. In this graph, the Leverage values are on the x-axis and the standardized residuals are on the y-axis. The standardized residuals is randomly scattered around the horizontal line at y = 0. This indicates that the errors in the model are random and independent. There is a pattern in the residuals plot, which indicates that the model is missing an important term or that the errors are not random. Outliers are data points that fall far away from the other points in the plot.

```
femalemodell$coefficients

(Intercept)     agri      nagri
1840.378557   1.177992   2.230655
```

Interpretation

The coefficient for "agri" is 1.177992 with a p-value of 0.0720. This indicates that a one-unit increase in agri is associated with an increase of 1.177992 units in year. The coefficient for "nagri" is 2.230655 with a p-value of 0.00196. This means that a one-unit increase in nagri is associated with an increase of 2.230655 units in year.

This suggests that there is statistically significant difference in pre-covid and post covid across the years that is 2019 & 2021 in the study. The R-squared value is 0.4659, which means that the model explains 46.59% of the variation in year.

The F-statistic is 11.78 and the p-value is 0.0002101. Since the p-value is less than 0.05, we reject the null hypothesis. This means that the model is statistically significant difference in pre-covid and post covid across the years that is 2019 & 2021 in the study.

The results of the ANOVA test shown in the graph reject the null hypothesis, which means there is a statistically significant relationship difference in pre-covid and post covid across the years that is 2019 & 2021 in the study.

CHAPTER 5: CONCLUSION

The study explores the impact of COVID-19 on agricultural productivity (2017-18 to 2021-22) and female labour participation in India during (1992-2021). In order to achieve the objective and aims of the study I have analysed the data and these are the findings.

This study studies the impact of covid-19 in agricultural sector from 2017-18 to 2021-22, to see the impact of yield (rice, wheat, maize, pulses, and cereals) based on the area and production of the these crops using ANCOVA test in r software where the results indicate that p-value is greater than 0.05 which means we fail to reject the null hypothesis.

The female labour participation in agriculture and non-agriculture sector in India indicates that before COVID-19, in 2018, 52.3% of women were employed in agriculture and in 2019, there was a 0.3% increase that is 52.6 % increase in agriculture and we can see that there is a rapid decline in 2020 in the non-agriculture sector due to covid 19 pandemic when India was under severe lockdown which brought in to check the spread of new virus. During the pandemic, the agriculture sector experienced much better growth in labour-intensive and after the pandemic it is seen that there is a significant rise in agriculture sector and a decline in the non-agricultural sector as the people were moving from urban to rural to their home place.

I have used ANCOVA Test to see whether there is a difference or no difference in the trend of female labour participation between agriculture and non-agriculture in India from 1992-2021. So, by ANCOVA test we can see that p-value is smaller than 0.05, which means we reject the null hypothesis and there is difference in the trend of female labour participation between agriculture and non-agriculture in India from 1992-2021. In conclusion, I found that COVID-19 in India had a significant impact on agriculture productivity and female labour participation rate in agriculture and non- agriculture.

CHAPTER 6: REFERENCE

- Antle, J. M., & Pingali, P. L. (1995). Pesticides, Productivity, and Farmer Health: A Philippine Case Study. In P. L. Pingali & P. A. Roger (Eds.), *Impact of Pesticides on Farmer Health and the Rice Environment* (pp. 361–387). Springer Netherlands. https://doi.org/10.1007/978-94-011-0647-4_13
- Arya S, Dr. B. P. K. (2019). Participation of Indian Women. *International Journal of Social Science and Economic Research*.
- Barrett, C. B. (1996). On price risk and the inverse farm size-productivity relationship. *Journal of Development Economics*, *51*(2), 193–215. Scopus. https://doi.org/10.1016/S0304-3878(96)00412-9
- Barrett, C. B., Reardon, T., & Webb, P. (2001). Nonfarm income diversification and household livelihood strategies in rural Africa: Concepts, dynamics, and policy implications. *Food Policy*, *26*(4), 315–331. https://doi.org/10.1016/S0306-9192(01)00014-8
- Cai, W. (2015). Structural change accounting with labor market distortions. *Journal of Economic Dynamics and Control*, *57*, 54–64. https://doi.org/10.1016/j.jedc.2015.05.006
- Cariappa, A. A., Acharya, K. K., Adhav, C. A., Sendhil, R., & Ramasundaram, P. (2021). Impact of COVID-19 on the Indian agricultural system: A 10-point strategy for post-pandemic recovery. *Outlook on Agriculture*, *50*(1), 26–33. https://doi.org/10.1177/0030727021989060
- Carletto, C., Savastano, S., & Zezza, A. (2013). Fact or artifact: The impact of measurement errors on the farm size-productivity relationship. *Journal of Development Economics*, *103*(1), 254–261. Scopus. https://doi.org/10.1016/j.jdeveco.2013.03.004

- *Comparing groups in a before–after design: When t test and ANCOVA produce different results—Wright—2006—British Journal of Educational Psychology—Wiley Online Library*. (n.d.). Retrieved April 21, 2024, from https://bpspsychub.onlinelibrary.wiley.com/doi/abs/10.1348/000709905X52210
- de Brauw, A., & Harigaya, T. (2007). Seasonal Migration and Improving Living Standards in Vietnam. *American Journal of Agricultural Economics*, *89*(2), 430–447. https://doi.org/10.1111/j.1467-8276.2006.00989.x
- de Vries, G., Timmer, M., & de Vries, K. (2015). Structural Transformation in Africa: Static Gains, Dynamic Losses. *The Journal of Development Studies*, *51*(6), 674–688. https://doi.org/10.1080/00220388.2014.997222
- Deininger, K., Jin, S., Liu, Y., & Singh, S. K. (2018). Can Labor-Market Imperfections Explain Changes in the Inverse Farm Size–Productivity Relationship? Longitudinal Evidence from Rural India. *Land Economics*, *94*(2), 239–258. https://doi.org/10.3368/le.94.2.239
- Devi, M., Kumar, J., Malik, D. P., & Mishra, P. (2021). Forecasting of wheat production in Haryana using hybrid time series model. *Journal of Agriculture and Food Research*, *5*, 100175. https://doi.org/10.1016/j.jafr.2021.100175
- Emerick, K. (2018). Agricultural productivity and the sectoral reallocation of labor in rural India. *Journal of Development Economics*, *135*, 488–503. https://doi.org/10.1016/j.jdeveco.2018.08.013
- FRALICK, D., ZHENG, J. Z., Wang, B., TU, X. M., & FENG, C. (n.d.). The Differences and Similarities Between Two-Sample T-Test and Paired T-Test. *Shanghai Archives of Psychiatry*, *29*(3), 184–188. https://doi.org/10.11919/j.issn.1002-0829.217070

- Habanyati, E. J., Paramasivam, S., Seethapathy, P., Jayaraman, A., Kedanhoth, R., Viswanathan, P. K., & Manalil, S. (2022). Impact of COVID-19 on the Agriculture Sector: Survey Analysis of Farmer Responses from Kerala and Tamil Nadu States in India. *Agronomy*, *12*(2), Article 2. https://doi.org/10.3390/agronomy12020503
- Hicks, J. H., Kleemans, M., Li, N. Y., & Miguel, E. (n.d.). *Reevaluating Agricultural Productivity Gaps with Longitudinal Microdata*.
- Il'in, M., Kalinina, L., Zelenskaya, I., Kalinin, N., Vlasenko, O., Trufanova, S., & ZHdanova, N. (2021). Impact of COVID-19 on the production and consumption of agricultural food. *E3S Web of Conferences*, *247*, 01061. https://doi.org/10.1051/e3sconf/202124701061
- Imai, K. S., Gaiha, R., & Thapa, G. (2015). Does non-farm sector employment reduce rural poverty and vulnerability? Evidence from Vietnam and India. *Journal of Asian Economics*, *36*, 47–61. https://doi.org/10.1016/j.asieco.2015.01.001
- Internationales Arbeitsamt / World Employment Programme, Berry, R. A., & Cline, W. R. (1979). *Agrarian structure and productivity in developing countries: A study prepared for the International Labour Office within the framework of the World Employment Programme*. Baltimore [u.a.] : Johns Hopkins Univ. Press.
- Jaacks, L. M., Veluguri, D., Serupally, R., Roy, A., Prabhakaran, P., & Ramanjaneyulu, G. (2021). Impact of the COVID-19 pandemic on agricultural production, livelihoods, and food security in India: Baseline results of a phone survey. *Food Security*, *13*(5), 1323–1339. https://doi.org/10.1007/s12571-021-01164-w
- Kim, H.-Y. (2018). Statistical notes for clinical researchers: Analysis of covariance (ANCOVA). *Restorative Dentistry & Endodontics*, *43*(4), e43. https://doi.org/10.5395/rde.2018.43.e43
- Maiti, S. K. (2021). *IMPACT OF COVID-19 ON INDIAN AGRICULTURE*.

- McCullough, E. B. (2017). Labor productivity and employment gaps in Sub-Saharan Africa. *Food Policy*, *67*, 133–152. https://doi.org/10.1016/j.foodpol.2016.09.013
- Mondal, D. (2019). Structural transformation and productivity growth in India during 1960–2010. *Economic Modelling*, *82*, 401–419. https://doi.org/10.1016/j.econmod.2019.01.019
- Poudel, P., Poudel, M., Gautam, A., Phuyal, S., Tiwari, C., Bashyal, N., & Bashyal, S. (2020). *COVID-19 and its Global Impact on Food and Agriculture*. https://doi.org/10.35248/2322-3308.20.09.221
- Rawal, V., & Kumar, M. (n.d.). *COVID-19 Lockdown: Impact on agriculture*.
- Shruthi, M. S., & Ramani, D. (2021). Statistical analysis of impact of COVID 19 on India commodity markets. *Materials Today: Proceedings*, *37*, 2306–2311. https://doi.org/10.1016/j.matpr.2020.07.729
- Stephens, E. C., Martin, G., van Wijk, M., Timsina, J., & Snow, V. (2020). Editorial: Impacts of COVID-19 on agricultural and food systems worldwide and on progress to the sustainable development goals. *Agricultural Systems*, *183*, 102873. https://doi.org/10.1016/j.agsy.2020.102873
- Sunil, Loura, D., Dhankar, A., Akshit, Paras, & Bhatia, R. (2020). Impact of COVID-19 on Indian agriculture. *Journal of Pharmacognosy and Phytochemistry*, *9*(6S), 275–280.
- Vemireddy, V., & Pingali, P. L. (2021). Seasonal time trade-offs and nutrition outcomes for women in agriculture: Evidence from rural India. *Food Policy*, *101*, 102074. https://doi.org/10.1016/j.foodpol.2021.102074

- Andrew D. Foster, Mark R. Rosenzweig. (2011, June). *Brown University and Yale University*. Retrieved from https://www.bu.edu/econ/files/2009/09/Rosenzweig_Seminar-Paper.pdf
- H Pathak, J. M. (2022, july). *Indian Council of Agricultural Research.* Retrieved from icar.org: https://icar.org.in/sites/default/files/2023-02/Indian-Agriculture-after-Independence.pdf
- Sen, A. K. (1962). An aspect of Indian agriculture. *Cabi digital library*, 243-246.