ESSAYS IN AGRICULTURE ECONOMICS, CLIMATE CHANGE, AND NUTRITION

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Anna David Thottappilly

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Anna David Thottappilly, Ph.D.
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The dissertation consists of three essays in the field of agriculture economics, climate change, and nutrition. I have structured it as three chapters, namely *'Fertilization Impact Of Atmospheric Carbon Dioxide On Agricultural Yield'*, *'Are Production And Consumption Decisions Independent? Identifying Separability In Indian Agriculture'*, and *'Identifying The Income Nutrition Pathway For Agricultural Households'*.

In the first chapter I test for the effect of atmospheric carbon dioxide on agricultural yield. Plant physiology suggests an increase in agriculture yield with increase in atmospheric carbon dioxide, as plants fix carbon dioxide in the process of photosynthesis. In the study I find there is a positive effect of atmospheric carbon dioxide on agriculture yield of wheat in India, and the effect of atmospheric carbon dioxide on rice depends on the variety of the rice crop used. This is a first of its kind, large scale study for India identifying the effect of atmospheric carbon dioxide on agriculture yield.

In the second chapter I test for separability or its failure in India's agriculture markets. Separability is the property of households making production decisions independent of their consumption preferences. I make use of a 960 household panel data from Chandrapur district for the test. I derive the condition that under separability the agriculture farm revenue is independent of input endowment of the farming households. I find that there is a breakdown of separability in the households . Identifying separability provide insights in to the performance and functioning of markets.

The third chapter establishes the linkage from income to nutrition for the agriculture households where separability does not hold, making use of the panel of 960 households from the study on separability in the second chapter. I find that the diet diversity improve with increased farm revenue for these agriculture household.

BIOGRAPHICAL SKETCH

Anna David Thottappilly received her Masters degree in Economics from Delhi's Jawaharlal Nehru University and Bachelors degree in Economics from University of Delhi's St. Stephen's College. She was raised in Kochi, India and did her schooling there. She has conducted research in Agriculture Economics and the interactions of the field with climate change.

To Kathiri Ammama.

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CHAPTER 1

FERTILIZATION IMPACT OF CARBON DIOXIDE ON AGRICULTURAL YIELD

1.1 ABSTRACT

There have been limited studies that identify the large-scale impact of atmospheric carbon dioxide on agricultural yield, especially for developing countries. I use NASA's Orbiting Carbon Observatory – 2 (OCO-2) data to assess the impact of carbon dioxide on the yield of wheat, rice, and maize in India for 398 districts between the years 2014 to 2017. Using district level panel fixed effects model, I find that wheat yield increases by 0.8 percent with a 1 part per million (ppm) increase in atmospheric carbon dioxide. Rice yield declines by 1 percent for a 1 ppm increase in carbon dioxide, while there is no significant effect of carbon dioxide on maize. There is an endogeneity problem arising from the simultaneity of plants being a source of CO2 by respiring it out, which I overcome by controlling for vegetation in a region using the solar induced chlorophyll index (SIF). The decline in the rice yield with increased CO_2 in the atmosphere does not hold for the districts along the Indo - Gangetic plain (IGP), where the rice cultivars used are known to be superior to the rest of the country. I also test for the heterogeneity in the effect. For states that are leading in agriculture development in India (states with high GDP per capita and larger share of agriculture in GDP, Pingali 2017) I find that atmospheric carbon dioxide has no significant effect on agricultural yield across the three crops in these leading states, while there is a positive effect on wheat and maize yield for states that are lagging in agriculture growth. There is difference in the impact of carbon dioxide on yield based on water availability. There is no negative effect of atmospheric carbon dioxide on rice yield in districts without drought proneness.

1.2 INTRODUCTION

Studying all factors that impact agriculture is important for future food and nutrition security. The effect of water, temperature, fertilizer use, and soil types have been researched both in controlled environment and over long term on field level. These studies help to tailor agriculture policies to meet future food requirements under vagaries of weather and increasing population. The availability of remote sensing data largely aided the studies that identify the effect of atmospheric factors on agriculture. Remote sensing data has also aided the expansion of these studies to larger geographical reach than was earlier possible, where data limitations was a problem. In this paper I test the impact of atmospheric carbon dioxide on agriculture yield of rice, wheat and maize in India using remote sensing data. Rice and wheat are the most consumed staple crops and maize is grown across all agriculture seasons in the country. This paper adds to the literature of agriculture economics by studying the impact of a hitherto unassessed input at a large scale; atmospheric carbon dioxide and its impact on agriculture production.

Plants fix carbon in the atmospheric carbon dioxide (CO_2) into sugar (glucose) during the process of photosynthesis by converting solar energy into chemical energy. This forms the source of food for the plants and hence agriculture yield, and eventually the source of food for all living beings. Since CO_2 is the source of carbon in the sugars that feeds the plants, it is in fact the most important input in agriculture. One would expect an increase in sugar production and thus overall agriculture yield with increased photosynthesis from higher availability of atmospheric CO_2. There is recorded positive effect of atmospheric CO_2 on plant yield under controlled experimental conditions [6, 24, 20, 61]. Recent study on the impact of atmospheric CO_2 on yields of wheat and soybean in the USA shows a postive effect [106]. This resemblance of positive yield effect of atmospheric CO_2 to that of fertilizer induced yield increase, make it the 'fertilization effect of atmospheric CO_2.' The fertilization effect is due to increased net photosynthesis and decreased transpiration [73]. The fertilization effect may partially explain the greening of regions post industrialization [106].

There is a consistent increase in CO_2 in the atmosphere owing to various human activities including agriculture. According to the Global Monitoring Laboratory [1], atmospheric CO_2 has increased 2.16 ppm annually on average in the years 2000 to 2022, globally. In India this figure is much higher and increased 2.63 ppm annually between the years 2014 to 2017 [2].

I test the effect of atmospheric CO_2 on agriculture yield of rice, wheat and maize in India by making use of a panel fixed effects model for 398 districts over the years 2014 to 2017 while controlling for agriculture inputs, weather variables and atmospheric pollutants. Though there have been controlled environment experiments assessing the effect of CO_2 on yield of plants, to my knowledge this is the first study to test the impact of atmospheric CO_2 on agriculture yield for India at a large scale. I adopt the estimation strategy used by Taylor et al, [106] where they find a positive effect of atmospheric carbon dioxide on the yield of wheat in the USA.

I find wheat yield increase by 0.8 percent with a 1 ppm increase in CO_2. The positice effect is in consonance with the controlled envrionment experiments and plant physiology [3]. The effect of atmoshperic CO_2 on rice yield varies by the cultivar of the crops used. I

[1] Part of NOAA's Earth System Research Laboratory

[2] The time period of this study. During these years globally there was a growth of 2.5 ppm of CO_2 according to the Global Research Laboratory

[3] As plants fix the atmospheric CO_2, plant physiology suggests an increase in yield with increase in CO_2 in the atmosphers

find that for districts to the west of Lucknow along the Indo - Gangetic plain [4], where the most efficient cultivars [5] of rice crop is used there is a 0.9 per cent increase in yield with each ppm increase in atmospheric CO_2. I find no effect on maize yield by atmospheric CO_2, which again is what plant physiology predicts as maize is a C4 crop [6]

I test for heterogeneity in the effect. Other inputs of agriculture such as water, fertilizer use, pesticide use, and so on can be a limiting factor on the effect. I try to see how the differences in these input use or availability can alter the CO_2 - yield effect. One way of classification of states to capture differences in input use is based on the levels of GDP per capita and share of agriculture to total GDP [82]. The states with high GDP per capita (greater than national average) and contribution of agriculture to state GDP is greater than national average are classified as agriculture growth - led (leading henceforth) states. While those below national average on both indices are lagging states [7]. Leading states historically have better access to irrigation, higher yielding varieties of crops, and better technology access. While the vice versa hold for lagging states. I find that there is no significant effect of atmospheric CO_2 on yield of wheat, rice or maize for districts in the leading states. There is a positive effect of atmospheric CO_2 on wheat yield among the lagging states and no effect on rice and maize yield. As agriculture production is expected to happen at the highest on the production on the leading states the lack of any effect on yield from CO_2 is attributable to this.

[4] Plain region along the Indus and Ganges river systems. The states of Punjab, Haryana, Uttar Pradesh, Bihar and West Bengal is on the Indo - Gangetic plain from west to east of the country. Lucknow serves as midpoint on the map along the plain in India.

[5] Plant variety that is developed by breeders on field during cultivation

[6] There are two kinds of plants based on how CO_2 is fixed during photosynthesis, namely C3 and C4 plants. C3 plants absorb CO_2 from the atmosphere for photosynthesis, while C4 plants concentrate CO_2 in their leaves constantly and use that for photosynthesis. Hence we expect variations in atmospheric CO_2 to impact C3 plants but not the C4 plants.

[7] This classification is taken from Pingali et al [82] and was used to understand the differences in structural transformation in these states. According to this classification the leading states are Punjab, Haryana, Andhra Pradesh, and Himachal Pradesh and lagging states are Bihar, Madhya Pradesh, Uttar Pradesh, Odisha, Jharkhand, Chhattisgarh, West Bengal, Rajasthan, Jammu & Kashmir, and northeastern states.

An important input that can play a limiting role on CO_2 fixation is water. I run the tests for drought prone and non - drought prone districts. For both drought prone districts and non - drought prone districts wheat yield increases with atmospheric CO_2, and there is no effect on maize yield. However, for drought prone districts rice yield declines with increase in atmospheric CO_2, while this negative effect does not hold for non - drought prone districts [8].

This show the heterogeneity in the fertilization effect of CO_2 under limitations from other inputs. I find that when inputs such as water play a limiting role rice yield declines with increase in CO_2. And when agriculture production is occuring at the most efficient utilization of inputs, an increase in atmospheric CO_2 cannot cause any additional increase in yield.

1.3 LITERATURE

Research on agriculture productivity shifts based on exogenous input use is a significant area of agriculture economics literature. Weather variables such as temperature and rainfall cause shifts in agriculture productivity [80, 87, 8]. This strand of literature aids our policy in ensuring food security under the imminent threat of climate change. My research focus on understanding the aspect of yield changes due to an important input hitherto not studied in the agriculture economics literature, that is, carbon dioxide in the atmosphere. Thus, this paper serves as the basis and initiation point to test production

[8] Paddy is an irrigation intensice crop, more than both wheat and maize.

function shifts from elevated carbon dioxide. The research on the impacts of green revolution has recenlty started attributing some of the productivity changes to atmospheric inputs [43].

There is extensive plant physiology research on the effect of atmospheric carbon dioxide on plant yield. Based on scientific experiments and trials it was predicted that plant yields might increase by a third with doubling of atmospheric carbon dioxide [61]. Yield studies that were initially conducted in laboratory conditions showed a positive impact of carbon dioxide on crop biomass and grain yield [20, 61]. Free air carbon dioxide enrichment (FACE) experiment [9] also predicted a positive impact on yields [10] of various crops [63, 24, 39, 73].

I test if the positive yield response of crops to atmospheric carbon dioxide manifest in agriculture production on field. There has been only limited research under uncontrolled field conditions to test this positive impact of carbon dioxide on agriculture yield. One such study find a positive effect of atmospheric CO_2 on the yield of wheat and soybean in the USA [106]. Particularly for a developing country like India such a study is limited by data availability as well. My research contributes to literature in being one of the initial ones to study the impact of caarbon dioxide on yield using field level data over a longer period of time, that is four years, unlike the controlled experiments and FACE trials.

Wheat yield responses to elevated carbon dioxide under the FACE trials have been positive [39] ubiquitously. However, rice yield response to elevated carbon dioxide under FACE trials seem to depend a lot on other environmental consideration such as nitrogen

[9] Field expermient conditions where concentrations of atmospheric carbon dioxide can be simulated
[10] Yield is physiologically measured as crop biomass, grain yield, flower production or leaf production

and on the cultivar of the rice crop used [63, 10, 74, 11, 5]. Rice yield studies are also more limited as they are not the staple diet of a large number of the more developed economies where FACE trials in the past have been more prevalent. I study the effect of atmospheric carbon dioxide on wheat, rice and maize in India. Rice and wheat are the two most proiminent staple crops in the country and maize is grown in all seasons. To my understanding this would be one of first such studies attempting to see how wheat, rice and maize yields are altered by atmospheric carbon dioxide in the true agriculture environment.

The other strand of literature that is tied to this research is weather impacts on agriculture yield. Economists have tried to understand all variables that could alter the production function of agriculture and recently weather variables have recieved much attention. These studies are particularly important in the face of global warming and ensuing climate change. Weather extremes such as rainfall and temperature negatively alters agriculture production [28, 92]. The study by Taraz, 2018 [105] establish that extreme heat negatively effect agriculture production in India. This literature particularly ties to the one on my research as I am studying the impact of an atmospheric input's impact on agriculture yield much like weather. These results hence incites me to control for the weather variables besides the endogenous physical input use while studying the impact of carbon dioxide on agriculture yield in India. Increase in CO_2 is a contributing factor of climate change manifesting as temperature increase and rainfall shocks. So understanding the effect of atmospheric CO_2 on agriculture yield provides a comprehensive approach to understand the effect of climate change on agriculture.

1.4 CONTEXT

Photosynthesis is the process of fixing atmospheric CO_2 and water into sugar (glucose), hence converting solar engergy into food. It is the process that is the source of all food. The carbon dioxide fixation by plants can follow two different chemical reaction cycles; namely the C3 carbon cycle and C4 carbon cylce [11].

1.4.1 C3 and C4 photosynthesis cycle

Based on the chemical reaction involved in the process of photosynthesis, plants are categorized into C3 and C4 plants. C3 plants follow the C3 pathway for a specific chemical reaction of photosynthesis called dark reaction, for which sunlight is not required. C4 plants follow the C4 pathway for the dark reaction of photosynthesis.

C3 plants use up CO_2 from the atmosphere to fix into sugar and hence is dependent on atmospheric CO_2 directly for photosynthesis and thus yield. While C4 plants stock up CO_2 in their cells throughout and as atmospheric CO_2 is always present in the atmosphere, it does not play a limiting role in their process of photosynthesis as their cells are always saturated with CO_2. Thus we would expect to not see any significant impact of atmospheric CO_2 on the yield of C4 plants. The most prominent C4 agricultural crops are maize and sugarcane. While 95 per cent of all plants including staples such as rice, wheat and so on follow the C3 cycle of photosynthesis.This is partially the reason why maize plant can be grown during different seasons. Hence, I test for the maize yield - CO_2 effect too in the paper.

[11] C3 carbon cycle is the Calvin cycle of CO_2 fixation and C4 is the Hatch - Slack pathway of CO_2 fixation

1.4.2 Solar Induced Chlorophyll Fluorescence & Endogeneity

Plants respire like all the other living organisms by breathing in oxygen and breathing out carbon dioxide. So, plants are a source of atmospheric CO_2 besides absorbing it for photosynthesis. Here we will run into the problem of simultaneity where more plants mean more yield, implying higher carbon dioxide emission due to increase in respiration. On the other hand increase in carbon dioxide in the atmosphere aids photosynthesis and thus increase yield. Hence, it gives rise to a problem of endogeneity. To overcome this endogeneity I control for the vegetation in a particular region by controlling for solar induced chlorophyll fluorescence (SIF). It is the fluorescent light that is radiated into the atmosphere by the chlorophyll molecule [12] present in the leaves of the plants. SIF is the part of the solar light that is not the visible part of the spectrum [13] and is observed by the remote sensing satellite.

When solar light is absorbed by the chlorophyll molecule in the leaves of plants, one of the following three outcomes can take place. One, the solar energy can be used for photosynthesis. Two, the absorbed solar energy gets converted to thermal energy and is disspated out by the leaves. Three, the chlorophyll molecule emits back the solar energy as fluorescent light in to the atmosphere. There is no fixed probability as to the occurence of each of these three outcomes. This mean that a higher level of SIF does not cause an increase in yield. But we can conclude that where there is higher vegetation there will be higher fluorescent light (SIF) emissions observed. Thus, I use SIF as a measure to control for the

[12] It is the chemical compound in green plants that gives the plants the green color and aids in trapping solar energy

[13] The visible part of the spectrum is 400 - 700 nanometer

amount of vegetation in a given region, thereby solving the problem of endogeneity from simultaneity.

1.5 DATA

The unit of this study is districts as it is the lowest possible unit for which agriculture data is available consistently over a considerably longer period of time. I make use of a panel of 398 districts for the years 2014 to 2017 with atmospheric, weather, and agriculture data. The atmospheric variables include atmospheric concentrations of carbon dioxide, ozone, nitrogen dioxide, and carbon monoxide [14]. The solar induced fluorescence is the other atmospheric variable in the panel data. The data summary is in table 1.1.

The atmospheric carbon dioxide data is from NASA's Orbiting Carbon Observatory-2 (OCO-2) mission. I make use of the OCO-2 level 2 data, version 9 (OCO-2 L2 V9). The estimates of the average carbon dioxide in a column of dry air extending from the earth's surface to the top of the atmosphere (X_{CO_2}) is the proxy variable for the surface level carbon dioxide. The atmospheric carbon dioxide is available at a spatial grid of 2.25 km by 1.29 km resolution, every 16 days. For the purpose of this study, I average these variables first at the monthly level and then annually for each of the districts. The annual spatial variation in X_{CO_2}, district wise is shown in figure 1.1 and the average increase in the level of carbon dioxide in India is in figure 1.2. Spatially we see an increase in carbon dioxide across all districts during the period which resulted in the average carbon dioxide levels for the country to increase from 394.96 ppm in 2014 to 405.48 ppm in 2017. This leads to

[14]Ozone, nitrogen dioxide, and carbon monoxide are the top three pollutants of air besides particulate matter [118]

Table 1.1: Average district summary statistics

Variable	2014	2015	2016	2017
Atmospheric and environmental variables				
Carbon dioxide (ppm)	394.96	399.12	402.89	405.48
Ozone (DU)	264.25	272.59	261.65	265.27
Nitroden dioxide ($molecules/cm^2$)	4.65	4.51	4.93	4.99
Carbon monoxide ($ppbv$)	66.36	66.99	66.52	66.75
Solar induced chlorophyll fluorescence ($W/m^2/sr/\mu m$)	0.71	0.81	0.85	0.72
Average temperature (^oC)	21.61	21.82	22.32	22.18
Annual precipitation (mm)	1036.42	1020.12	1057.12	1084.73
Agriculture variables				
Rice yield (kg/ha)	2451.01	2201.18	2526.37	2491.28
	(502)	(500)	(526)	(535)
Wheat yield (kg/ha)	2185.19	2375.34	2697.21	2784.88
	(462)	(462)	(480)	(456)
Maize yield (kg/ha)	2665.96	2503.51	2685.81	3180.11
	(485)	(485)	(510)	(517)
Irrigated area under rice cultivation (1000 ha)	46.67	45.19	49.47	44.52
Irrigated area under wheat cultivation (1000 ha)	57.79	56.14	70.59	54.12
Irrigated area under maize cultivation (1000 ha)	4.45	4.1	5.22	5.27
Nitrogen fertilizer use per net cropped area (kg/ha)	133.24	141.7	139.85	143.85
Phosphate fertilzer use per net cropped area (kg/ha)	43.57	52.31	51.39	52.86
Potassium fertilizer use per net cropped area (kg/ha)	18.27	17.45	19.54	24.03
Total fertilizer consumption per net cropped ares (kg/ha)	195.08	211.46	210.78	220.74
Female agricultural wage rate ($Rupees/day$)	195.97	207.31	225.35	242.15
Male agricultural wage rate ($Rupees/day$)	272	292.59	296.55	316.67
Average population in 2011		1889592		

Atmospheric carbon dioxide measure is in parts per million, while carbon monoxide is measured in parts per billion of volume. Unit of measure of ozone is dobsun unit (DU). Nitrogen dioxide is measured in molecules per unit area. The unit of measurement of solar induced fluorescence is called spectral radiance. All the variables are averaged over each year for each district. Agricultural variable values are also annual averaged values calculated from the TCI-ICRISAT district level dataset.
The figures in parenthesis under the yield of each crop shows the number of districts from where the data is sourced.

an average annual growth rate of 2.63 ppm in the period in comparison to 2.5 ppm global annual average growth between 2014 to 2017 [65].

Figure 1.1: Average atmospheric carbon dioxide in parts per million (ppm)

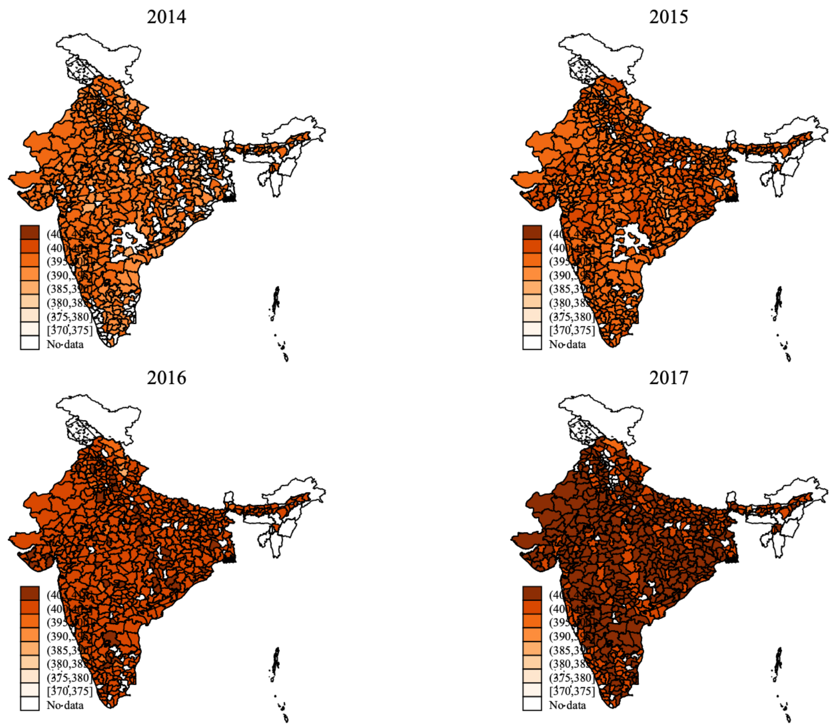
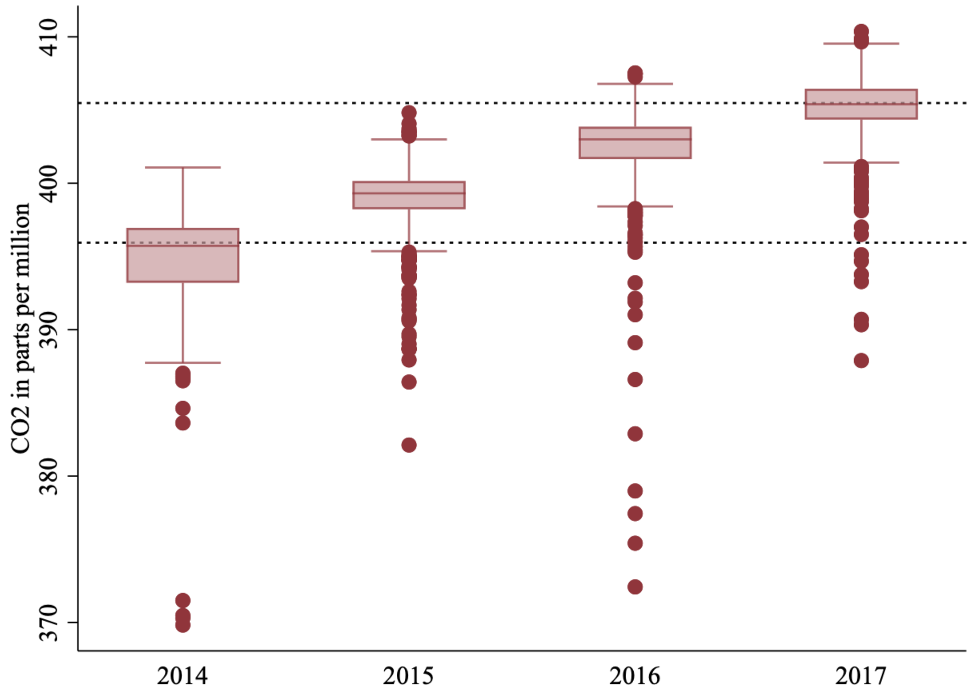


Figure 1.2: Atmospheric carbon dioxide (ppm) levels over the years



The panel data includes the SIF variable, measure of gross primary productivity of plants, sourced from OCO-2 data, to be used as a control for the amount of vegetation in a district. The OCO-2 data provides SIF values at 2.25 km by 1.29 km spatial variation, every 16 days, observed at the 740 nm wavelenght. I average the daily values over each year for the district by mapping the latitude and longitude coordinates using the shape file for India. Appendix has the spatial map of SIF (740 nm) for India. It is measured using the radiance unit of watt per steradian per square meter of surface per micrometer of span in wavelength [15] . The average SIF in 2014 is 0.71 flick, 0.81 in 2015, 0.85 in 2016 and 0.72 flick in 2017.

Ozone and nitrogen dioxide data is sourced from the remote sensing Ozone Monitoring

[15]This unit is called a flick of spectral radiance

Instrument (OMI) of the Aura or EOS CH-1 satellite [16]. The spatial granularity of the data is 0.25^o x 0.25^o [17] (latitude by longitude) observed daily. I plot this to India's districts using the district spatial map and average it for each year year. The average spatial distribution of ozone is shown in appendix. The average amount of ozone in a colum of atmosphere is 264 Dobsun Unit (DU [18]) in 2014, 273 DU in 2015, 261 DU in 2016 and 265 DU in 2017 respectively. Nitrogen dioxide data is also extracted from the OMI of EOS CH-1 satellite at 025^o x 0.25^o (latitude by longitude) granularity. It ranges from 4.65 in 2014, 4.51 in 2016, 4.93 in 2016 and 4.99 molecules per square centimeter area in 2017, respectively. The spatial distribution of average atmospheric nitrogen dioxide is in appendix. The carbon monoxide data is sourced from Modern-Era Retrospective Analysis for Research and Applications, version 2 (MERRA-2) which is reanalysis of the atmospheric data from NASA. This data provides daily carbon monoxide at the surface concentration gridded at 0.5^o x 0.625^o (latitude by longitude) which is plotted to each district and I average the daily data at annual level for each mapped district. On average it has ranged between 66 to 67 parts per billion in volume from 2014 to 2017.

Weather data include temperature and preciptation variables. Weather data is from the Indian Meterological Department (IMD) remote sensing data at 0.25^o x 0.25^o grid which I map to the districts in India. The average temperature over India across districts is 21.6^oC in 2014, 21.8^oC in 2015, 22.3^oC in 2016 and 22.2^oC in 2017. Precipitation data is also available at 0.25^o x 0.25^o grid from IMD. It is aggregated over the twelve months of each year and the average total precipitation in each year is 1036 mm in 2014, 1020 mm in 2015, 1057 mm in 2016 and 1085 mm in 2017.

[16] Aura is studying the ozone layer, air quality and climate of the Earth and is a major component of the Earth Orbiting System (EOS)

[17] 1 degree is approximately 111 km at the equator

[18] Unit of ozone measure

Agriculture variables are rice yield, [19] wheat yield, maize yield, irrigated area under each of the crops, fertilizer use per net cropped area, and agriculture wage rate. The agriculture production data of wheat and rice, the two main staples of India, and input use data at the district level is from the Tata Cornell Institute - International Crop Research Institute for the Semi Arid Tropics (TCI-ICRISAT) District Level Database (DLD). I also obtain yield data for maize crop, a significant food crop which follows the C4 photosynthesis pathway unlike rice and wheat that follow the C3 cycle during photosynthesis. In table 1 I show the summary statistics of the district level data. The yield, of rice measured as production per unit area (kilogram per hectare) was approximately 2420 kg/ha, the yearly disaggregated measure is in table 1, with the lowest yield in 2015 at 2200 kg/ha and the highest at 2526 kg/ha in 2016. Average yield of wheat production over the four year in India was 2512 kg/ha, with the lowest yield in 2014 at 2185 kg/ha and highest yield in 2017 at 2785 kg/ha. The average maize yield over the four years was approximately 2765 kg/ha. The average yield of cotton production in the period was 432 kg/ha.

Approximately 46500 hectares of land under rice cultivation is irrigated on average in the four year period I study. 59600 hectares under wheat cultivation, 4700 hectares of maize cultivated land and 11000 hectares of cotton raising land is under irrigation from 2014 to 2017 on average. The average fertilzer use over net cropped area range from 195 kg/ha in 2014 to 220 kg/ha in 2017. Table 1.1 has disaggregated values of nitrogen, phosphate and potassium fertilizer use per net cropped area in each of the years. I use the wage rate at the district level as a proxy for labor input use due to the unavailability data on labor input demand at the district level. The district level average agricultural wage rate is statistically higher for males than female [20]. The average female wage rate for agricultural work ranges from rupees 196 in 2014 to rupees 242 in 2017, while the same for men range

[19] All yields are in production per unit of area, kilogram per hectare
[20] t-test results in appendix

from rupees 272 in 2014 to rupees 317 in 2017. The average population of these districts in India according to the census 2011 [21] is 1889592. Since the level of urbanization is known to affect carbon dioxide emissions, I include it as a control in the analysis. It would be prudent to control for population of each of the years I study, however the decennial nature of census provides me with only the 2011 population figure, before the period of my study, and which could have a potential effect on carbon dioxide emissions.

1.6 ESTIMATION & RESULT

I use the panel fixed effects model specified below to identify the effect of carbon dioxide on agricultural yield, with controls for weather, major atmospheric pollutants that could affect plant growth, and urbanization.

$$Yield_{it} = \beta_{0_{it}} + \beta_1 CO_{2_{it}} + \beta_2 SIF_{it} + \beta_3 \mathbf{W_{it}} + \beta_4 \mathbf{P_{it}} + \beta_5 U_{i,2011} + \varepsilon_{it} \tag{1.1}$$

Here i stands for districts and t for years from 2014 to 2017. Yield is measured in kilogram per hectares. CO_2 is the average annual carbon dioxide in the column of air from the surface of the earth to the top of the atmosphere measured in parts per million. I run separate regressions for each of the three crops; rice, wheat and maize.

SIF is the solar induced fluorescence measured in flick. This controls for the plant cover in the district as it is a measure of the photosynthetic activity. Thus I control for carbon dioxide released into the atmosphere by plant respiration. This helps in overcoming the endogeneity problem arising from simultaneity.

[21] Indian census is decennially conducted and the most recent one is 2021

W includes weather control variables such as precipitation measured in millimetres and temperature in ^0C. I make use of different specifications of the weather variables as there is evidence for the extreme weather variations to have a non linear impact on yield than just average values of temperature and precipitation [92]. **P** are all other agriculture yield affecting control variables involving irrigation, fertilization use, labor wage rate and so on. $U_{i,2011}$ is the 2011 population for each of the districts i, as a control for the level of urbanization in the districts. ε_{it} is the idiosyncratic error term.

I hypothesize that atmospheric carbon dioxide has a positive effect on the yield of wheat and rice. I also hypothesize that there is no effect of atmospheric carbon dioxide on the yield of maize.

As a preliminary exercise I am showing the linear fit of yield of each crop on the atmospheric carbon dioxide in figure 1.3. Figure 1.4 has the preliminary effects of atmospheric carbon dioxide on agriculture yield of rice, wheat and maize while controlling for photosynthetic plants in the region with solar induced chlorophyll fluorescence (SIF), temperature, annual rainfall, fertilizer use, and agriculture wage using male wage rate with district level fixed effects. The coefficients are in appendix. I see that there is a significant positive effect of atmospheric carbon dioxide on agriculture yield for all the three crops.

Figure 1.3: Linear fit of yield on atmospheric carbon dioxide

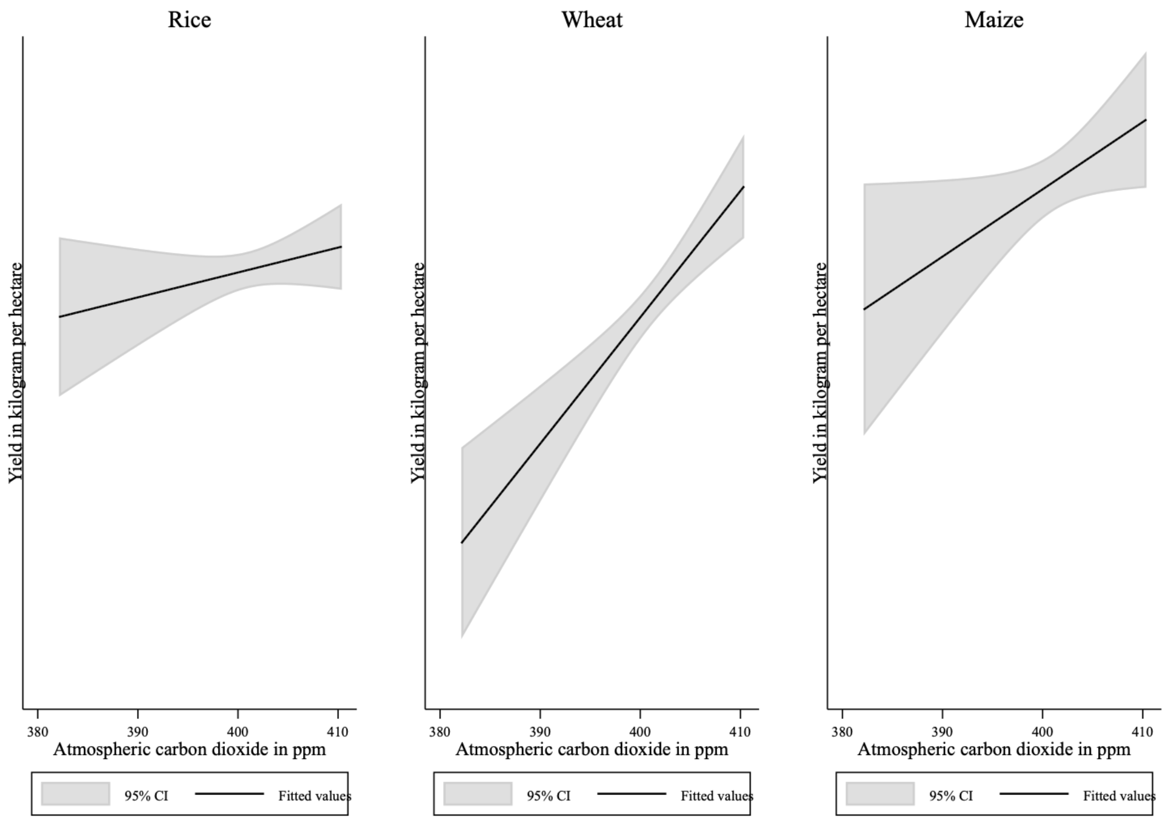
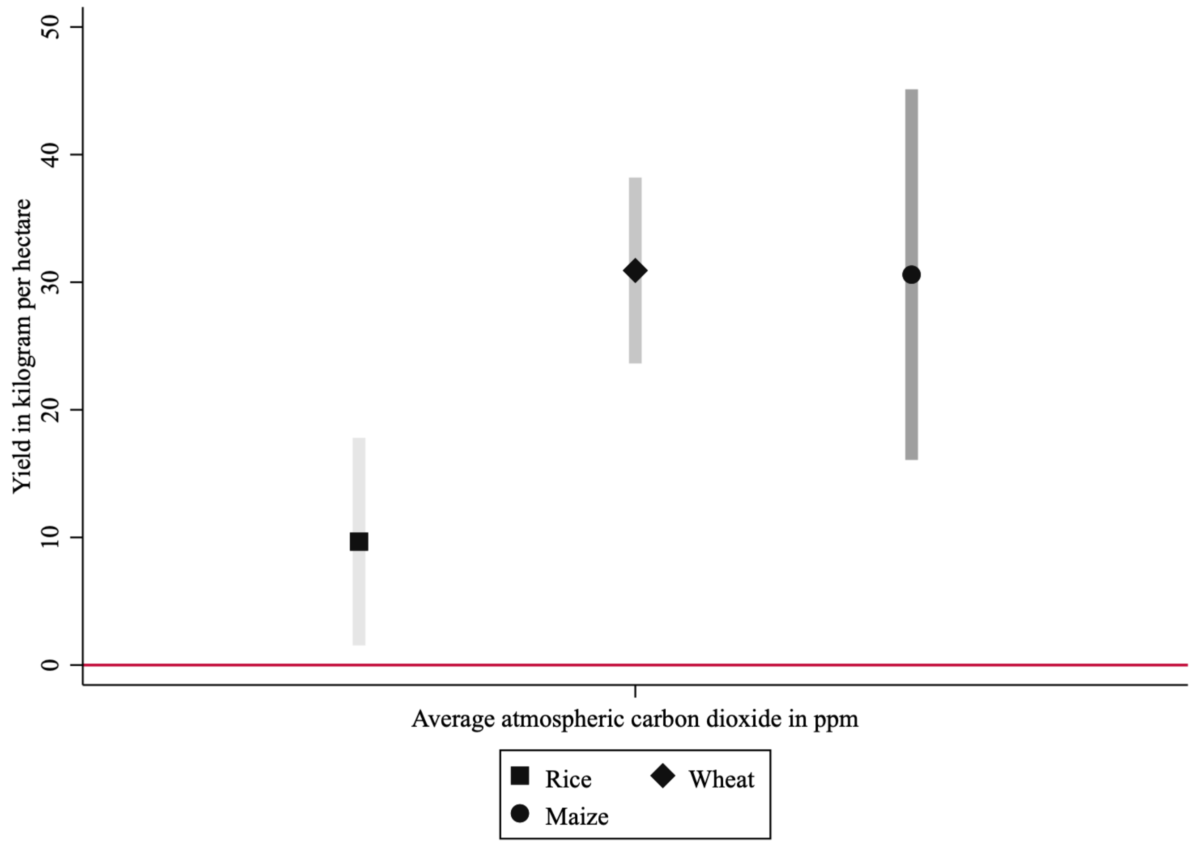


Figure 1.4: Preliminary regression between yield and atmospheric carbon dioxide



The coefficients represent panel regression results with district fixed effects and control for SIF, temperature, rainfall, fertilizer use and agriculture wage rate

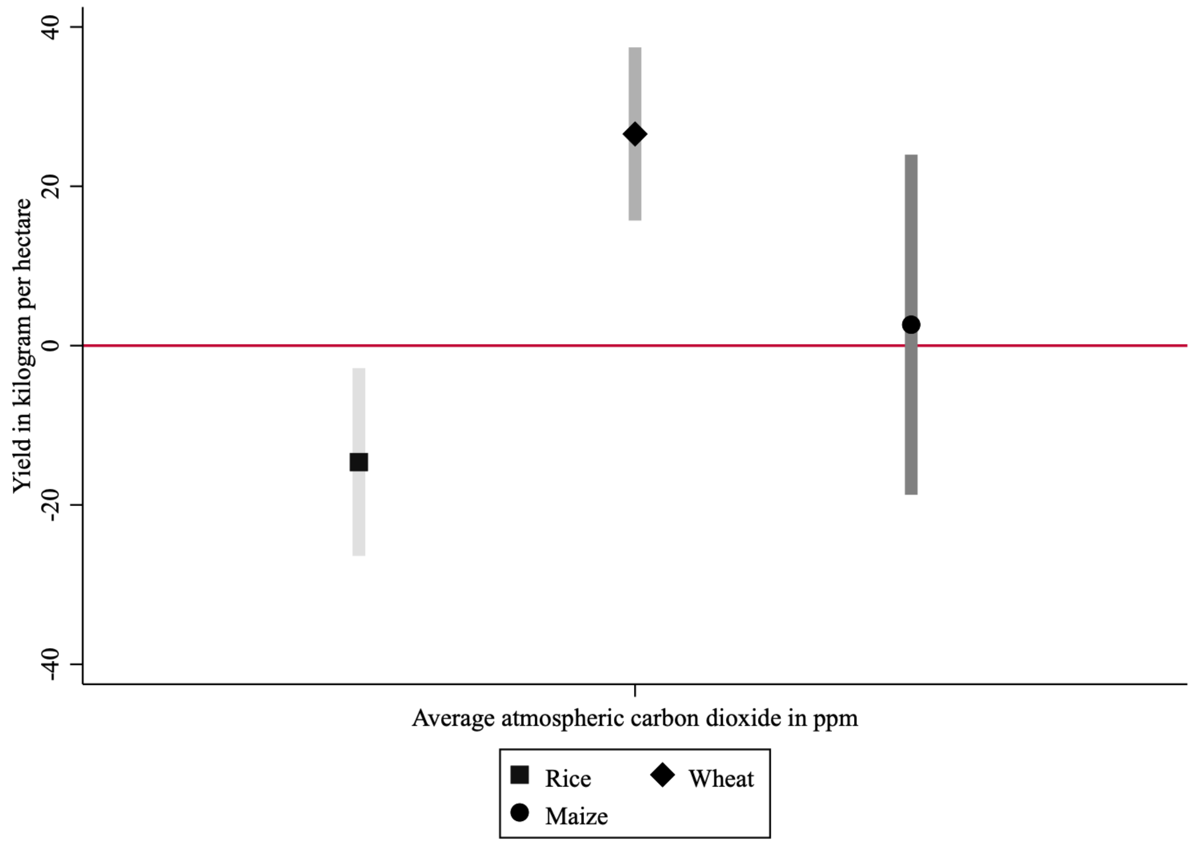
Model 2 in appendix A.3 involve crop specific irrigated area without atmospheric pollutant controls. In this regression we see that rice yield increases by 12.09 kg/ha, wheat yield by 35.64 kg/ha and maize yield by 24.15kg/ha with a 1 ppm increase in atmospheric carbon dioxide between 2014 to 2017.

There is evidence in plant physiology that suggest atmopsheric pollutants impact crop yield [56]. Hence, in the preferred specification of model 3 I use controls for the important atmospheric pollutants; ozone, nitrogen dioxide and carbon monoxide but do not include irrigation controls as there is numerous missing data points for the same. The coefficient estimates for this is in figure 1.5. Here, I find that wheat yield increases by 26.57 kg/ha with each part per million increase in atmospheric carbon dioxide. There is no significant effect of atmospheric carbon dioxide on maize yield, which is expected as maize is a C4 crop and C4 crops have a constant store of carbon dioxide in their leaves [22]. However, while controlling for atmospheric pollutants there is a negative effect of atmospheric carbon dioxide on rice yield, contrary to what is expected. There is evidence that rice yield effects of atmospheric carbon dioxide is largely dependent on the cultivar [23] and on the interactive effects of atmospheric carbon dioxide, water availability, and nitrous oxides [74]. I try to explain the negative effect of atmospheric carbon dioxide on rice with the difference in the rice crop varieties used.

Annual rainfall positively affects agricultural yield of both rice and wheat at 95 per cent level of significance. Ozone, which is a significant atmospheric pollutant that is also a main cause for global warming has a significant negative effect on rice yield. Nitrogen dioxide has a positive impact on rice and maize yield. This resut is not entirely surprising despite nitrogen dioxide being antagonistic for plant growth since in areas with saturated levels of oxides of nitrogen [24] it pushes out ozone out of the atmosphere [25] and prevent plants' exposure to ozone [72].

[22]See section 3.1 for elaborate explanation on the physiological difference between C3 and C4 crops
[23]Selective breeding on field produces different varieties of the crop which called a cultivar of the crop
[24]Nitric oxide (NO), nitrogen dioxide (NO_2), nitrous oxide (N_2O) and nitrogen pentoxide (NO_5)
[25]This is the indirect effect of nitrogen dioxide on plant growth and yield

Figure 1.5: Regression between yield and atmospheric carbon dioxide



The coefficients represent panel regression results with district fixed effects and control for SIF, temperature, rainfall, fertilizer use, agriculture wage rate and major atmospheric pollutants

Since the level of urbanization can contribute to the amount of atmospheric carbon dioxide and other pollutants, I need to include data on level of urbanization measured by the population in each of these districts. Census in India is conducted every 10 years and the most recent census prior to 2014 was conducted in 2011. I include the 2011 population as an additional variable in the panel. In model 4 in appendix, the fixed effects include the 2011 population values too. I see that the results are similar to that of the preferred model 3 in appendix A.3. I prefer model 3 over 4 as controlling for all major pollutants, and the inclusion of a proxy for agriculture labor also controls for urbanization implicit.

In the regression analysis of appendix A9 there are controls for season specific temperature and rainfall in the period of growth of rice [26] and wheat[27]. Hence for rice and wheat I control the average temperature and precipitation for the specific months of growth of both the crops. Since maize is grown round the year I use the average annual temperature and total annual rainfall than any specific season average. The results are in appendix A9. Here, wheat yield is seen to increase by 27 kg/ha for each part per million increase in carbon dioxide in the atmosphere. There is no effect of carbon dioxide on maize. Both these results is in agreement with my hypothesis. There is no effect of carbon dioxide in the atmosphere on the yield of rice.

In table 2 I use log of the yield values as dependent variable which is consistent with the result of the model with absolute agriculture yield in kilogram per hectare as the dependent variable. In table 1.2, one can see that rice yield declines by 1 percentage point with each parts per million increase in atmospheric carbon dioxide. Wheat yield increase by 0.8 percentage point for every parts per million increase in carbon dioxide. There is no effect of atmospheric carbon dioxide on maize yield.

Table 1.2: Regression of log yield on atmospheric carbon dioxide with controls

Variable	Rice	Wheat	Maize
Carbon dioxide (ppm)	-0.01***	0.008***	0.003
	(0.003)	(0.003)	(0.004)
District FE	✓	✓	✓
N	914	834	910
No. of districts	309	282	308
R^2	0.248	0.095	0.123

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

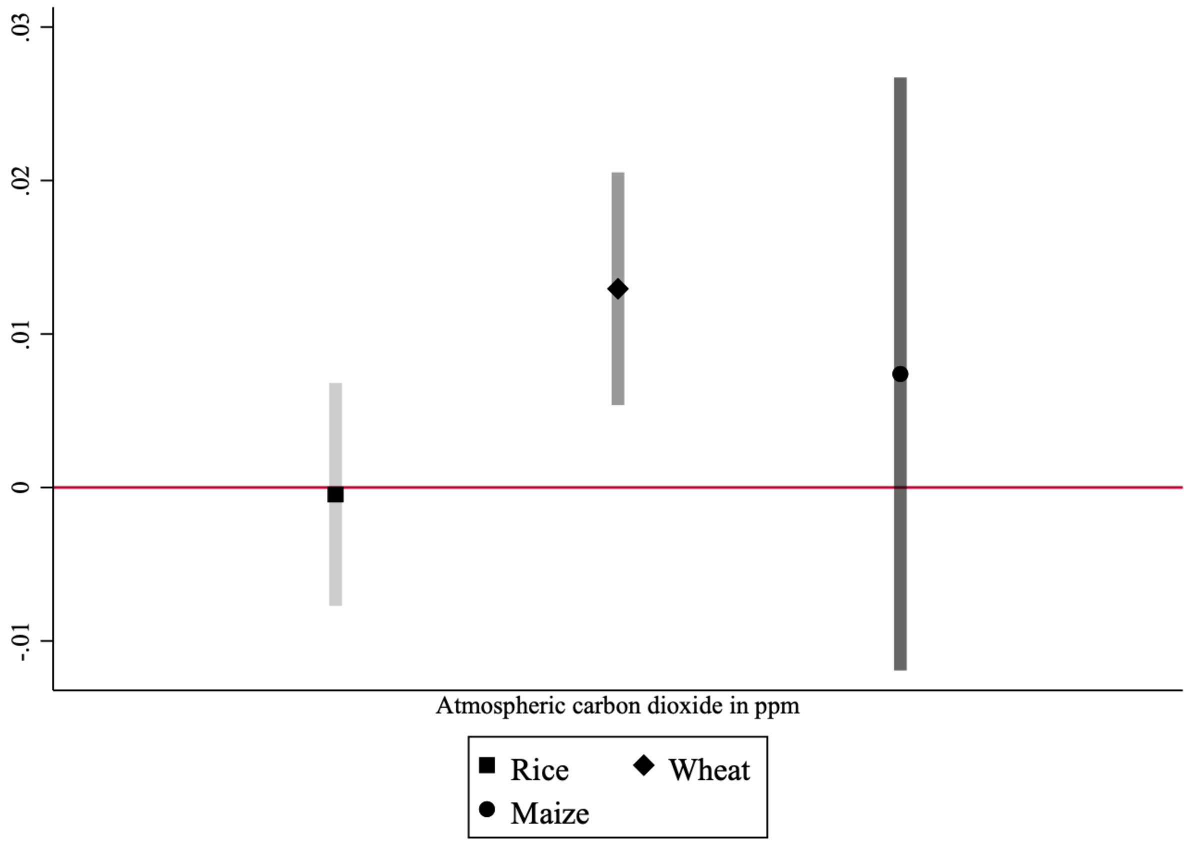
[26] Both kharif and rabi rice
[27] Rabi wheat

1.6.1 Atmospheric carbon dioxide and rice yield effect

Research has documented mixed results as to the effect of atmospheric carbon dioxide on rice yield based on the cultivar of rice used [74]. Since there is prior knowledge on the difference in the cultivars and varieties of rice crop used across India, I try to incorporate the difference in the varieties of the rice crop to understand the negative effect I observe in regression analysis of table 1.2. Though data is limited on the true variety of the rice crop used in each of the districts, it is known that districts along the Indo - Gangetic plain (IGP) [28] historically have had access to better yielding rice crop. Here I restrict my analysis to the districts along the IGP, with log rice yield as the dependent variable, while attempting to uncover how the differences in the rice crop varieties can alter the yield - carbon dioxide effect. The results are summarized in figure 1.6. The precise and comprehensive estimates of the regression is in appendix A.6.

[28]The map of the IGP is in appendix A.6

Figure 1.6: Regression of log yield and atmospheric carbon dioxide along the Indo - Gangetic plain

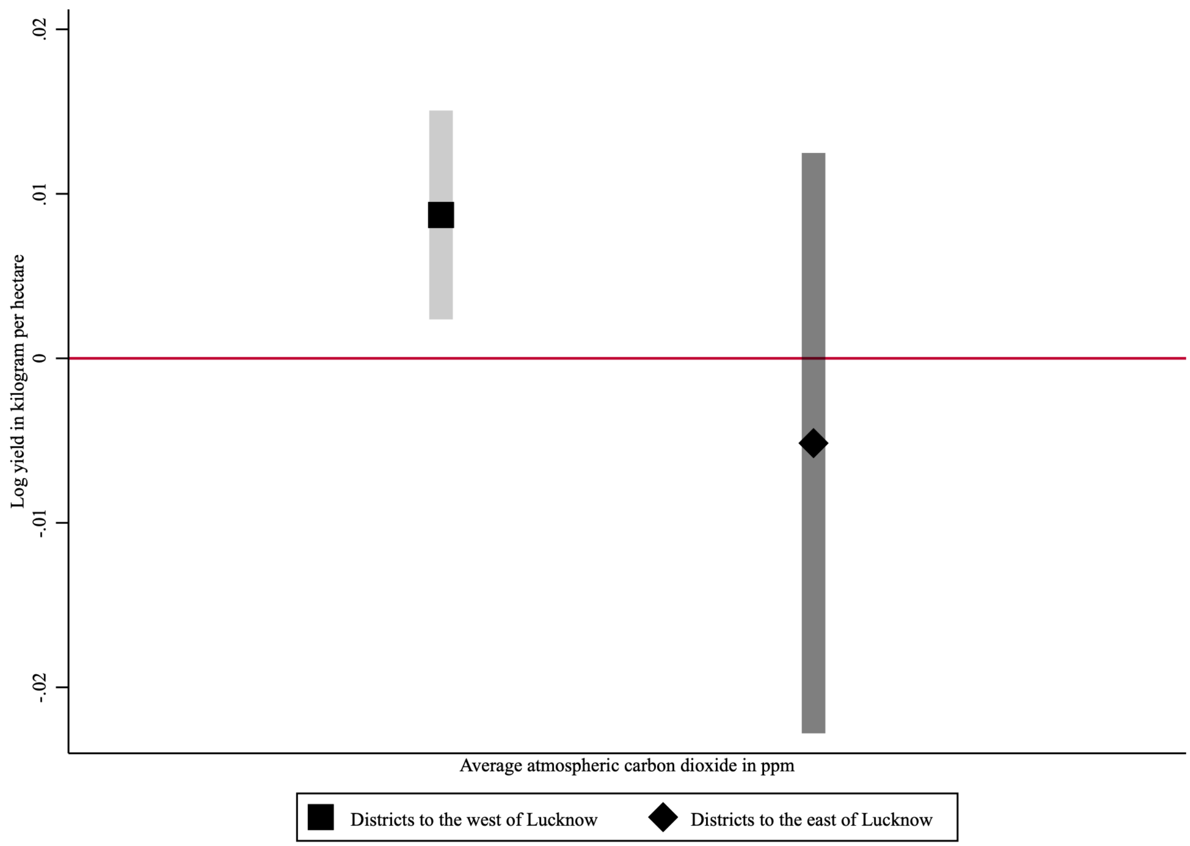


The coefficients represent panel regression results with district fixed effects and control for SIF, temperature, rainfall, fertilizer use, agriculture wage rate and major atmospheric pollutants for districts in the Indo-gangetic plain

There is no effect of atmospheric carbon dioxide on rice yield for districts on the IGP. So the negative effect observed when conducting the analysis for all the districts in the country disappears. This result is indicative of the difference in the crop variety utilized to be a potential reason aiding the yield - carbon dioxide effect for rice crop.

It is known that the western states of Punjab and Haryana along the IGP gained more advantages than those to the eastern part of the plain [82]. To further ascertain the difference in rice variety leading to heterogeneity in the carbon dioxide - yield effect, I divide my sample districts on the IGP to the east and west of Lucknow. I choose Lucknow because it serves as the center point, as one can see in the map of the IGP. The regression results of rice yield on atmospheric carbon dioxids by IGP districts to the east and west of Lucknow is in figure 1.7.

Figure 1.7: Regression of log rice yield and atmospheric carbon dioxide to the west and east of Lucknow on the IGP



The coefficients represent panel regression results with district fixed effects and control for SIF, temperature, rainfall, fertilizer use, agriculture wage rate and major atmospheric pollutants for districts in the Indo - Gangetic plain

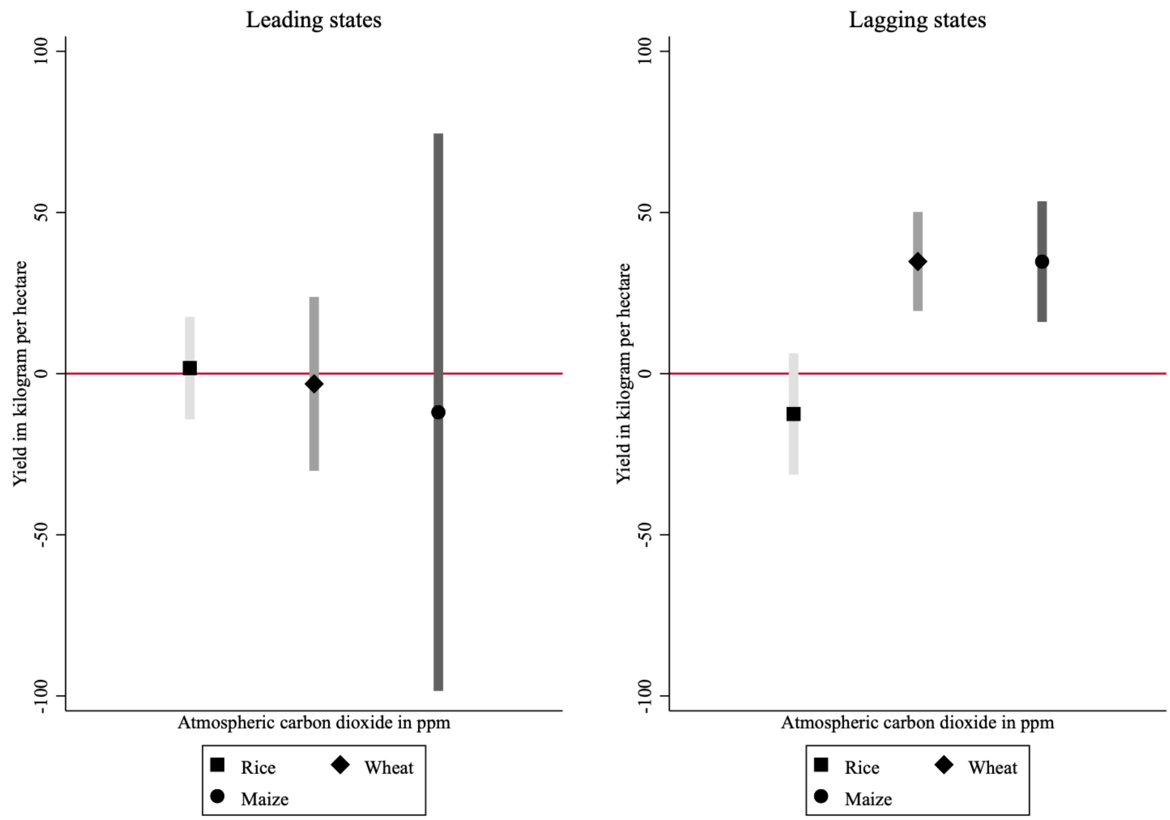
From figure 1.7 and appendix A.7, it is evident that rice yield increases by 0.9 percentage points for every part per million increase in atmospheric carbon dioxide for IGP districts to the west of Lucknow, with no significant effect of atmospheric carbon dioxide on rice yield for IGP districts to the east of Lucknow. This confirms the result that the effect of atmospheric carbon dioxide on rice crop is dependent on the variety of the crop.

In appendix A.8 I have included the power of the regressions in figure 1.6 and 1.7. The power of the tests in both cases is 1. This is essential as the number of observation drops significantly as I restrict the analysis to districts along the IGP. In order to atleast have 80 percent as the power of the test, the sample size requirement is 43, which is satisfied in all the regression analysis I carry out.

1.6.2 Heterogeneity in the carbon dioxide - yield effect

Other inputs as water and fertilizer use, is a potential limitation or interactive factor in the carbon dioxide - yield effect. To understand the heterogeneity in result, I disaggregate Indian states into agriculture lead growing states and agriculture lagging states. This classification is from Pingali et al.

Figure 1.8: Regression of log yield and atmospheric carbon dioxide for leading and lagging states



Leading states : Andhra Pradesh, Haryana, Himachal Pradesh and Punjab
Lagging states: Bihar, Chattisgarh, Jharkhand, Madhya Pradesh, Odisha, Rajasthan, Uttar Pradesh and West Bengal

There is no effect of carbon dioxide on the yield of rice, wheat, and maize for the leading states. This can be attributed to the fact that states experiencing agricultural-led growth achieve the highest level of efficiency for input use. The lagging states have a positive effect of atmospheric carbon dioxide on wheat yield. The estimates are in appendix A.10.

1.6.3 Robustness checks

Weather extremes affect plant yields than the averages [92]. To account for this I run robustness check using the deviation of the temperature and precipitation from the national average for each year and deviation from the districts' respective average values over the four year period. The results are in table 1.3 and 1.4 respectively.

Table 1.3: Regression of log yield on atmospheric carbon dioxide

Temperature and precipitation is measured as deviations from the national average

Variable	Rice	Wheat	Maize
Carbon dioxide (ppm)	-0.008**	0.009***	0.004
	(0.003)	(0.003)	(0.004)
District FE	✓	✓	✓
N	902	818	894
No. of districts	306	278	304
R^2	0.252	0.107	0.123

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 1.4: Regression of log yield on atmospheric carbon dioxide

Temperature and precipitation is measured as deviations from the district averages

Variable	Rice	Wheat	Maize
Carbon dioxide (ppm)	-0.009***	0.009***	0.004
	(0.003)	(0.003)	(0.004)
District FE	✓	✓	✓
N	902	818	894
No. of districts	306	278	304
R^2	0.252	0.107	0.124

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

The atmospheric carbon dioxide and yield effects are consistent with the use of average temperature and annual rainfall.

1.7 CONCLUDING REMARKS

Each part per million increase in atmospheric carbon dioxide corresponds to a 1 percentage point increase in the agriculture yield of the wheat crop. In 2014, the average wheat yield in India was 2185 kg/ha, accompanied by an atmospheric carbon dioxide level of 395 ppm. By 2017, the average wheat yield had risen to 2785 kg/ha, with an atmospheric carbon dioxide level of 405 ppm. This indicates a 600 kg/ha increase in wheat yield over the four-year period. The 10 ppm increase in atmospheric carbon dioxide contributed approximately 218 kg/ha of the total 600 kg/ha increase in wheat yield. This means one - third of the yield increase in the period is attributable to the fertilization effect of atmospheric carbon dioxide.

The case for the rice crop is not as straightforward as wheat crop. The cultivar of the crop used is a significant determinant of the atmospheric carbon dioxide - yield relationship for rice. There is an increase in rice yield to the tune of 0.9 percent with each part per million increase in atmospheric carbon dioxide for districts utilizing the best variety of the crop; IGP districts to the west of Lucknow.

There is no significant effect of atmospheric carbon dioxide on maize yield, validating the result that C4 [29] crop yields are not affected by atmospheric carbon dioxide.

Extreme weather outcomes are a manifestation of the climate change phenomena, the major contributing source of which is the increasing atmospheric carbon dioxide. Research has established that these extreme weather outcomes have adverse impact on agriculture yield of crops. Here, I show that atmospheric carbon dioxide has positive effect

[29] Maize is a C4 crop

on agriculture yield for wheat and rice, albeit crop dependent for rice. This imply two things. One, the adverse impact of climate change on agriculture yield may be greater than hitherto established as the fertilization effect of the atmospheric carbon dioxide is masking part of it. Two, the adaptive measures towards climate change farmers implicitly or explicitly undertake are less conservative than what would have been if not for the fertilization effect of atmospheric carbon dioxide.

Nascent literature show that there is a reduced nutrient content for crops with the increased atmospheric carbon dioxide [6]. The increase in yield due to atmospheric carbon dioxide documented cannot be treated exclusively, but with the nutrient content effect of atmospheric carbon dioxide if we are to meet the nutrition security of the future.

I make use of a reduced form approach to identify the effect of atmospheric carbon dioxide on the yield of wheat, rice, and maize in India. The reduced form approach falls short of enabling me to tease out the direct and indirect effects of the atmospheric carbon dioxide effect on crop yield. Just as in the case of weather impacts on yield, farmers may be implicitly utilizing adaptive measures to the fertilization effect of atmospheric carbon dioxide. A structural identification is required for the purpose [16].

The usual caveats of the classical measurement error of using remote sensing data applies to this paper as well, which in the absence of other data source cannot be done away with. The study will gain immensely from further availability of agriculture data for longer periods of time, and in a true sense can render as a long term study.

CHAPTER 2

ARE PRODUCTION AND CONSUMPTION DECISIONS INDEPENDENT? IDENTIFYING SEPARABILITY IN INDIAN AGRICULTURE

2.1 ABSTRACT

Production and consumption is said to follow *separability* when production decisions are made independent of consumption preferences. It has been explored in the past for agriculture households as it tends to breakdown for them due to the specific nature of their output, that these outputs can also be self consumed. Indian agriculture underwent major changes in terms of market access, input use and farm technology since the green revolution of the 1960s.There is limited research characterizing Indian agriculture recently, as the country is undergoing the process of structural transformation. In this paper I develop the theoretical model to test if farming households follow separability, extending the model by Dillon et al (2017). I show that household farm revenue is independent of household characteristics under separability. I then use this to test if farmers in Chandrapur district in the Indian state of Maharashtra follow separability, using a panel of 960 households for the years 2014 and 2016. I find that they fail to make production decisions independent of their consumption preferences as the household land and labor endowments positively impact the revenue received from crop sales. Under all specifications I use, land endowment is positively associated with the farm revenue from crop sales and, both land and labor endowments jointly affect farm revenue. For small and marginal land owning households, that is, less than 2.5 acres of land and for households that grow food crops, land and labor endowments, both individually and jointly affect farm revenue positively.

2.2 INTRODUCTION

All rational households make consumption choices to maximize their utility, given their income. Households make income through productive activities with a goal of maximizing income, not conditioned by consumption preferences, only constrained by production function. This is the separability condition. When production is not altered by consumption choices and is only driven by profit maximization, we say separability condition is adhered to. The separability condition may not hold for households which are involved in production of goods that can be self consumed, for instance primary production activity. Agricultural households produce crops that could be used for self consumption. The households which can simultaneously produce and consume their outputs and for whom separation does not hold are modeled using the Agricultural Hosusehold Model (AHM). [14]

Besides characterization of the agrarian economy of a country there is a need to identify separabilty or lack thereoff due to some of the following reasons. First, policy implications could be different under the non separation model as opposed to that anticipated under the separation model. For instance, pricing policy of agriculture output have had unprecedented own price elasticities of demand where separability failed [4]. Second, under separable conditions input allocation and demand is based on the general equilibrium point arrived at based only on the price ratios. Inefficient input or resource allocation is thus a feature of non-separable production process as witnessed in developing economies' agriculture [19]. Finally, most small land holding farmers particularly in developing economies tend to be functioning under non separabilty due to their limited access to markets, both inputs and output. Identifying this shall help tailor welfare improving policies. For example, recent research in sub Saharan African context has shown that market access improving measures worked better towards nutrition status of the smallholder households than production diversity [77]. Though this is not an exhaustive list of reasons, it invokes the need to identify separability or lack thereoff, particularly in developing countries, whose economies have evolved greatly and yet, there is limited research on the topic.

In this paper I test to see if separability holds for agriculture in the Indian context, with specific data collected for Chandrapur district in Maharashtra. Researching separability for developing countries in recent history has been constrained by the lack of availability of input demand data, especially for India.

There are recent papers that test separability for the sub Sahara African economies. However India's structural transformation is different from the sub Saharan African experience and one cannot extrapolate from the sub Sahara African studies that all developing economies' agriculture is non-separable. My study extends the most recent and acceptable method by Dillon & Barrett [30] to use total revenue as the dependent variable of interest, and test whether it is affected by household characteristics. Under separable conditions it should not be the case. While Dillon & Barrett (2017) make use of labor demand as the dependent variable of interest, India has limited data availability on agriculture labor demand and most other input demands also. Hence, my extension of the model helps future studies to tailor to the needs of limited data available economies.

I find that there is failure of separability condition by establishing land and labor endowments of the households affect their agriculture revenue. If the households followed the separation hypothesis this will not be the case. Their agriculture production and hence revenue would depend only on the market prices of inputs and outputs as I show in the paper.

Land endowments of the household affect farm revenue [1], under all specifications I considers. It positively affects farm revenue for all the three blocks in the study, for large and small land owning households, and across different kinds of crops grown[2].

Though labor endowment does not affect agriculture revenue as unanimously across all the different categorizations I consider, I show that land and labor endowments jointly increase agriculture revenue in all cases. This result is significant with both input endowments positively altering agriculture revenue in the case of households that have land endowment of less than or equal to 2.5 acres [3]. This difference in significance for land and labor endowments across different specifications could indicate a difference in the degree of non separability [4]. Since food crop growing household and small and marginal landowning household tend to be more subsistence based farmers, this result is a confirmation of the theory that subsistence farmers tend to function under non separability.

Paddy and cotton are the two most important food and cash crop respectively grown in Chandrapur. I test for heterogeneity in the results for paddy growing and cotton growing households. While land endowment positively significantly affect farm revenue for both paddy and cotton farmers, labor endowment only impacts farm revenue for paddy farmers. This result is similar to the ones observed for cash and food crops regressions. The degree of non separability indicatedly higher for paddy farmers.

[1]Farm revenue is the revenue generated from the sale of crops

[2]Regression for cash crops (cotton, soybean, sugarcane, and spices), food crops (paddy, wheat, and maize.), and specifically for paddy and cotton as they are the most important food and cash crop respectively grown in Chandrapur

[3]2.5 acres is defined as small and marginal land size by the Reserve Bank of India

[4]Failure of separability is non separability

By establishing that there is a positive significant relationship between input endowments and agriculture revenue, I show atleast two of the input markets are not functioning properly or is non-existent. If markets are complete and efficient, prices would ensure separation of household production and consumption [34]. Complete markets is sufficient and necessary to ensure separability [99]. However characterizing all markets associated with agriculture [5] is laborious and generally not a feasible way to identify separability. This paper provides a pragmatic approach for identifying separability or lack thereoff and functioning of agriculture markets, when input demand data is limited or unavailable.

With structural transformation in the Indian economy, it is essential to understand the functioning of the agriculture markets and farming households and my work is a preliminary analysis that can be extended to the whole of the country.

The rest of the paper contains a summary of the existing literature in section 2.3. In section 2.4 I expound the theory underlying the paper and the estimation strategy I use stemming from the theory. In section 2.5, I discuss the characteristics of the data I use. Section 2.6 has the main results and I conclude with section 2.7.

2.3 LITERATURE

Agriculture Household Model (AHM) was first introduced in an attempt to explain the conundrum of sluggish response of market surplus of a staple crop in rural Japan during the 1970s as its price increased [64]. The authors explain this to be the result of the

[5] Agriculture markets involve output markets and input markets (land, labor, fertilizer, credit)

dual character of farming households, that is, they are both producer and consumer of the output. Non farming households would generally maximize their profits or income and later use this income to maximize utility

If complete and perfect markets existed, consumption from own production and buying from markets for consumption would be perfect substitutes. The dual role of the farmer as producer and consumer makes production and consumption choices interdependent. This is why non-separability is a characteristic of developing economies' agriculture markets [107] where markets are not complete.

Separability condition has been tested and studied under different context in economic literature. One, as the plausible explanation for the inverse farm size and productivity [6] observed in the agriculture sector of developing economies. Under conditions of market failure that cause breakdown of separability, small land holding farms having restricted market access [7] may allocate all of its household labor and other inputs, even when greater than the efficient [8] allocation level, leading to higher output per unit of land than larger farms. The inverse relationship between farm size and productivity has been tested and established for developing economies such as Indonesia, China, Vietnam and so on[22, 50, 95, 66, 18, 69]. Tests for India has also confirmed this inverse relationship [15, 27, 75, 93, 102, 38]. All of these tests are for the period before market oriented reforms in India. Deininger et al. [26] find the persistence of the inverse farm size productivity relationship in Indian during the period 1982 to 2008. My paper test for separability during more recent years when the structural transformation of Indian is manifesting itself in better markets and access.

[6] A stylized fact in rural development [50]

[7] Either due to market failures or high transaction costs of access

[8] Defined by the general equilibrium model

Two, failure of separability is the reason for the positive relationship between dietary diversity and production diversity of small holder farms in sub Sahara Africa, which has been extensively researched recently [62, 77, 78, 96, 97]. Some of these studies have also shown that there is weakening in this positive relationship over the years. The non substitutability between production and consumption, a feature of separability breakdown is the underlying cause of the positive relationship and hence is not a surprise that as markets become more developed this relationship weakens. Using these results to extrapolate that all developing countries' may have non-separable agriculture conditions comes with a caveat - Asian developing economies are further ahead in the structural transformation and market reforms than the sub Saharan African countries. My hypothesis directly tests for separability in the Indian agriculture sector.

There are prominently two sets of tests for separability in literature. One, tests the relationship between production decisions and consumption preferences [34, 84, 69]. Two, tests the relationship between shadow wages and market wages, which will be unequal when separability fails [19, 54, 57]. Dillon et al's [30] hypothesize that input demand is not a function of household endowment in farming households that follow separability. This test belongs to the first set of tests and established separability for agriculture markets in sub Saharan Africa. Deriving from this, my paper tests for separability in India by hypothesizing that under separable conditions farm revenue is not a function of endowments.

2.4 ECONOMIC MODEL & ESTIMATION

In this section I outline the basic economic model for the agricultural households and arrive at the empirical test for separation. This is motivated by the most recent and accepted test for separation hypothesis by Dillon and Barrett [30] which they use to characterize the agriculture market of Sub Saharan Africa. The essence of the agriculture households' optimization problem is contained in the model.

Suppose an agriculture household h is endowed with land $\bar{T}$ and labor $\bar{L}$ whose market prices are r and w respectively. For simplicity I am not concerning with other inputs and exogenous factors such as weather in the model. This does not change the main takeaway from the model.

When households follow the separation hypothesis, first they maximize their profits in the production process and later use the optimized profits to attain the maximum possible utility. They have to choose the amount of land T and labor L for agriculture. p is the market price of the agriculture output Y, following the concave production function $f(L,\ T)$. Production happens according to the problem:

$$\underset{L,T}{max}\ \Pi = \underset{T,L,K}{max}[pY - wL - rT] \tag{2.1}$$

subject to

$$Y \leq f(L,T) \tag{2.2}$$

$$L,T \geq 0 \tag{2.3}$$

Since the production function is concave in inputs, the inequality constraint (2.2) is binding and the solution to the above system is

$$T^* = T(w, r, p) \tag{2.4}$$

$$L^* = L(w, r, p) \tag{2.5}$$

and the maximized profit $\Pi^* = \Pi(w, r, p)$. and farm revenue $TR^* = TR(w, r, p)$ Input choice is made under the production problem. We shall thus have the profit maximizing point total revenue (TR) :

$$TR^* = pf(L^*, T^*) \tag{2.6}$$

$$\Rightarrow TR^* = TR(w, r, p) \tag{2.7}$$

Once the households have the optimized profits, they maximize their utility from consumption of good C priced at p and leisure l. I am assuming the consumption of only one commodity[9] here, but it is fairly simple to extend the exercise to all the goods the household h consumes. The household has to identify the quantity of labor it implements on its farm L_f, supplies to the market L_{sm} from its endowment $\bar{L}$. Given the profit maximizing labor L, it also chooses the quantity of labor it buys from the market L_{dm}. Similarly household h also has to choose the amount of land it rents in from the market T_{dm}, rents out to the market T_{sm}. and employ on the own farm T_f The household faces the consumption problem:

$$\max_{C,l,L_f,L_{sm},L_{dm},T_f,T_{sm},T_{dm}} \mathscr{U}(C, l) \tag{2.8}$$

[9]A commodity that the household can produce and is in its consumption basket

subject to

$$pC \leq \Pi^*(w, r, p) + wL_{sm} + rT_{sm} \tag{2.9}$$

$$l + L_f + L_{sm} \leq \bar{L} \tag{2.10}$$

$$T_f + T_{sm} \leq \bar{T} \tag{2.11}$$

$$L^* \equiv L_f + L_{dm} \tag{2.12}$$

$$T^* \equiv T_f + T_{dm} \tag{2.13}$$

$$C,\ l \geq 0 \tag{2.14}$$

$$L_f,\ L_{sm},\ L_{dm},\ T_f,\ T_{sm},\ T_{dm} \geq 0 \tag{2.15}$$

Preference are locally non satiated and homothetic. This assumption lends the equality of the budget constraint (2.9).The solution to the problem gives

$$C^* = C(p, w, r, \bar{L}, \bar{T}) \tag{2.16}$$

Now, consider the case there is a failure of separability. Then production and consumption problem is solved simultaneously and gives the following total farm revenue. The optimization problem is in appendix A2.

$$TR^* = TR(w, r, p, \bar{L}, \bar{T}) \tag{2.17}$$

So, when separation hypothesis, holds all input implements shall be a function of the input prices and output price but not on household endowments, while consumption is a function of the input prices, output price and the endowments the household has. A necessary condition for separation between production and consumption is complete and perfect factor markets. Under separation, households can optimize their production irrespective of their endowments as they can source inputs from the factor market, and not depend on the endowments the households have.

The equations 2.7 and 2.17 provide the basis for my empirical test for separation. This is different from the test used in the literature [10], which makes use of input demand function 2.6 as the basis for the test of separability. The lack of availability of input demand data in the Indian case may be overcome with the use of total revenue function, testing for separability. I implement this test. From the equations 2.6, 2.7 and 2.17, we conclude under separable condition total revenue is independent of input endowment and when separability fails total revenue from farm sale is dependent on input endowments.

Stemming from the theory developed above, for a household h at time t with characteristics Z, I use the following empirical test for separation:

$$TR_{ht} = \beta_0 + \beta_1 \bar{L}_{ht} + \beta_2 \bar{T}_{ht} + \beta_3 \, input \ prices + +\beta_4 Z_{ht} + \varepsilon_{ht} \tag{2.18}$$

The ε is the independent and identically distributed error term with mean 0.

The proposed test for separation is $H_0 : \beta_1 = 0$ and $H_0 : \beta_2 = 0$. Rejection of the null hypothesis implies that there is market failure and by extension, there is no separation between production and consumption. However, I cannot conclude which market fails and how. This is in essence a test of exclusion, of labor and land endowments not affecting total revenue.

[10] [14] expounds the theory of separability tests and and [34, 30] implements the test of separability using input demand

2.5 DATA

I make use of data collected for Chandrapur [11] district in Maharashtra state, India [12]. I construct a panel from the household surveys of 960 households conducted by the Tata-Cornell Institute in 2014 and 2016 respectively [47, 116]as part of a study to analyse nutrition, gender empowerment and time use patterns in agriculture households in India.

Chandrapur has a population of 2.2 million with more than half the population engaged in agricultural work and allied activities [13]. It is one of the districts classified as backward by the state of Maharashtra. It has different cropping patterns within the district, with primarily cotton growing households on its western side and paddy growing farms on the eastern side. It is also drought prone seasonally. According to the National Family Health Survey 37.1 percent of women and 41.6 percent of men had below normal body mass index in the rural regions of Chandrapur [14], indicating poor nutrition and health outcomes.

The households were selected in 2014 after triangulating the lists of blocks and villages within the district. Three blocks were then selected for the study namely, Gondpipri, Korpana and, Mul based on the differences in their cropping patterns.

Mul has a large proportion of its farming households engaged in paddy cultivation, Korpana mainly has cotton growing households while Gondpipri grows both. These crops have been grown in these regions historically and were chosen in the past due to the to-

[11] ($19.9615^0 N$, $79.2961^0 E$, area of 11,443 sq km)
[12] Map in appendix
[13] Census of India, 2011
[14] Chandrapur District Fact Sheet, National Family Health Survey - 4, 2015-16

pographical preferences.

Eight villages each were chosen from these blocks based on their probability of selection based on proportion of total population. From each of these twenty four villages, forty households were selected randomly. The study thus had 960 households that were surveyed in 2014 and subsequently in 2016, giving a panel.

Both 2014 and 2016 rounds collected information on nutrition, agriculture paractices, income generation, time use pattern of household members, and socio - economic characteristics of these households. There was an attrition of 16 households in 2016 with 2 missing from Gondpipri, 11 missing from Mul and 3 households missing from Korpana.

In table 2.1 I show the summary statistics of the 960 households and categorized by blocks as well. On average there are around 4 members in the households, and this is the case for Gondpipri, Mul and Korpana. The household size does not change between the two years of the study. A little less than half the household size consists of females which is closer to equal proportion of male and female in Gondpipri. The average age of the households is approximately 29 years in 2014 and increases to almost 31 years in 2016. This is true for all three blocks of the study.

The labor endowment is calculated as the working age population. I count every household member greater than eighteen years of age as 1 unit of labor while children above twelve years of age but below eighteen years of age contribute to 0.5 units of labor [15]. The average labor endowment for all the households is 4.4 units in 2014 which falls to 4.2

[15]Common practice in labor studies literature

Table 2.1: Block wise and overall summary statistics

Variable	Total		Gondpipri		Mul		Korpana	
	2014	2016	2014	2016	2014	2016	2014	2016
Household size	4.62	4.42	4.58	4.36	4.54	4.41	4.75	4.49
Percentage of females	46.87	46.53	48.61	47.33	45.68	45.94	46.32	46.29
Average age of the household head	40.09	43.02	40.15	42.42	40.42	44.48	39.69	42.21
Average age of household	28.64	31.49	28.9	31.77	28.43	31.77	28.58	30.93
Asset ownership (factor analysis index)	1.06	1.39	0.98	1.27	1.28	1.68	0.92	1.24
Labor endowment[a]	4.4	4.2	4.37	4.15	4.3	4.19	4.52	4.25
Land endowment (acres)	3.16	3.11	3.07	3.32	1.84	1.86	4.58	4.11
Agriculture revenue (rupees)	43984.52	40594.31	23923.33	32397.87	15498.41	12734.71	92991.27	76144.1
N	960	944	320	318	320	309	320	317

[a]Children below 18 years and above 12 years have been included in the labor endowment as 0.5 units of adults

units in 2014. We see a similar figure for the respective blocks and the labor endowment is consistently lower than the household size which points to not counting children below twelve years of age and accounting for children between twelve and eighteen years to only 0.5 units of adult labor.

On average the households own 3 acres of land, which is only approximately 1.8 acres for Mul while it is 4 acres for households in Korpana. The land ownership for households in Gondpipri is approximately 3 acres.

Table B.1 in the Appendix show the assets the households might own in Chandrapur. There are 26 asset goods I consider. I make use of the priniciple component analysis [16] to arrive at an asset index by assigning different weights to each of these. Overall Chandrapur has an asset index of 1.06 in 2014 which increases marginally to 1.39 in 2016. Gondpipri and Korpana have an asset index of less than 1, below the district average in 2014 which increases to above 1 in 2016 for both the blocks. Mul has an asset index figure of 1.28, above the district average in 2014 and increases to 1.68 in 2016.

The average agriculture revenue is rupees 44000 in the year 2014 and is rupees 41000 in 2016. There is variation in the agriculture revenues across the three blocks with Korpana having the highest revenue while Mul has the lowest.

[16] PCA is used as asset index as assets are measured in discrete numbers

Figure 2.1: Distribution of labor endowment in the households

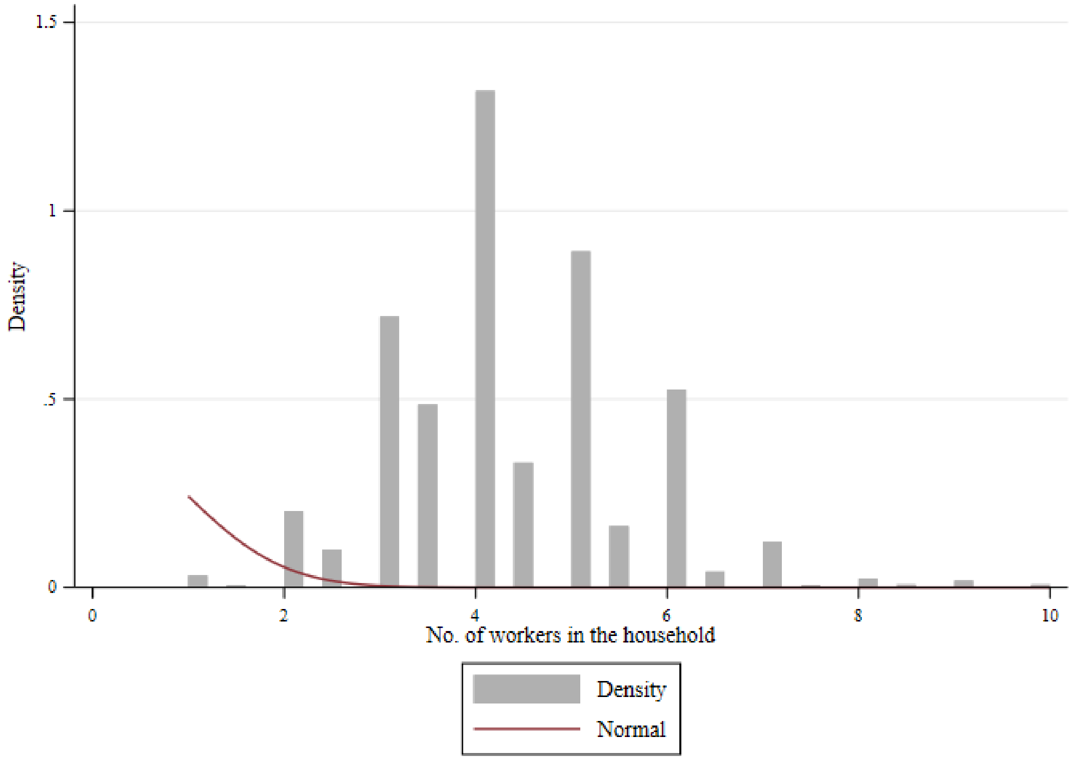


Figure 2.1 shows the density distribution of labor endowment in the households. The distribution peaks at 4, which shows households have the highest probability of having 4 units of labor endowment.

Figure 2.2: Probability distribution of land ownership

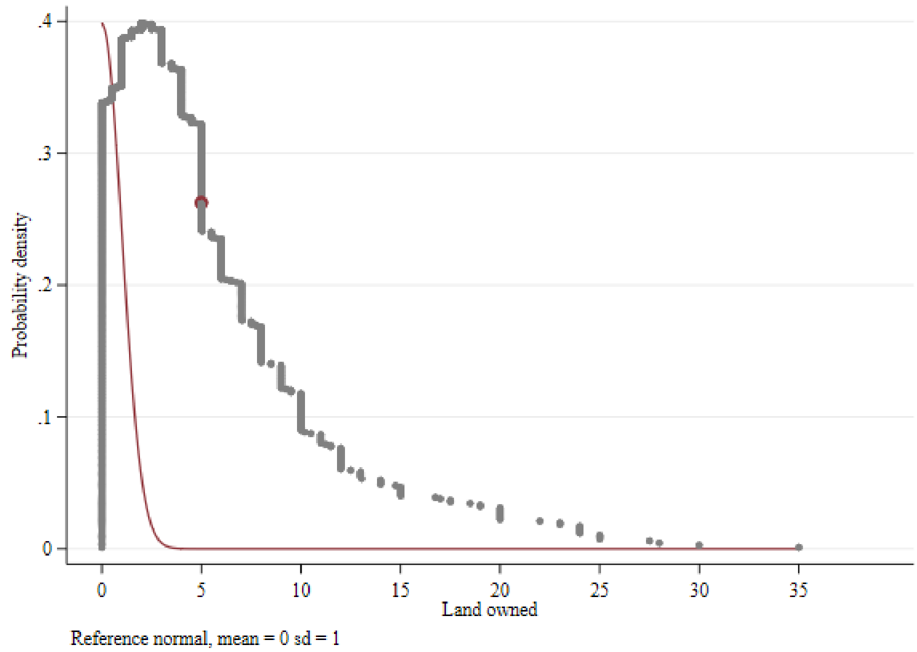


Figure 2.2 provides the probability distribution of land ownership, which is concentrated in the area less than 5 acres showing that there is the highest probability that households in the sample own less than 5 acres of land.

2.6 RESULT

As a preliminary attempt to understand the existence and functioning of agriculture markets in Chandrapur, I have variables of market participation of the households summarized in table 2.2.

Table 2.2: Market participation of households

Variable	Total		Gondpipri		Korpana		Mul	
	2014	2016	2014	2016	2014	2016	2014	2016
% of hh renting out land	0.52	0.95	0.63	1.26	0.94	0	0	1.58
% of hh renting in land	18.13	18.54	22.19	20.13	11.88	10.03	20.31	25.24
% of hh selling labor	68.75	72.03	70.94	73.74	75.31	71.37	60	70.86
% of hh marketing output	66.15	51.91	68.75	53.77	52.19	32.04	77.5	69.4

Less than 1 per cent of all the households rent out their land. This meager figure is because majority of the households are themselves involved in agriculture and use their land for the same. However 18 per cent of households rent in land in 2014 and 2016. While approximately 20 per cent of households rent in land in Gondpipri, only 10 per cent do so in Korpana and this figure range between 20 to 25 per cent rent in Mul in the two years.

Labor market involvement is much higher than land market transactions. 69 per cent and 72 per cent of the households sell their labor in 2014 and 2016 respectively. In Gondpipri 70 per cent of households sell their labor in 2014 which increases to almost 74 per cent in 2016. In Korpana 75 per cent of households work for some form of agricultural wages in 2014 and 71 per cent in 2016. 60 per cent of households in Mul have their members working for wages in 2014 which increases to 71 per cent in 2016. This is a strong indication of the functioning and existence of the labor market in Chandrapur.

In 2014, while 66 per cent of all the households sell some or all of their in the output market, 52 per cent do the same in 2016. 69 per cent of households in Gondpipri is participating in the output market in 2014 and 54 per cent in 2016. Though the proportion of households selling their output is lower for Korpana than the total average, 52 per cent households in 2014 and 32 per cent in 2016 do. Mul has a considerably higher market participation with 77 per cent households in 2014 and 69 per cent households in 2016 selling part or whole of their farm produce.

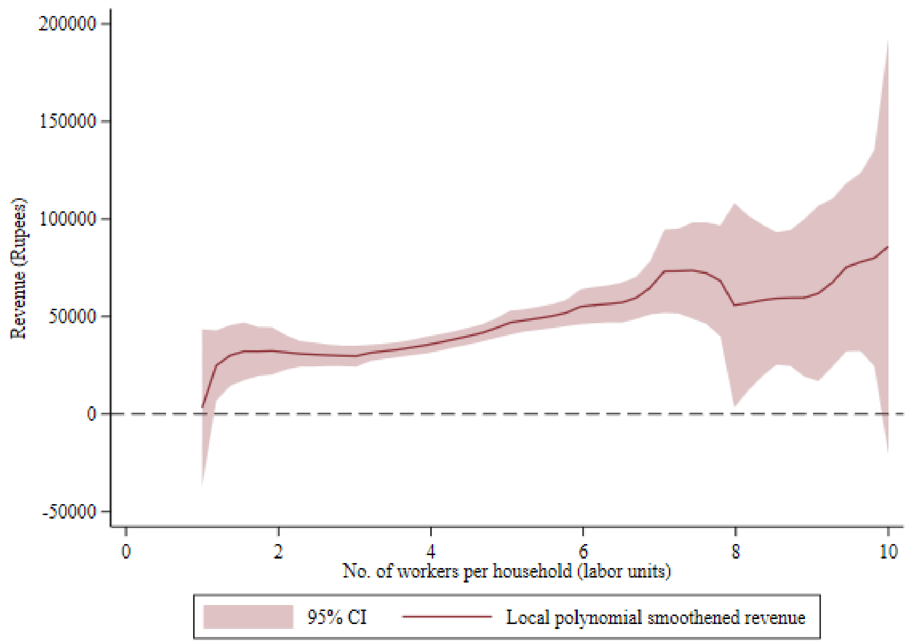
From the figures we can see that from the year 2014 to 2016 there is a consistent fall in the selling of outputs in the market for all the three blocks. 2015 was declared as a drought year for Chandrapur district [17] by the district administration and later by the state of Maharashtra too with agriculture production severely affected. This may be the attributable reason for the marked decline in output market participation in 2016.

Table 2.2 indicates the existence of the output market and the major input markets which is a necessary condition for separation between production and consumption. There is consistency across blocks in lower proportion of households renting out their land as opposed to renting in land for cultivation. This is not entirely surprising as these households are agricultural producers. Renting in land is a good indicator for the existence of a market for land. We can also see that this table provides cursory proof for the existence of labor and output markets.

I test the empirical hypothesis equation 2.18. Figure 2.3 shows the local polynomial regression of agriculture revenue from the sale of crops on the labor endowment. The revenue is calculated as the sum of the income generated for the households by selling crops in the output market. The figure shows that there is a positive relationship between the labor endowment and revenue at 95 per cent confidence.

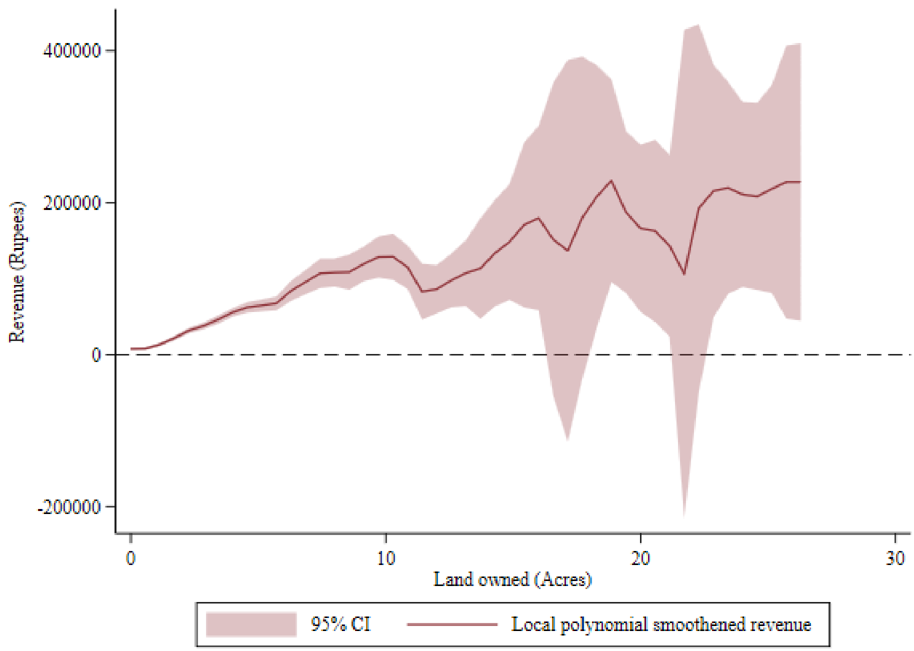
[17]Chandrapur falls in the Vidarbha region of Maharashtra which is known to be highly prone to droughts and associated crop losses [79]

Figure 2.3: Local polynomial relationship between labor endowment and agriculture revenue



In figure 2.4 we have the local polynomial relationship between agriculture revenue and the land endowment of the households. The local polynomial relationship show a positive relationship between land endowment of the households and their farm revenue.

Figure 2.4: Local polynomial relationship between land endowment (less than 30 acres) and agriculture revenue



Appendix B.2 and B.3 has the same relationship plotted for households that are endowed with less than 5 acres. The positive relationship between labor and, land endowments with agriculture revenue still holds in the case. This non parametric regression result is in consensus with a breakdown of separability between consumption and production in the agricultural households.

I make use of kernel regression with epanechnikov kernels to identify the relationship between the input (land and labor) endowments of each household and their agriculture revenue. The results of this preliminary kernel regressions are given in table 2.3. We can see that both land endowment and labor endowment positively correlates with agriculture revenue. I also run the same kernel regression for households that have less than 5 acres of land which is shown in columns 3 and 4 of the table. The positive relationship between input endowments and agriculture revenue holds for small landowning households as well. This indicates the improper working of markets and hence breakdown of separability.

Table 2.3: Kernel regression of agriculture revenue with labor and land endowment as independent variable

Variable	(1)	(2) (<5 acres)	(3)	(4) (<5 acres)
Mean agriculture revenue (Rs)	39,922***	40,246***	22,150***	22,323***
Labor (units)	6699***		5249***	
Land (acres)		10,230***		8636***
N	1882	1883	1405	1405
R^2	0.027	0.315	0.021	0.184
Epanechnikov kernel				

Figure 2.5: Preliminary fixed effects OLS relationship between agriculture revenue and endowments

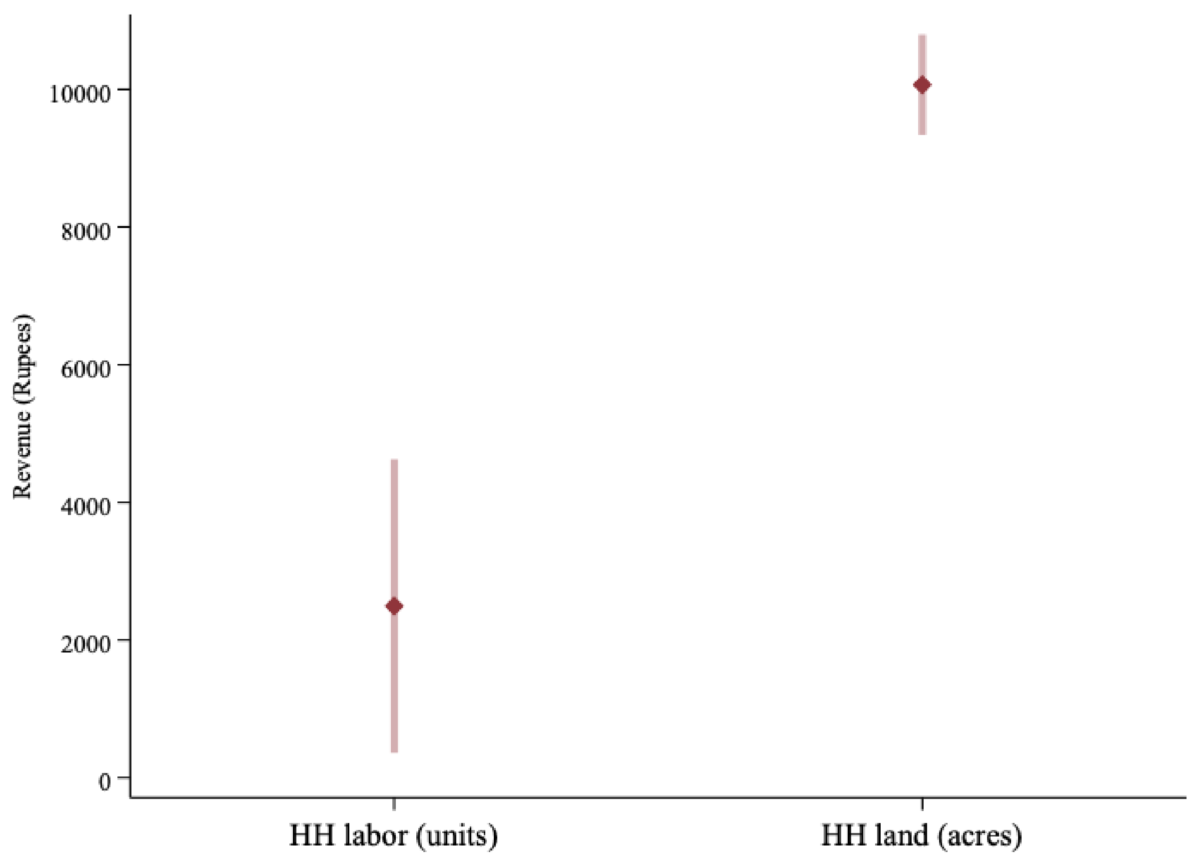
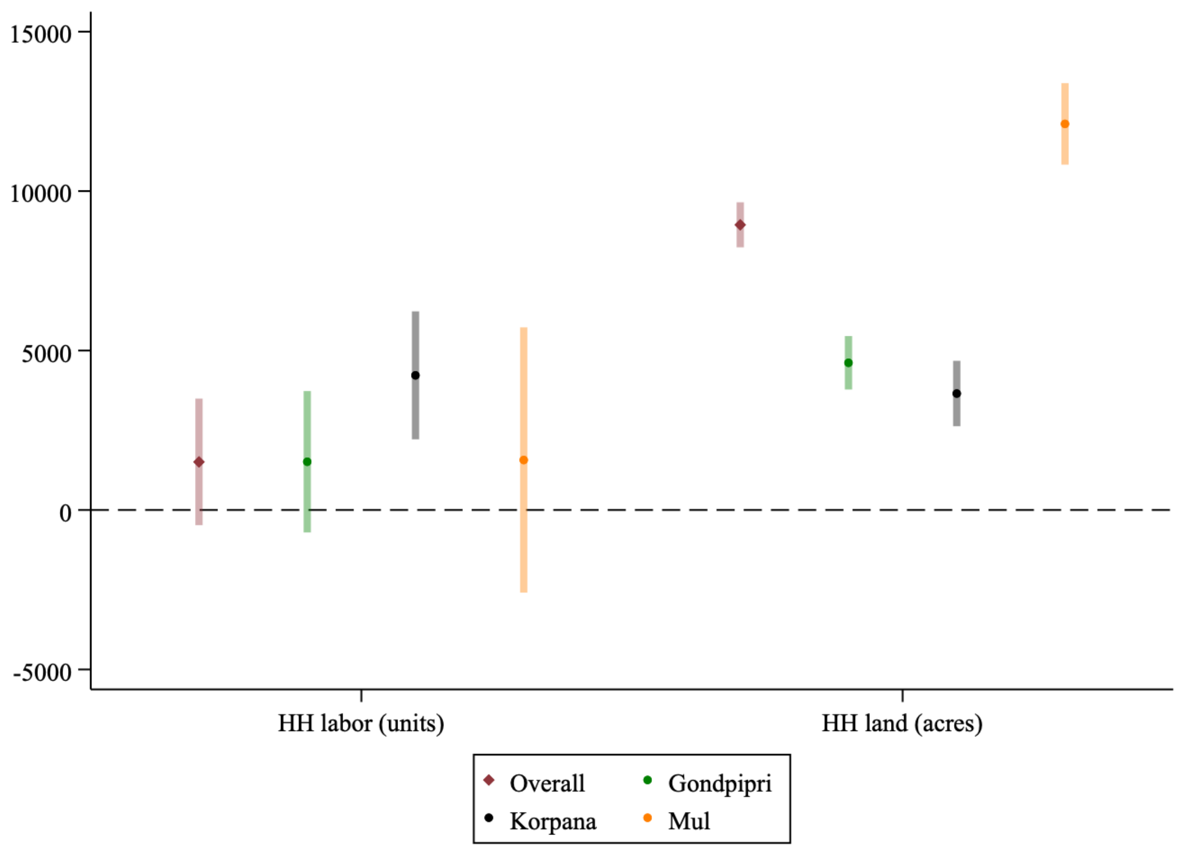


Figure 2.5 has the fixed effects panel estimation results of agriculture revenue on land and labor endowments in the absence of other controls with 99 per cent confidence interval. The results of the preliminary ordinary least square regression results of equation 2.18 with fixed effects control is shown in appendix B.2. There is a significant positive relationship between the labor endowment and agriculture revenue at 1 per cent level of significance. Same is the case for the land endowment and agriculture revenue relationship.

Figure 2.6: Panel fixed effects relationship between agriculture revenue and household input endowments



In figure 2.6, I show the results of the complete panel fixed effects model including control for wages paid to household labor, rental income, categorical variable for whether land has been rented in for cultivation and index for assets owned by the household. The estimates are shown in the appendix B.2. I have done the regression analysis by the three different blocks as well. From figure 2.6 and the appendix B.2 we can see that number of units of labor in the household does not impact agriculture revenue overall and in the blocks except for Korpana. However land owned has a positive significant impact on agriculture revenue overall and for the three blocks separately as well. I also run F test to see the joint impact of land and labor endowment on agriculture revenue. The results of it are in table B.3 For Chandrapur as a whole and for the respective blocks. Except Korpana land and labor endowments jointly impacts agriculture revenue positively at 95 per cent level of significance.

I can infer from the above test breakdown of separability in Chandrapur. However, I am only able to conclude from these results that there are atleast two markets that is incomplete or imperfect in the agriculture setup in Chandrapur. One cannot identify which market is incomplete or imperfect. This is so because in a general equilibrium framework even when a single input market or output market is incomplete the relative prices can so adjust to make sure there is an equilibrium point of functioning. For separation to fail, thus atleast two markets need to be incomplete or imperfect. Identifying which of the markets are failing require further tests comparing prices and the respective shadow prices.

In the appendix B.3 we can see that all the control variables have effects we would expect to see. A one rupee increase in rent received causes the agriculture revenue to fall by 0.4 rupees. This is in consensus with the fact that the more land you rent out,lesser land each household has for their own cultivation and hence lower revenue from agriculture production. By similar reasoning renting in land increases agriculture revenue as there is more cultivation. The positive effect of wage received for household laborers have a positive impact on overall agriculture revenue. There is a substitution effect and income effect as well, here the income effect seem to dominate and hence cause the positive impact. Owning more assets as implied by the higher asset index causes an increase in agriculture revenue which is the total sale value of all crops grown by the household. Higher asset ownership is an indicator of a higher income household overall and it is not suprising that the relationship is positive.

I also look at heterogeneity in the results by land ownership of the households. I try to see how the results hold for households that have land less than or equal to 2.5 acres [18] as opposed to households that have more than 2.5 acres land ownership. The coefficient estimates of the regression is in figure 2.7 and complete results is in appendix B.4. Household labor endowment does not affect agriculture revenue for households that own more than 2.5 acres of land while land endowment does affect their revenue. The F-test for joint siginificance show that land and labor endowments jointly alter revenue positively. Labor endowment positively affecting agriculture revenue for only marginal land owning households show the breakdown of separability for subsistence households as theory would suggest. The plausible explanation for this is a difference in the degree of non separability. While both input endowments impact farmr revenue for small and marginal farmers, only land endowment affect farm revenue for larger farmers, pointing to a greater degree of non separability for the small and marginal famrers.

Besides, if we were to consider the estimate magnitude as a degree of separation measure, we see that the magnitude for land endowment is stronger for the marginal land owning households indicating that the degree of separability failure would be higher in

[18] I make use of Reserve Bank of India's definition that 1 hectare (= 2.5 acres) as marginal land holding of land

these households. This result is in concurrence with what we expect from theory for subsistence based farming households.

Figure 2.7: Panel fixed effects relationship between agriculture revenue and household input endowments by land ownership

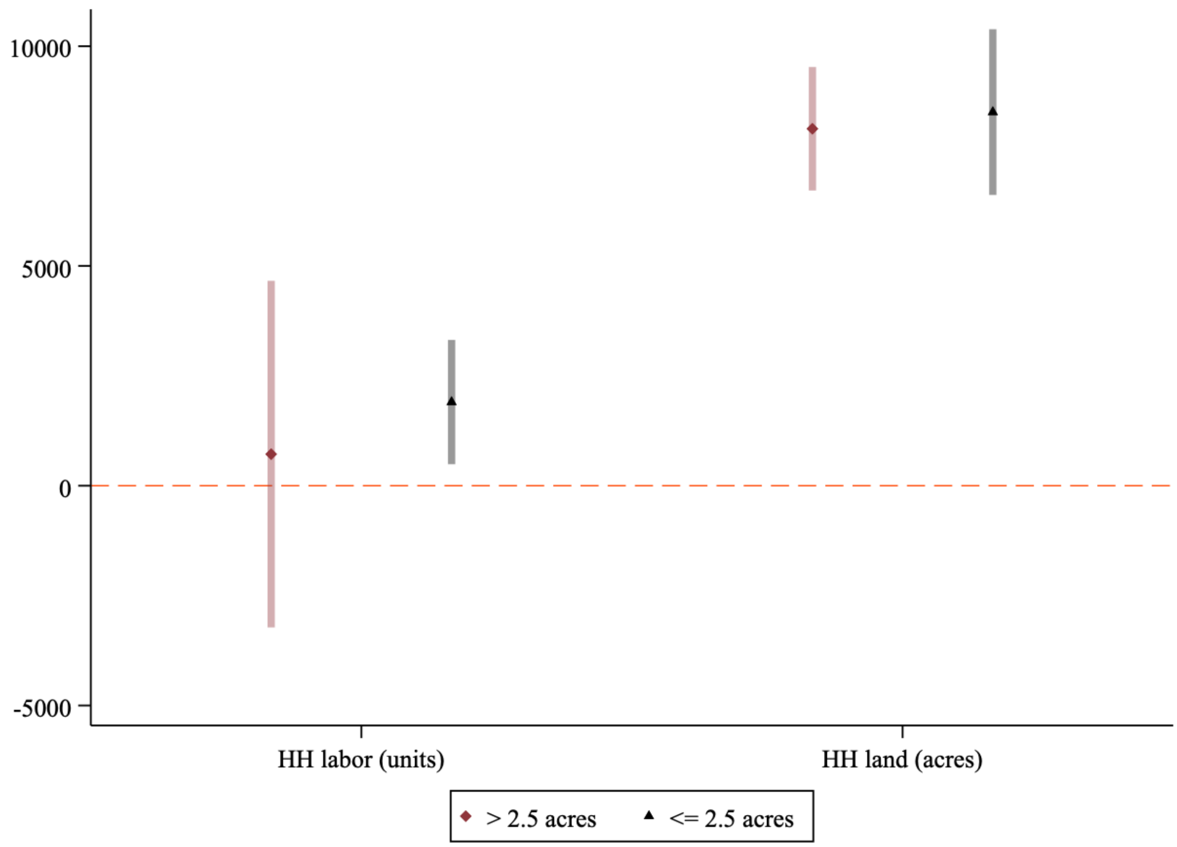


Table 2.4: Panel fixed effects regression between agriculture revenue and household input endowments by food crops and cash crops [19]

	(1) Food crop	(2) Cash crop
Mean	-32489.7***	-23605.4***
HH labor (units) [L]	1969.9*	812.9
HH land (acres) [T]	8918.5***	9137.3***
Fixed effects	Yes	Yes
N	1184	1338
R^2	0.423	0.391

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

I test for separability in households that grow cash crops and food crops in table 2.4. Cash crops include cotton, soybean, sugarcane and spices. Food crops are paddy, wheat and maize. There is a failure of separability for both food crop and cash crop growing households. While the amount of land endowment positively affects both food crop and cash crop growing households, labor endowment positively affects food crop growing households only. Agian, this is an indicator of the degree of failure of separability as well.

Table 2.5: Panel fixed effects regression between agriculture revenue and household input endowments by crops grown

Variable	(1) (No cotton raised)	(2) (Cotton raised)	(3) (No paddy raised)	(4) (Paddy raised)
Mean	-12,964***	-1234	-26,569***	-24,393***
HH labor (units) [L]	2156***	1408	922.1	4182**
HH land (acres) [T]	3787***	10,017***	9314***	6405***
Fixed effects	Yes	Yes	Yes	Yes
N	1386	492	1489	389
R^2	0.215	0.401	0.428	0.313
F-test (joint significance of L & T)	124.77***	75.72***	272.37***	46.32***

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

I further test for separability among cotton and paddy growing households separately.

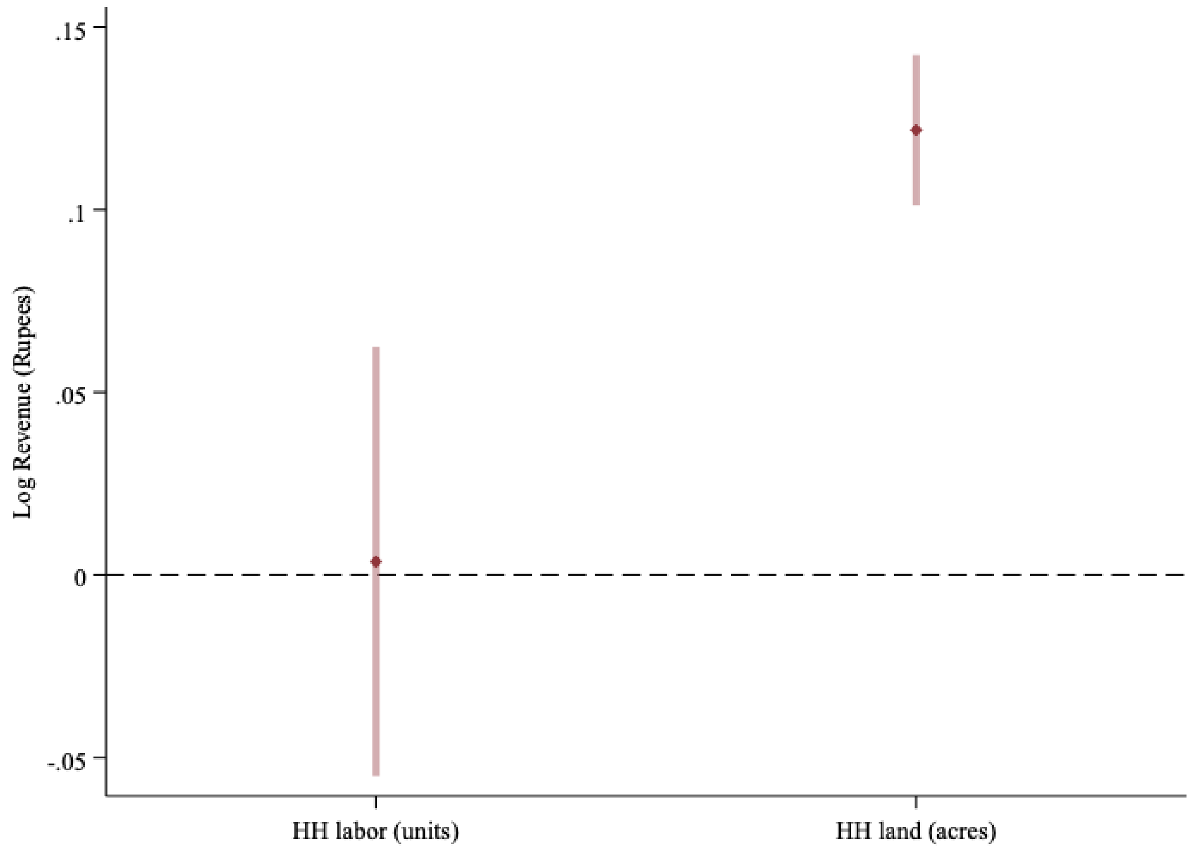
[19]Food crops: paddy, wheat & maize
Cash crops: cotton, soybean, sugarcane & spices

In table 2.5 we can see that acres of land endowment positively influences agriculture revenue in all kinds of classification by crops raised. I separately run the panel fixed effects model for cotton growing and non - cotton growing households. I do the same for paddy growing and non - paddy growing households.On the one hand for paddy growing households labor endowment positively affect revenue while it has no impact for households that raise cotton. While cotton is a cash crop, paddy is a food crop and hence the difference in the effect, where paddy could also be used for household consumption and thus could have a higher degree of separability breakdown. Jointly the inputs do impact agriculture revenue as the F-test statistic show.

The results of heterogeneity tests show a higher degree of separability breakdown for small and marginal farmers, and food crop growing farmers. The results prove that separable production and consumption is not the case for farmers in Chandrapur.

I run the fixed effects panel model with different specifications as robustness checks, the results of which is shown in appendix A.5. Column (1) of the appendix make use of log revenue as the dependent variable and the results for all of Chandrapur hold as it does for our preferred specification of using absolute value of agriculture revenue. The coefficient estimates of labor and land endowments are shown in figure 2.8. The labor endowment does not signficantly affect agriculture revenue but land endowment does impact it positively. Jointly the input endowments impact log of agriculture revenue. The result is in concurrence with the original specification. The number of observations in this model is lesser than the preferred model as we are considering log values and there are households that do not earn any agriculture revenue.

Figure 2.8: Panel fixed effects relationship between log agriculture revenue and household input endowments



In further specifications I include squared terms of the labor and land endowments in the columns (2) - (5). The results are similar to the specification in appendix B.8, that is, land endowment positively impacts farm revenue, and land and labor endowment jointly also impacts farm revenue. The table provides evidence that though the effect of land endowment is positive it has reducing positive impacts with increasing agriculture revenue, as we can see from the negative coefficients on the square term of land endowments. Labor endowment effect direction on revenue is not as clear as is the case for land input.

Input endowments of the household impact their agricultural revenue. Hence, the agricultural households do not separate between their production and consumption decisions breaking down the separability condition. The agricultural market is either incomplete or imperfect or non-existent.

2.7 CONCLUDING REMARKS

I establish that agriculture farm revenue from the sale of crops is independent of land and labor revenue under separability. Thus showing it is a necessary condition for separability. I find that there is non-separability among the 960 agricultural households of Chandrapur district. The panel fixed effects regression results for Chandrapur district in Maharashtra show that the land endowments affect agriculture revenue categorically under all conditions. While labor endowments impact agriculture revenue positively for marginal land owning households and for food crop raising hosuehold s. Jointly both the input endowments impact agriculture revenue when controlled for all other effects as well and under heterogeneous conditions of crops raised, blocks within Chandrapur and land ownership of the households.

Characterizing the Indian agriculture market as one that follows separability or not is an important exercise for many policy reasons. The Commission for Agricultural Costs and Prices (CACP) in India has the mandate in the country for the pricing policy of most crops. The pricing policy would have unprecedented supply response farmers if these recommendations were made under the assumption of separability. For instance, an increase in the market price fixed by the CACP might not cause an expected change in supply if the farmers were not making production decisions independent of consumption choices.

There are other policy implications of non - separable farming conditions. The work by Kaur [57] show nominal wage rigidities in India, which can be expected under conditions of non - separability. Non - separability is the result of failure of atleast two markets, and hence this wage rigidity can be explained in the context.

Policy implications are not only restricted to inputs and output. Agriculture households' quality of living targeted policies also may have unprecedented effects, unlike under separability. For instance nutrition targeted kitchen gardens produce better nutrition outcomes when separability fails [62].

Furthermore, the theoretical extension where I identify that farm revenue needs to be independent of input endowments for separability, provides a theoretical basis to identify separability or its failure in the event of lack of input demand data, which is a major limitation in developing economies such as India. Previous studies have used input demand data for the purpose.

In this study I find that under conditions of small and marginal landholdings, and food crop growing households both land and labor endowment impact farm revenue. While only land endowment positively effect farm revenue for large landowning households and cash crop raising farmers. This is suggestive of a difference in the degree of failure of separability. Farm revenue dependent on more input endowments is suggestive of a greater degree of breakdown of separability.

As the discussion suggests there are multiple reasons for having to test for separability. And identifying separability will go a long way in tailoring better agricultural policies.

CHAPTER 3

IDENTIFYING THE INCOME NUTRITION PATHWAY FOR AGRICULTURAL HOUSEHOLDS WIHT NON-SEPARABLE PRODUCTION

3.1 Abstract

I identify the farm income effects on the nutrition of agriculture households in Chandrapur district. In the previous chapter I have shown that farming households in Chandrapur do not follow the separability condition. Here, I test the impact of farm income from sale of crops on the nutrition of these households that do not follow the separation hypothesis. I make use of the data collected for 960 households of Chandrapur district by Tata Cornell Institute.By using a household level fixed effects model and controlling for all observable household characteristics that cound impact the nutrition outcomes, I identify that the dietary diversity score for the index women of these households increase by 0.002 units for every 1 rupee increase in the income received from crop sale. By making use of a multinomial logistic regression, I see that households with women consuming less than 3 categories of food have an increased probability of increasing their diet diversity score to 3 with an increase in income from crop sale. Similarly, as price of the crop sold increases households have an increased probability of consumption of fruits and vegetables.

3.2 Introduction

Rational households make consumption choices to maximize their utility, given income. Households derive their income through profit maximizing actions that is not conditioned on consumption preferences, but are only constrained by their production functions [99]. This need not be true for agricultural households, since they produce crops which can be self consumed. Due to this exception, households that are jointly engaged in production and consumption of their output are modeled using the Agricultural Household Model (AHM [14]. AHM models household behavior by assuming that production is not separable from consumption. When production decisions are affected by consumption preferences, we say that the processes are non-separable.

For Chandrapur district in India [1] using a two period panel in 2014 and 2016 for 960 households I find that agriculture happens under non-separable conditions using the exclusion test. The exclusion test for separability states that when total farm revenue derived from the crop sales of these household depend on household characterstics such as land and labor endowment, the separation criterion is not satisfied. I show that household land and labor endowments affect the farm crop revenue, showing non-separable production and consumption conditions for these households. Given the non-separable production and consumption conditions, this paper identifies the effect farm revenue from crop sales have on the nutrition of the households.

There is extensive research that identifies the relationship between income and nutrition in developing economies context [31, 33, 112, 81, 62]. Another related literature in this context is the identification of crop diversity effects on dietary diversity of the farming households [97, 86, 96]. This paper adds to literature in that, having established non-separable agriculture for the 960 households in Chandrapur, I identify the impact of farm income on nutrition outcome, measured as diet diversity score. The main contribution of this paper is understanding how nutrition of farming households that are situated under conditions of local market failures [2] respond to farm income in the context of the price

[1] *2023, Are Production And Consumption Decisions Independent? Identifying Separability In Indian Agriculture*

[2] Perfect and complete input and output markets are a necessary condition for separation hypothesis to

they receive for their crop increases. The work is important for policymakers in developing economies where there is a breakdown of separability, to frame policies intended to improve nutrition of these farming households and have an impact on the human capital development of the economy.

Making use of a panel fixed effects model for the 960 households in Chandrapur district I establish the income - nutrition pathway. I use the dietary diversity score for women as the dependent variable of interest, as the sampling of the household explicitly survey the index woman of the household. It is reasonable to assume that the household overall would have a diet diversity score atleast as high as the index woman of the household. Along with household level fixed effects, I control for observable household characteristics. Using a panel fixed effects model I find that a 1 rupee increase in the farm income from sale of crops increases the index women's diet diversity by 0.002 units. However, when I study the heterogeneity of the effects for households that own greater than 3 acres of land I find that this pathway does not exist for them, as these are households where the average diet diversity score is statistically higher than those of households that own less than or equal to 3 acres of land [3].

Making use of a logistic regression model I also find that the index women having diet diversity score are more probable to increase their diet diversity score to 3 as price they receive for their crop sale increases. And making use of a logit regression I also show that as price received from crop sale increase households increase the probability of consumption of fruits and vegetables by 2 percentage points.

hold [38]

[3]On average in 2014,households with less than or equal to 3 acres of land had an approximate MDDW of 2.8 while households with greater than 3 acres of land had a MDDW of 3. And in 2016 the MDDW for households with greater than 3 acres of land was almost 4 while the same figure for households that owned 3 or less than 3 acres of land was approximatel 3.5

3.3 Literature

Agricultural Household Model (AHM) was first introduced in an attempt to explain the conundrum of sluggish response of market surplus of a staple crop in rural Japan during the 1970s as its price increased [64]. The authors explain this phenomenon to be the result of the dual character of farming households - both as producer and consumer. Agricultural households make production decisions such as labor allocation and consumption choices interdependent on each other. Non-farming households would generally maximize their profits and later use these profits to maximize utility. The breakdown of separation between production and consumption in farm households is called non-separability.

The non-separability of production and consumption in farm households arise from the dual character of these households acting as both the producer and consumer of a commodity and due to the presence of imperfect markets. If complete and perfect markets existed consumption from own production and buying from markets for consumption would be perfect substitutes. The dual role of the producer and consumer makes the production choices and consumption choices interdependent. This is why, non-separability is a characteristic of developing economies' agriculture markets [107].

Since its introduction farm household model (interchangeably AHM) has been used to explain trends in off-farm labor supply, nutrition policy, income distribution, family planning, and so on. Singh and Subramanian [98] used AHM to explain the cropping patterns of farms in Korea and Nigeria. The paper by Strauss [103] determines how food and calorie consumption is affected by a price change for Sierra Leone using the farm household model. Barnum and Squire [17] study the impact of labor migration, output price intervention and technological change on the agriculture sector in Malaysia.

I identify the effect of income on nutrition outcome of agricultural households that are functioning under non-separable production and consumption conditions.

Numerous studies in the past have tried to establish the link from income to nutrition, mostly correlational and for non - agricultural households[108, 109, 32, 76, 33]. They have been able to establish a link from income to nutrition in varying geographic context. These work involve developed countries and urban markets, where one can find complete markets and profit maximization by households.

Establishing the income - nutrition pathway for rural farming households in developing countries is very important from a policy perspective. Farming households can access better nutrition through the *direct* pathway by consuming what they produce and, the *indirect* pathway by accessing consumption goods using the farm income [112, 83].

So, a closely related literature for agricultural sector in the developing economies is the analysis of the link from farm production diversity to diet diversity and hence nutrition. These two different yet closely linked studies form the basis for many policy intervention, an important one being the debate of crop specialization versus diversification. Research has found a strong positive relationship between farm production diversity and diet diversity [29, 81, 55, 101] in developing countries. These studies also attempt to understand the relationship between farm income and diet diversity [29, 81], and have found a positive correlation between the two. More recent research on the topic, though found positive relationship between production and diet diversity, also show that market integration and access lead to far better nutrition outcomes for rural farming households in developing countries [96, 97, 62]. The paper by Sibhatu et al [96] found that the rate of return to diet diversity was declining as production diversity increased, implying that the two did not have a linear relationship. These studies have mostly focussed on sub - Saharan African countries and Indonesia.

There is new evidence, showing the importance of markets in sub - Saharan African context.Mulenga et al [77] find that increased market participation increases diet diversity for Zambia. The same results is shown to hold for Kenya but there is differential effect based on gender, with women's market access improving diet diversity more than that of men's access to market [60]. This evidence supporting market access enhancing dietary outcomes of households, complement literature that establishes linkage from income to nutrition.

A 5 year panel data for the country has found a significant positive relationship between agricultural income and women's body mass index [85]. This paper establish the income - nutrition pathway given that separability is failing in these households. It also contributes to literature by identifying how the probability of consumption various categories of food under the diet diversity score measure change with farm sale value increase. The paper also looks into heterogenity of the income-nutrition effect based on farm size and different crops raised by farmers.

3.4 Economic Model

After having established non- separability I am identifying the income effect on nutrition for the housheholds. For this, I model household behavior by assuming non - separability and proceed from there.In general, households have a choice between food, non-food and leisure given their income. Agricultural households try to maximize their utility by choosing quantities of food consumption Q_F, non-food consumption Q_{NF} and leisure l. There is no separation between production and consumption, which is observed in numerous developing economies' agriculture sector. Then farm output Y is not exogenous to the consumption problem unlike the earlier utility optimization problem under the assumption of separability. The production function of the household becomes an added constraint in the consumption problem. The new utility maximization problem is

$$\underset{Q_F, Q_{NF}, l, L^f, L^w}{Max} U(Q_F, Q_{NF}, l) \tag{3.1}$$

subject to

$$p_F Q_F + p_{NF} Q_{NF} + wl \leq wL^m + \bar{R} + p_F^* Y \tag{3.2}$$

$$Y \leq F(L, A) \tag{3.3}$$

$$L = L^f + L^w \tag{3.4}$$

$$l + L^f + L^m \leq \bar{T} \tag{3.5}$$

$$p_F = f(p_F^*) \tag{3.6}$$

$$Q_F, Q_{NF}, l, L^f, L^w \geq 0 \tag{3.7}$$

where,

$$L^f = L^f(\alpha^f) \tag{4.i}$$

$$L^w = L^w(\alpha^w) \tag{4.ii}$$

Here w is the market wage received, L^m is the labor sold in the market by the household, L^f is the labor employed on one's own farm, $\bar{R}$ are all other sources of income besides agricultural revenue, such as remittances, and so on. p_F^* is the price farmers receive for their crops while p_F is the price paid for food and p_{NF} is the price of non-food commodities. Y is the agricultural output. Since consumption and production are assumed to be separated, Y is determined exogenously outside the field of the consumption problem. It is normally the profit maximizing quantity of output that is determined in the sphere of production. $\bar{T}$ is the total endowment of time available. L is the amount of labor to be employed on the household farm. A is the amount of other inputs such as land employed on the household farm and $F()$ is the production function.

Equation (3.2) is the budget constraint of the farming households and equation (3.3) is the production function. When production and consumption are not separated, the production function directly enters the utility maximization problem of the households, and hence the constraint (3.3). Due to non - separation households also need to make production decisions such as choosing the amount of labor L to be employed on the farm as part of the utility maximization problem. Here, households will have to choose the household labor to employ on the farm L^f and the quantity of labor to rent from the market L^w. Equation (3.4) represents the choice of labor. It would not be incorrect to assume that the labor characteristics α^f and α^w, of family and market labor respectively, determine L^f and L^w.

In this problem, I am assuming all other inputs A as given. This assumption can easily be relaxed and the results would still hold.

Equation (3.5) is the labor constraint of the household. Equation (3.6) shows that food prices are a function of the prices at which the farmers sell their crops. There is also the standard non - negativity constraint (3.7).

Appendix C1 shows the steps to solving the optimization problem. Assumption of locally non - satiating and homothetic preferences, and non - decreasing utility in the choice variables gives the result

$$Q_F = f(p_F^*, p_{NF}, w, \alpha^f, \alpha^w; z) \tag{3.8}$$

where z includes all other household characteristics.

Food consumption is a function of labor characteristics α^f and α^w as well when separation fails, besides price at which crops are sold (p_F^*), price of non - food commodities (p_{NF}), the wage (w) and the household characteristics (z).

3.5 Estimation

This study establishes the income - nutrition pathway for index women of the agricultural households thus showing that the price farmers' receive for their crop affects the food consumption (equation 3.8). I identify the effect of income changes on nutrition using panel fixed effects model, with the following empirical equation derived from the optimization solution.

$$N_{ijvt} = \beta_0 + \beta_1\ p^*_{f,ivt} + \beta_2\ X_{nf,ivt} + \beta_3\ w_{ivt} + \beta_4\ z_{ivt} + \nu_i + \varepsilon_{ivt} \tag{3.9}$$

Here i represents the household, which is the unit of observation and j represents the index woman of the household, v is the village and t is the time period of observation.

N is a measure of nutrition which is a function of quantity of food consumption. Here I make use of the diet diversity score (DDS) for women as the nutrition measure. The index women's DDS is used as the dependent variable owing to the sampling and survey questions directed at the index women of each of the households. The minimum diet diversity score of women shall serve as a good proxy for the diet diversity score of the households. There is evidence in the nutrition literature showing strong positive correlation between nutrition outcomes and diet diversity [3, 59, **?**, 111, 110, 9]. The Food and Agriculture Organization (FAO) has recommended DDS as an indicator for nutrition outcomes [4]. Besides, for the data I use, it has been established that the higher diet diversity score for the index woman results in their better micronutrient (iron) status [47].

[4] I make the case for the use of DDS as a measure of nutrition in Section 3.6.

In appendix C.1 and C.2, I plot the predicted values of the iron consumption (mg) against the diet diversity score of women for the years 2014 and 2016. We can see that there is a clear positive correlation between the diet diversity score and the micronutrient iron consumption. This justifies our use of the DDS as the dependent variable of choice. However, due to limitations of non -comparability across years I cannot use the iron consumption data for further robustness checks.

Panel data allows us to control for all fixed effects that can affect diet diversity score at a given time. Panel fixed effects model overcomes endogeneity issues arising from omitted variables that are time invariant. I try to control for the other time variant household characteristics z that could potentially affect diet diversity score of the index woman.

The independent variable of interest is the price of the crops sold by household i in village v at time t ($p^*_{f,ivt}$). I identify the crop which contributes the maximum proportion to the total crop sale income of the household. The price of that main crop received is the independent variable $p^*_{f,ivt}$. I also create a price index by assigning weights to the prices of each crop as a proportion of their contribution to the total sales income. I run robustness checks using this price index. Since the price the households receive is an indicator for farm income a significant positive relationship between diet diversity score of the index women and the crop sale price establish the income - nutrition pathway for them.

$X_{nf,ivt}$ is the non - food expenditure of the farming household i in village v at time t [5]. . w_{ivt} is the wage received for various farm and non - farm activities by the household labor. z_{ivt} controls for all time varying household characteristics such as the gender empowerment variable [6], type of crops grown by the household - food or cash crop, asset ownership and

[5] The non - food expenditure is a proxy for the non - food prices p_{NF}

all incomes besides farm sale revenue. . v_i is the household level fixed effects and ϵ_{ivt} is the household level error term.

The null hypothesis I test is $H_0 : \hat{\beta}_1 = 0$. This implies that diet diversity score of the index woman is not affected by the sale price of the agricultural product by the household. I expect to reject the above null hypothesis and show that there is a positive significant relationship between the two.

3.6 Data

3.6.1 Diet Diversity Score

The diet diversity score (DDS) is a cumulative score aggregated over different food groups given a particular recall particular period and depending on the population of interest. Studies in nutrition have found encouraging positive correlation between diet diversification and bioavailability of micronutrients [119, 42, 89]. There are studies that show positive correlation between the different food group indicators, nutrient adequacy and the probability of nutrient adequacy in resource poor settings [111, 110, 9, 59]. Specific studies related to women and children have found positive relationship between diet diversity and women's anthropometric indices, and children's iron status [3]. Research has also shown that the strength of the relationship between nutrient adequacy and food group indicators vary over season though it remain positive always [9]. FAO has also issued guidelines regarding the use of diet diversity score as measure of nutrition [36].

[6] It is necessary to control for gender empowerment since I am studying the diet diversity score of the index woman of the household

However, one should treat using DDS as a measure of nutrition with caution because very small and insignificant amount of food consumption could also count towards a category of food. I show in appendix C.1 and C.2 that there is a correlation between iron in the blood and the diet diversity score. Iron bioavailability was collected as part of the houeshold survey. However I do not find a positive effect of farm crop sale revenue on the iron bioavailability C.5. Micronutrient biavailability in the blood is a function of multiple factors and not just food intake [53].

I tabulate DDS for the index woman as a 10 point score aggregated over 10 different food groups[7] using a 24 hour recall period. For each category of food consumed in the previous 24 hours the index woman of the household gets a score of 1 for that particular category and this score is aggregated over the ten different food groups. So the DDS range from 0 to 10. Thus a higher score means a more diverse diet consumed by the woman.

3.6.2 Data summary

This study uses a panel data for Chandrapur district ($19.9615^o N, 79.2961^o E$) of Maharashtra state in India [8]. It has a population of 2.2 million according to the Census of India, 2011. The panel is constructed using household survey from the years 2014 and 2016 respectively [48, 115] conducted by the Tata-Cornell Institute.

Chandrapur has different cropping patterns within the district. It has cotton growing

[7]The 10 different food groups are (1) grains, white roots & tubers, and plantains, (2) pulses (beans, peas and lentils), (3) nuts and seeds, (4) dairy products, (5) meat, poultry and fish, (6) eggs, (7) dark green leafy vegetables, (8) other vitamin A rich fruits and vegetables, (9) other vegetables, and (10) other fruits

[8]Map in Appendix C

households on its western side and paddy growing households on the eastern side. More than half the population is engaged in agricultural work [9]. 37.1 percent of women and 41.6 percent of men had below normal body mass index in rural regions of Chandrapur according to the National Family Health Survey - 4 (NFHS-4) (2015-16). Close to half the women were anemic as well (*NFHS - 4, 2015-16*).

The households were selected for a study conducted by Tata - Cornell Institute in 2014 and were re-surveyed in 2016 to identify nutrition, gender empowerment and time use pattern in agricultural households in India [10]. The households were selected in 2014 after triangulating the lists of blocks and villages within the district. The three blocks selected for the study were Gondpipri, Korpana and Mul based on the cropping pattern differences in these blocks.
The households were selected for a study conducted by Tata - Cornell Institute in 2014 and were re-surveyed in 2016 to identify nutrition, gender empowerment and time use pattern in agricultural households in India [11]. The households were selected in 2014 after triangulating the lists of blocks and villages within the district. The three blocks selected for the study were Gondpipri, Korpana and Mul based on the cropping pattern differences in these blocks.

Mul has a large proportion of households engaged in paddy cultivation, Korpana chiefly grows cotton while Gondpipri grows both the crops. These crops have been grown historically in these regions and were chosed in the past due to the topographical preferences. Eight villages each were chosen from the blocks based on probability proportional to pop-

[9] Chandrapur District Fact Sheet, National Family Health Survey - 4, 2015-16

[10] The study was conducted by Dr. Soumya Gupta and Dr. Vidya Vemireddy as part of their doctoral research, and funded by the Tata - Cornell Institute

[11] The study was conducted by Dr. Soumya Gupta and Dr. Vidya Vemireddy as part of their doctoral research, and funded by the Tata - Cornell Institute

ulation. Forty households were then chosen from each of these villages randomly, thus totalling 960 households for the study. Both 2014 and 2016 rounds collected household level data on nutrition, income, time use and gender empowerment besides socio - economic variables. There was an attrition of 8 households in 2016.

The main reason for considering the index woman as the observation unit and not the household for DDS is the limitation the survey mechanism presents. The data on consumption pattern was collected specifically for the index woman of each households. However this does not inhibit us from establishing the income - nutrition pathway as the minimum diet diversity score for women serves as a proxy for that of the households. It is reasonable to expect that the household index woman's diet diversity score is correlated to the household's diet diversity score.

Table 3.1 summarizes the important variables. There is an attrition of 8 households from the 2014 sample owing to reasons such as migration or members being not available for survey in 2016.

Table 3.1: Summary Statistics

Variable	2014 x_0	N	2016 x_1	N	Difference $(x_0 - x_1)$	p-values
DDS	2.884	945	3.614	952	-0.7309***	0.000
Household size	4.626	960	4.371	952	0.255***	0.000
Average age of the hh members	28.952	960	31.461	939	-2.509***	0.000
HH dependency	0.301	960	0.264	939	0.037***	0.000
Proportion of females	0.469	960	0.463	939	0.005	0.486
Non-food expenditure	3362.442	620	2709.971	933	652.471**	0.032
Monthly remittance [12](Rs)	1.778	960	1.61	952	0.168***	0.000
Land ownership (acres)	3.163	960	3.703	952	-0.539	0.407
Cash crop growing HH	426	960	417	952		
Food crop growing HH	453	960	401	952		
Both cash & food crop HH	397	960	383	952		
Annual animal sale income (Rs)	773.438	960	900.21	952	-126.773	0.433
Monthly animal product sale (Rs)	31.334	960	78.256	952	-46.922**	0.049
Asset index	1.056	960	1.389	933	-0.334***	0.000
WEAI	67.5	960	56.8	952	10.6***	0.000
Average price in Rs/Quintal						
Cotton	4551.21	265	4471.09	246	80.12	0.192
Soybean	2846.85	220	3019.92	97	-173.07	0.536
Rice	2141.39	254	2298.59	147	-157.194	0.704

* denotes significance at 0.10; ** denotes significance at 0.05; *** denotes significance at 0.01

On average the index woman of the household consumes approximately 3 different food groups, and we can see a slight increase in the diet diversity score from 2014 to 2016. On average the households have 4 members and a dependency ratio [13] of 0.3. The average

[12]Remittance income is collected as a step function ranging from 1 to 9 with 1 meaning less than Rs 2000, 2 being Rs 2000 to Rs 3000, and so on. The average remittance figure is approximately 1.6 indicating household earning on average more than Rs 2000 but less than Rs 3000 monthly

[13]Dependency ratio is the proportion of household members who are below 15 years and above 60 years of age respectively

age of all the household members is approximately 29 years in 2014 and they have equal proportion of men and women for both the rounds.

Mean monthly non - food expenditure of these households is approximately Rs 3400 in 2014 which decreases by almost Rs 650 in 2016. It constitutes spending on electricity, cooking gas, school fees, medical expenses, fuel such as petrol and diesel and others. The average remittances from household members working outside does not change significantly between the years.

The average household own 3 acres of land and land ownership does not change significantly over the years. Almost an equal share of households grow cash crops and food crops respectively. There are over 400 households that grow both cash and food crops in 2014 and 2016.

These households earn annually Rs 800 in 2014 and Rs 900 in 2016 from sale of livestock. The difference is not statistically significant. They earn approximately 30 rupees per month from sale of animal products in 2014 which more than doubles in 2016.

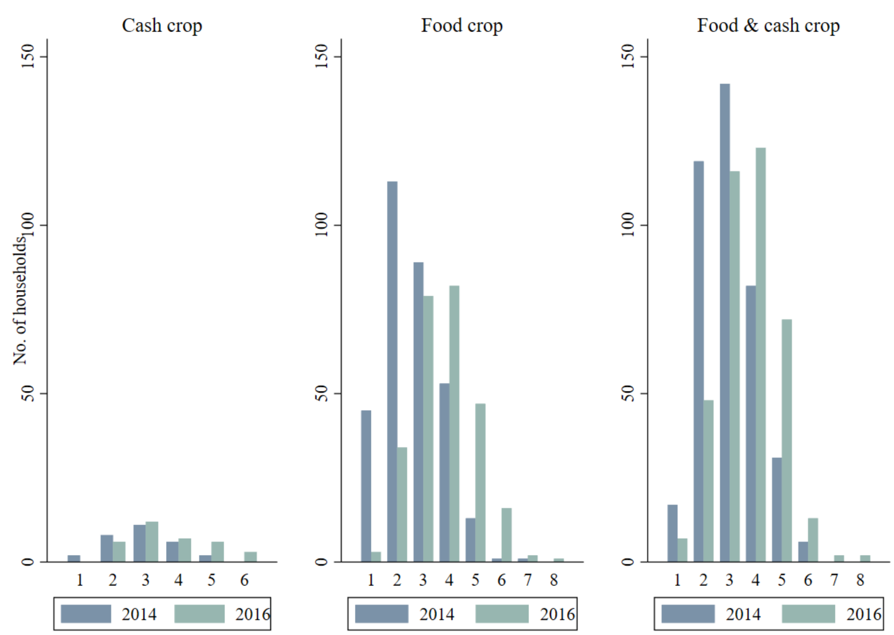
The asset index is calculated using a factor analysis approach with appropriate weights given to each of the 26 assets mentioned in the appendix. The households on average have an asset index of 1 in both the years. The WEAI is a measure of gender empowerment and makes use of a multidimensional approach to identify gender inadequacies in these dimensions [14]. This index enables one to understand gender equality from nu-

[14] The 5 key dimensions of the index as developed by IFPRI, OPHDI & USAID are (1) decision making in production related activities, (2) access to resources, (3) access to income of the household, (4) membership in any groups, and (5) time allocation

merous dimensions unlike a unidimensional approach which look at say, only differences in education achievement. The WEAI range from 0 to 100., with 100 being the score for equality between both men and women. The WEAI on average is around 60 points which does indicate considerable gender inequities and it decreases by 11 points from 2014 to 2016.

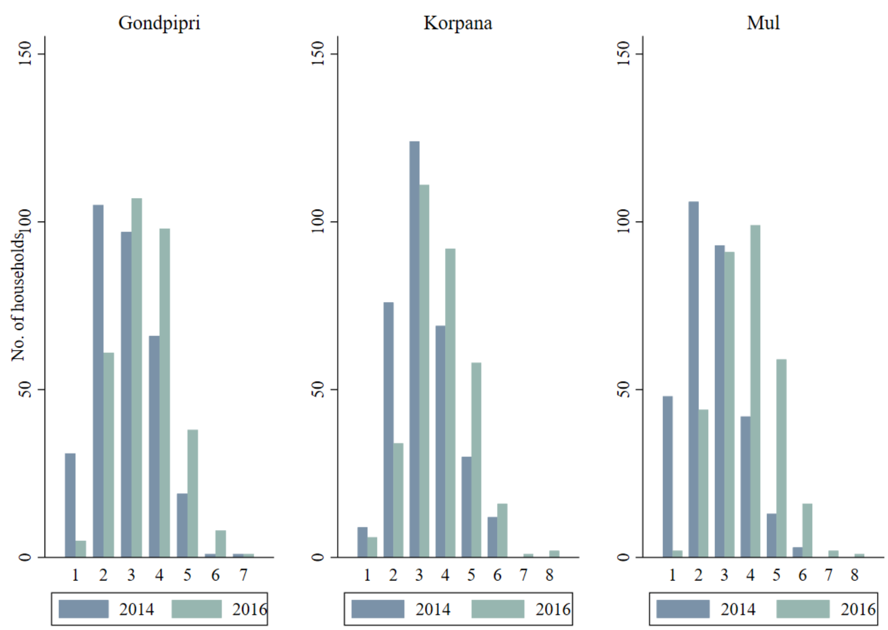
The average selling price of the main crops cotton, paddy and soybean are also provided. There is no significant difference in the selling price of these crops between 2014 and 2016.

Figure 3.1: Distribution of DDS for households that grow food, cash crops and both



The Figure 3.1 shows the distribution of DDS for households that grow cash crops only, food crops only, and the last panel in the figure shows the same for households that grow both cash and food crops. It can be clearly observed that there is a shift towards consuming more diverse foods from the year 2014 to 2016 as households that consume atleast 4 different categories of foods increase from 2014 to 2016. We can see the same trend when I plot the distribution of DDS across the different blocks of Chandrapur district as well. The number of households consuming less than 3 food groups decreases while those consuming more than 3 food groups increases between the two years. So, over the two year, the diet diversity score of the index women increases.

Figure 3.2: Distribution of DDS across blocks in Chandrapur



The figure 3.2 provides the distribution of DDS across the three block of Chandrapur. There is a concentration of households at the point where diet diversity score is between 2 and 4 across all the three blocks.

3.7 Result

I define market orientation of each household as the proportion of harvested crop sold in the market. Here, I am only considering the main crop as defined earlier. Since existence of markets is necessary for separability, a correlation between market orientation and diet diversity score of women would not be suprising in the event of the existence of strong income - nutrition pathway. I plot the predicted values of DDS against market orientation and we can see the positive association between the two in the figure in appendix C.1. Appendix C.1 shows that the linear predicted values of the diet diversity score of the women of the household are positively correlated with the price at which the households sell their main crops.

Table 3.2: Relationship between diet diversity score of index woman and price received for crop

Independent variable	Model 1	Model 2
Price of crop sold (Rs/kg)	0.003***	0.002*
	(0.004)	(0.068)
Wage for transplanting [15]		-0.07
		(0.371)
Wage for manual weeding		0.224**
		(0.010)
Monthly remittance income (Rs)		-0.444***
		(0.008)
Monthly non-food expenditure (Rs)		-4.47e-06
		(0.734)
Asset index		0.299**
		(0.014)
HH growing food crops		0.553**
		(0.044)
HH growing cash crops		0.035
		(0.910)
WEAI		-0.011**
		(0.012)
Household FE	Yes	Yes
Constant	3.08***	3.583***
	(0.000)	(0.000)
N	1428	1088
Number of groups	948	801
R - squared	0.017	0.189

The values in parentheses are the p-values. * denotes significance at 0.10; ** at 0.05; *** at 0.01

Table 3.2 gives the preliminary ordinary least square results for the panel fixed effects regression model. While Model 1 shows that there is a positive relationship between diet diversity and price received for the crop, Model 2 includes controls for all household characteristics that are time variant and monthly non - food expenditure as a proxy for non - food prices. The results show that on average the index woman's diet diversity increases

[15]The wage variable is also collected as a step function with 1 being less Rs100 per day, 2 being Rs 100 -125, and so on

by 0.002 units when the price the household receives for their chief crop increases by 1 rupee per kilogram. This increase imply that as the price of the crop sold increases by rupees 500 per kilogram, women consume one addtional category of food. Though such a large increase in prices might not materialize, the result establishes the income-nutrition pathway. Nutrition can be thus improved by income improving methods.

Transplanting and manual weeding are two main agricultural tasks that are assigned to women as they are less labor intensive than the rest of the work like ploughing. Hence I have included the wages women receive for these work in the regressions and I see that the wage from manual weeding significantly increases diet diversity. The plausible reason for the lack of effect transplanting wages have on the diet diversity of women stems from the time of data collection, when manual weeding was the main employer.

Having more assets is better for diet diversity of the index woman. This seem reasonable, households own more assets generally when they are more wealth and hence can also afford to have a more diverse diets. Growing food crops increase the woman's diet diversity score by 0.5 units. This could be because households have access to certain food categories directly from their farms besides the ones they acquire from the markets. This positive effect on diet diversity in lieu of growing food crops is not observed for households that grow cash crops.

As women's empowerment index increase by 1 unit, their diet diversity score decreases by 0.01 units. This is a result which seems counterintuitive. However the study by Vemireddy et al. [**?**] discuss how women's time trade - off of agricultural work and household chores can adversely affect their nutrition. This could be a possible explanation for the negative relationship we see here.

It is more difficult to understand the negative effect the monthly remittance has on the index woman's diet diversity score. To understand this result further and also to study the heterogeneity in the effects, I run separate fixed effects regressions for marginal and non-marginal land owning households. Here I define marginal land holdings as less than or equal to 3 acres of land. The effect of income on nutrition for differences in land ownership is given in table 3.3

Table 3.3: Income - nutrition pathway disaggregated by land ownership

Independent variable	Land (≤ 3 *acres*)	Land(> 3 *acres*)
Price of crop sold (Rs/kg)	0.003*	7.43e-04
	(0.064)	(0.767)
Monthly remittance income	-0.156	-0.779***
	(0.589)	(0.003)
Controls	Yes	Yes
Fixed effects	Yes	Yes
N	643	445
R - squared	0.194	0.224

The values in parentheses are the p-values. * denotes significance at 0.10; ** at 0.05; *** at 0.01

The income - nutrition pathway exists for index women of households that own less than 3 acres of land. However, this is not true for households that are not marginal farmers. This difference could be stemming from the fact land owning households are generally wealthier than the marginal farmers and hence the income was not an inhibiting factor for their acquiring more food groups.

Since diet diversity score is a discrete variable with values ranging from 0 to 10 an ordinary least square regression is not the optimal method to test the hypothesis. For further clarity I make use of a multinomial logistic regression using the average diet diversity score (approximately =3) as the base for the same. The multinomial logistic regressions are preferred in the case of the dependent variable being discrete. Table 3.4 has the results to the regression.

Table 3.4: Multinomial Logistic Regressions with DDS = 3 as the base outcome

Variable	DDS = 1	DDS = 2	DDS =4	DDS = 5	DDS = 6	DDS = 7	DDS = 8
Price of crop sold (Rs/kg)	-0.025**	-0.014**	6.65e-04	-0.007	-0.007	-0.045	0.044
	(0.043)	(0.018)	(0.647)	(0.232)	(0.539)	(0.319)	(0.328)

N : 1086
Pseudo R^2 : 0.063

The values in parentheses are the p-values. * denotes significance at 0.10; ** at 0.05; *** at 0.01

From the multinomial regression, we can see that households where the index women consume less than 3 categories of foods are tending towards increasing diversity in their diets as the income increases. Women who consume only 1 food group has a 2.5 percent probability of increasing diversity score to 3 as the price received for their crop sales increase. Similarly the probability of consuming 3 groups of foods increases by 1.4 percent for women who have a DDS score equal to 2 as the price of the crop sold increases. Households that consume more than 3 groups of foods have no tendency to reduce the diversity in their diets when income increases.

These results help us establish the income - nutrition pathway for women of farming households. It would be also interesting how the diet diversification happens as income increase. Inorder to understand this further, I try to see how the probability of consumption various food groups change as price received for the major crop increases. I make use of logit regressions and the results for the different food types are given in Table 3.5.

Table 3.5: Relationship between income and probability of consumption of food groups

Variable	Cereals, white roots & tubers	Pulses	Dairy	Meat, poultry & fish	Eggs	Fruits & Vegetables
Price of crop sold (Rs/kg)	0.021	0.023	-0.013*	1.02e-04	-0.001	0.019***
	(0.252)	(0.175)	(0.068)	(0.963)	(0.149)	(0.005)

The values in parentheses are the p-values. * denotes significance at 0.10; ** at 0.05; *** at 0.01

It shows that as income from crop sale increases via a price rise, there is a higher probability of consumption of frutis and vegetables. So, the increase in diet diversification of the index woman is aided by an increase in the consumption of fruits and vegetables. This result is in agreement with the study by Vemireddy et al. [115] which also establish that diversification in diets are lead by consuming fruits and vegetables. It is difficult to explain why the probability of consumption of eggs decrease as price received for crop sale increases.

3.8 Conclusion

I show that as price received for the crop sale for agricultural households their nutrition measured by diet diversity score increases. Thus I establish the income-nutrition pathway for agricultural households.

An increase of Rs 500 per kilogram in the price recieved for a crop sold, can lead to women consuming 1 more different category food according to the dietary diversity score for women classification. We would expect the household dietary diversity score also to increase in events of womens' diet diversity score increasing, especially in regions where gender biases exist. It shows that an increase in income can cause the diet diversity of women to increase. DDW has been accepted by FAO to represent women's micronutrient intake and hence nutrition. The significant result between income and DDW thus establishes the pathway from income to nutrition.

APPENDIX A

APPENDIX TO CHAPTER 1

Figure A.1: **Annual seasonal variations in atmospheric carbon dioxide**

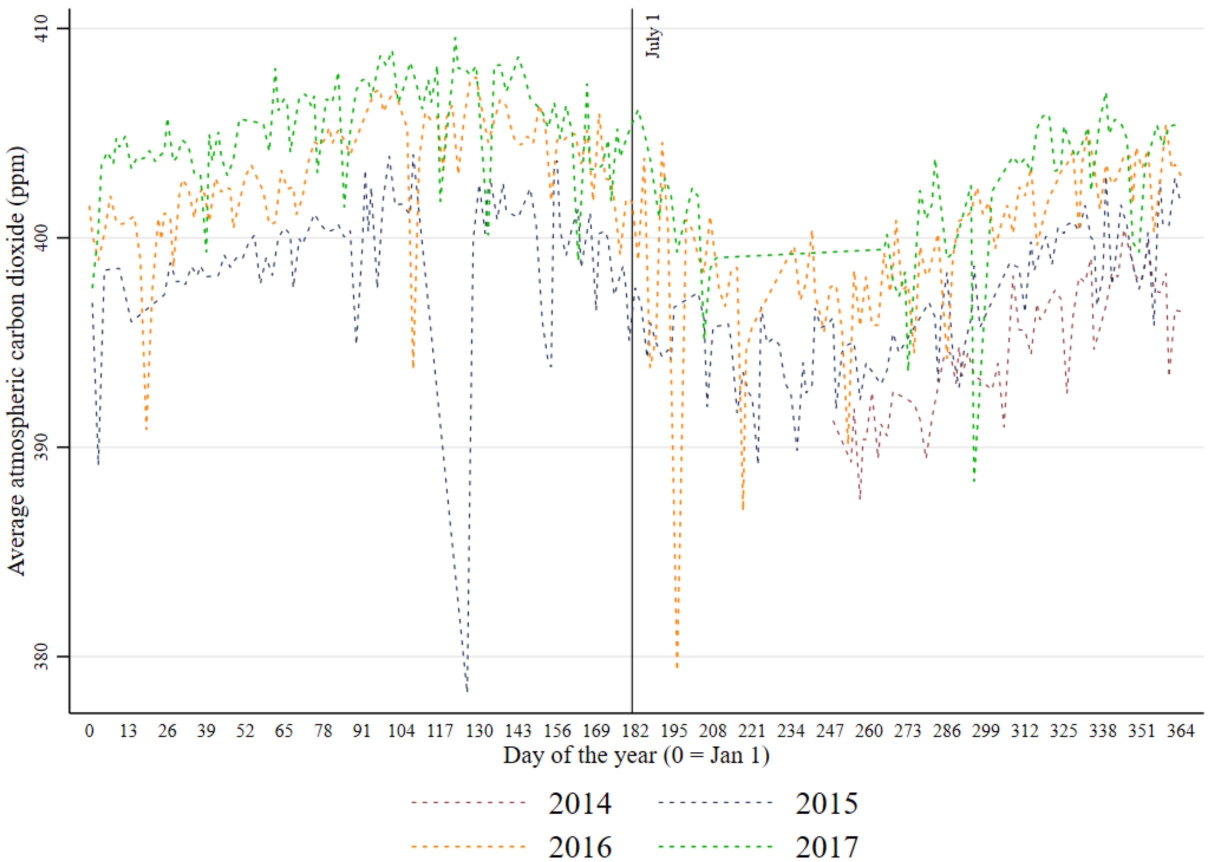


Figure A.2: **Solar induced chlorophyll fluorescence at 740 nm measured in $W/m^2/sr/\mu m$**

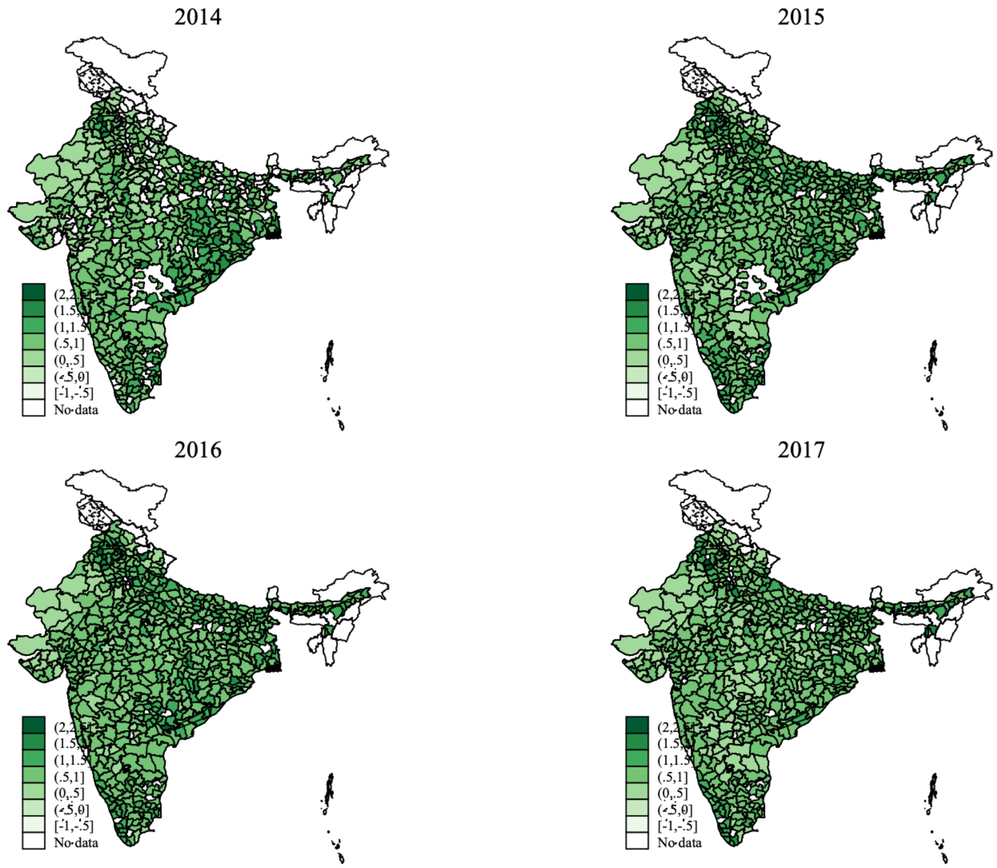


Table A.1: **t-test of difference between male and female agricultural wage rate**

Variable	2014	2015	2016	2017
Male wage rate - Female wage rate	63.19***	57.37***	74.21***	58.84***
	(6.24)	(8.03)	(8.64)	(7.57)

Standard errors in parenthesis
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure A.3: **Atmospheric ozone in a column of air measured in Dobsun Unit**

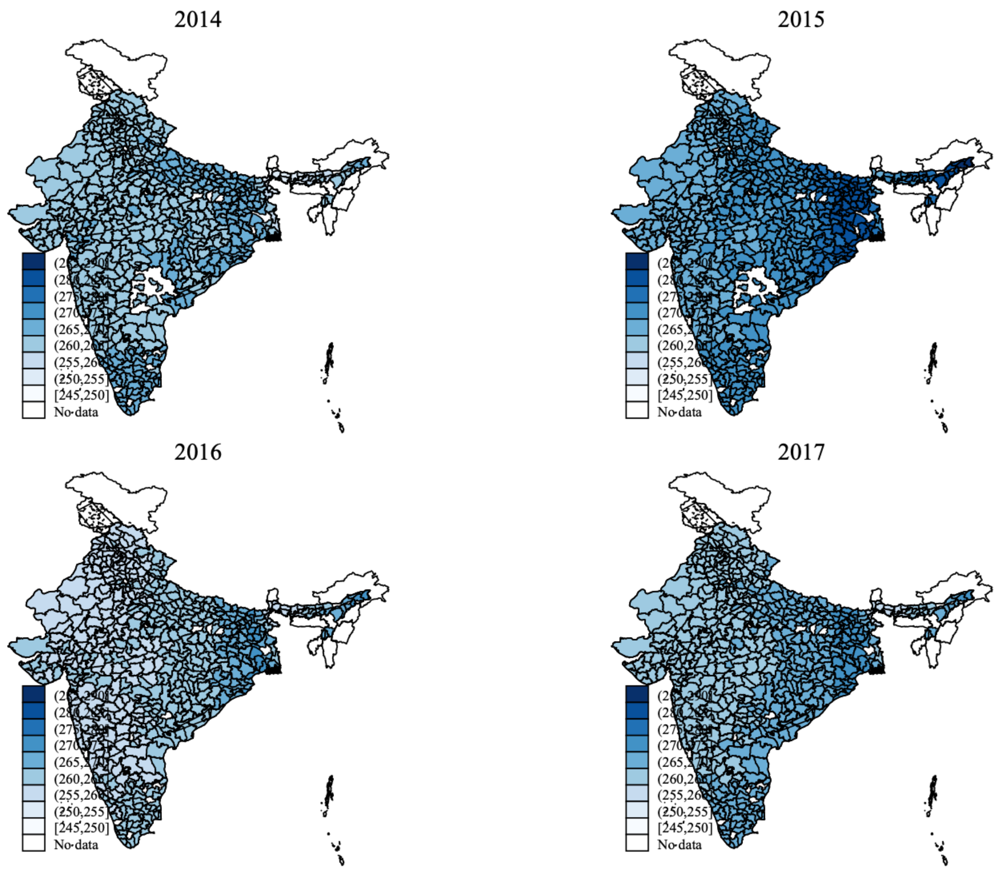


Figure A.4: **Average atmospheric nitrogen dioxide in** $molecules/cm^2$

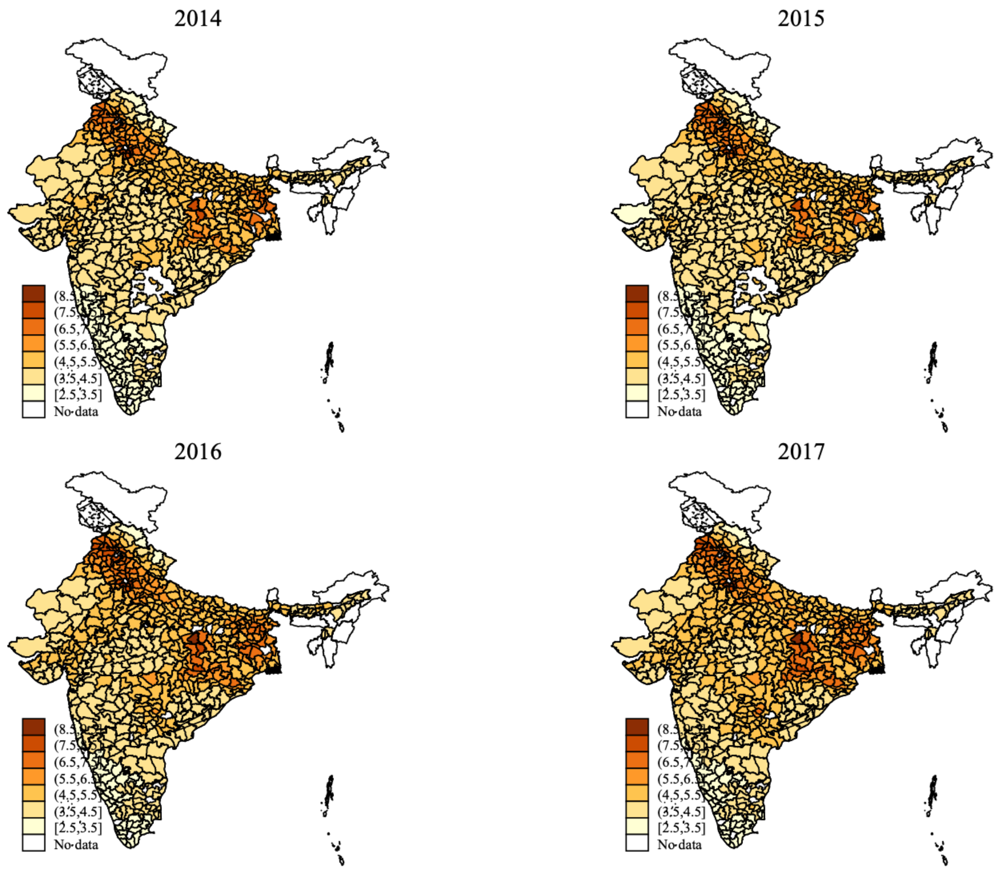


Figure A.5: **Average atmospheric carbon monoxide in parts per billion of volume**

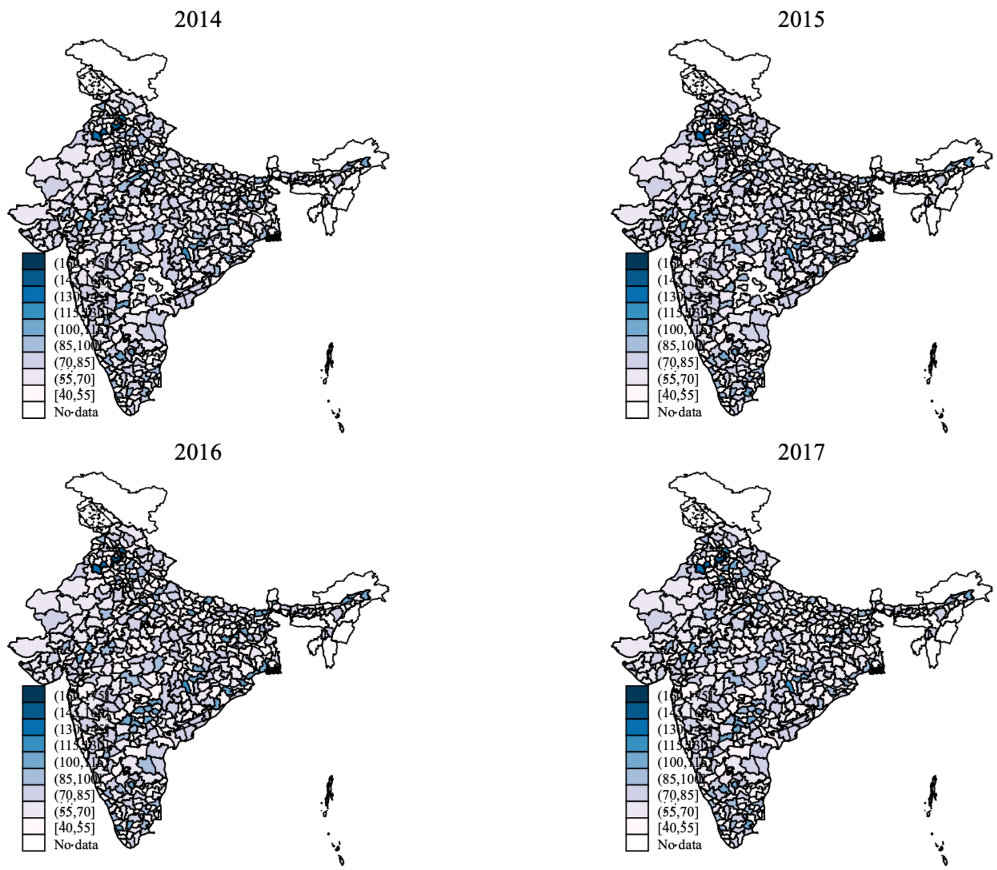


Table A.2: **Preliminary panel regression with agriculture yield as dependent variable**

Variable	Rice yield (kg/ha)	Wheat yield (kg/ha)	Maize yield (kg/ha)
Carbon dioxide (ppm)	11.90*** (2.56)	39.52*** (2.65)	33.60*** (5.21)
Mean (kg/ha)	-2584.03** (1025.95)	-13756.19*** (1061.2)	-11015.8*** (2088.36)
Fixed Effects	Yes	Yes	Yes
N	2057	2057 2057	
No. of districts	576	576 576	
R^2	0.001	0.012	0.002

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$
Carbon dioxide is the average atmospheric carbon dioxide in a column of atmosphere from surface of ground to the top of the atmosphere layer

Table A.3: **Regression results with agriculture yield, irrigation and atmospheric variables**

Variable	Model 1			Model 2			Model 3			Model 4		
	Rice	Wheat	Maize	Rice	Wheat	Maize	Rice	Wheat	Maize	Rice	Wheat	Maize
Carbon dioxide (ppm)	9.67**	30.92***	30.59***	12.09***	35.64***	24.15***	-14.61**	26.57***	2.62	-13.95**	28.59 ***	2.04
	(4.14)	(3.71)	(7.4)	(4.54)	(3.81)	(8.1)	(6.00)	(5.54)	(10.87)	(6.154)	(5.64)	(11.14)
SIF (($W/m^2/sr/\mu m$)	186.5**	224.7***	-157.1	160.7*	254.0***	-259.7*	180.0**	265.6***	-204.7	182.6**	279.2***	-205.9
	(78.90)	(70.67)	(140.9)	(87.76)	(73.18)	(156.1)	(87.57)	(80.76)	(158.6)	(88.86)	(81.36)	(160.8)
Average temperature (^oC)	21.60	6.96	16.16	30.31**	4.22	14.26	15.9	5.75	3.72	15.23	5.71	3.09
	(13.40)	(12.00)	(23.93)	(14.21)	(11.74)	(25.05)	(13.29)	(12.26)	(24.08)	(13.39)	(12.26)	(24.24)
Annual rainfall (mm)	0.37***	0.21***	0.16	0.33***	0.25***	0.06	0.35***	0.21***	0.10	0.350***	0.21***	0.088
	(0.08)	(0.07)	(0.14)	(0.09)	(0.07)	(0.15)	(0.08)	(0.08)	(0.15)	(0.083)	(0.076)	(0.15)
Fertilizer use per net	-0.23	0.14	-0.36	0.08	-0.59**	0.61	-0.22	0.13	-0.53	-0.23	0.13	-0.51
cropped area (kg/ha)	(0.23)	(0.20)	(0.40)	(0.32)	(0.26)	(0.60)	(0.28)	(0.26)	(0.51)	(0.29)	(0.26)	(0.52)
Male wage rate (Rupees/day)	0.47*	0.03	0.17	0.27	0.46*	0.61	0.17	-0.02	0.42	0.17	0.06	0.46
	(0.25)	(0.22)	(0.44)	(0.29)	(0.24)	(0.51)	(0.27)	(0.25)	(0.48)	(0.27)	(0.25)	(0.49)
Area irrigated under rice (ha)				4.36*								
				(1.7)								
Area irrigated under wheat (ha)					0.56							
					(1.81)							
Area irrigated under maize (ha)						3.249						
						(13.08)						
Ozone (DU)							-19.73***	-6.25	9.14	-20.68***	-6.84	8.45
							(5.87)	(5.41)	(10.62)	(5.95)	(5.45)	(10.77)
Nitrogen dioxide ($molecules/cm^2$) 773.1***							488.1***	20.84	776.2***		474.2***	-8.63
							(135.8)	(125.3)	(246.0)	(137.7)	(126.1)	(249.2)
Carbon monoxide (ppbv)							-2.95	9.59	-14.34	-2.698	10.81	-14.91
							(11.36)	(10.48)	(20.58)	(11.46)	(10.50)	(20.75)
Expected yield (kg/ha)	-2706	-10703***	-10181***	-4057**	-12546***	-7726**	10361***	-8054***	-3736	10400***	-8674***	-3256
	(1643)	(1472)	(2935)	(1799)	(1515)	(3196)	(2300)	(2121)	(4167)	(2357)	(2158)	(4266)
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	1170	1170	1170	1044	1044	1044	1006	1006	1006	990	990	990
No. of districts	398	398	398	373	373	373	329	329	329	325	325	325
R^2	0.056	0.118	0.036	0.061	0.182	0.031	0.166	0.111	0.071	0.169	0.119	0.070

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.4: **Regression of yield on atmospheric carbon dioxide with crop specific growth period weather variables**

Variable	Rice	Wheat	Maize
Carbon dioxide (ppm)	-0.25 (7.92)	26.98*** (6.64)	2.62 (10.87)
SIF (($W/m^2/sr/\mu m$)	198.6** (90.51)	257.1*** (83.72)	-204.7 (158.6)
Fertilizer use per net cropped area (kg/ha)	-0.265 (0.295)	0.122 (0.274)	-0.526 (0.514)
Male wage rate (Rupees/day)	0.209 (0.264)	-0.0327 (0.246)	0.423 (0.481)
Ozone (DU)	-23.93*** (7.617)	-6.105 (6.604)	9.136 (10.62)
Nitrogen dioxide ($molecules/cm^2$)	234.8 (154.2)	92.93 (138.8)	776.2*** (246.0)
Carbon monoxide (ppbv)	-8.351 (11.29)	8.147 (10.46)	-14.34 (20.58)
Average temperature (^oC)	✗	✗	✓
Annual rainfall (mm)	✗	✗	✓
January temperature & rainfall	✓	✓	✗
February temperature & rainfall	✓	✓	✗
March temperature & rainfall	✓	✓	✗
June temperature & rainfall	✓	✗	✗
July temperature & rainfall	✓	✗	✗
August temperature & rainfall	✓	✗	✗
Sept temperature & rainfall	✓	✗	✗
October temperature & rainfall	✓	✓	✗
November temperature & rainfall	✓	✓	✗
December temperature & rainfall	✓	✓	✗
Expected yield (kg/ha)	7967** (3511)	-6281** (2800)	-3736 (4167)
District FE	✓	✓	✓
N	1006	1006	1006
No. of districts	329	329	329
R^2	0.237	0.144	0.071

Standard errors in parentheses

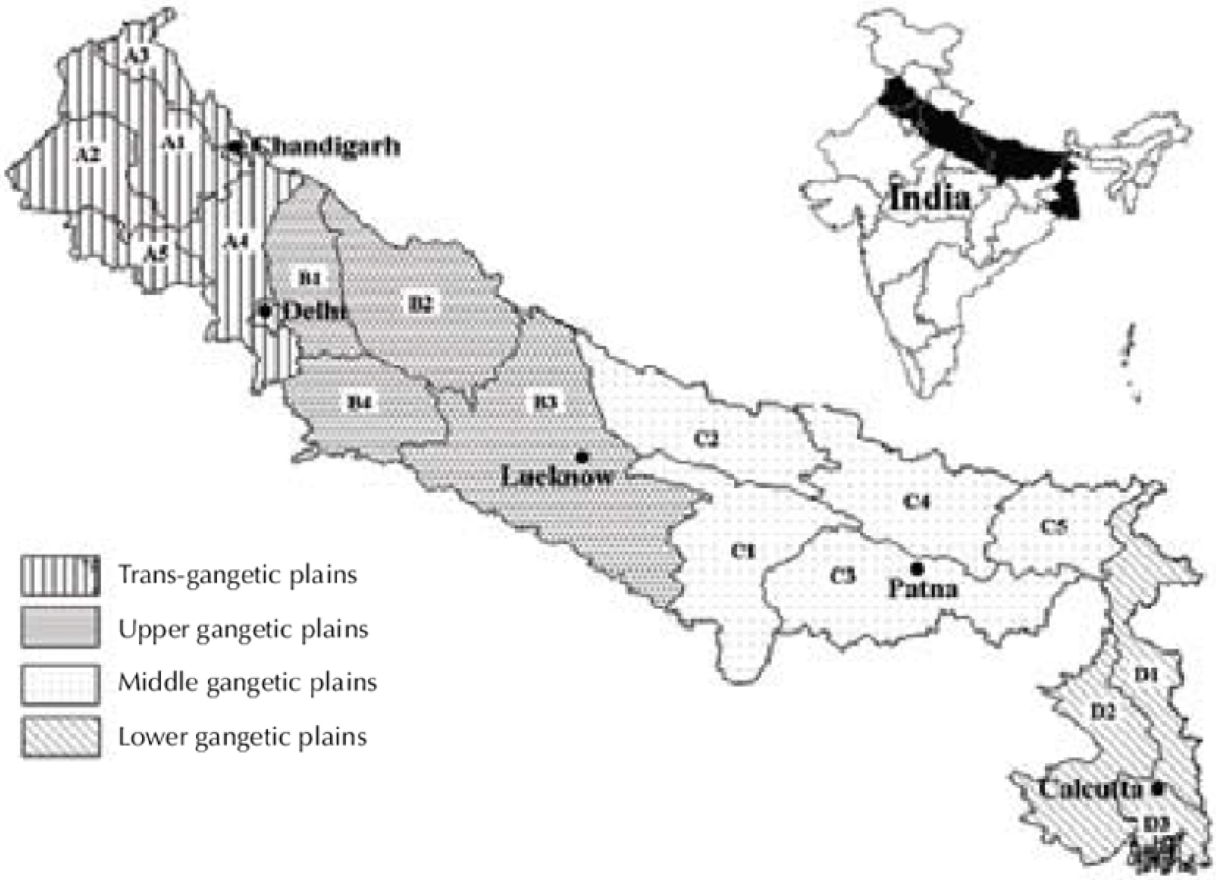
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.5: **Regression of log yield on atmospheric carbon dioxide with controls**

Variable	Rice	Wheat	Maize
Carbon dioxide (ppm)	-0.010***	0.008***	0.003
	(0.003)	(0.003)	(0.004)
SIF (($W/m^2/sr/\mu m$)	0.041	0.086**	-0.022
	(0.048)	(0.041)	(0.053)
Average temperature (^oC)	0.007	-0.004	0.009
	(0.007)	(0.013)	(0.008)
Annual rainfall (mm)	2.74e-04***	1.50e-04***	1.08e-04**
	(4.55e-05)	(4.56e-05)	(5.13e-05)
Fertilizer use per net cropped area (kg/ha)	-1.4e-04	-1.23e-04	-2.70e-04
	(1.51e-04)	(1.44e-04)	(1.65e-04)
Male wage rate (Rupees/day)	2.87e-04*	1.42e-04	4.68e-05
	(1.60e-04)	(1.36e-04)	(1.69e-04)
Ozone (DU)	-0.0166***	6.60e-04	8.81e-04
	(0.003)	(0.003)	(0.004)
Nitrogen dioxide ($molecules/cm^2$)	0.227***	0.0525	0.266***
	(0.074)	(0.066)	(0.081)
Carbon monoxide (ppbv)	-0.004	0.002	-0.009
	((0.006)	(0.005)	(0.007)
Expected yield (kg/ha)	14.94***	3.731***	5.311***
	(1.259)	(1.131)	(1.368)
District FE	✓	✓	✓
N	910	834	910
No. of districts	309	282	308
R^2	0.248	0.095	0.123

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure A.6: **The Indo-gangetic plain**



Source: Internet

States along Indo-gangetic plain are Punjab, Haryana, Uttar Pradesh, Bihar & West Bengal

Table A.6: **Regression of log yield on atmospheric carbon dioxide for the Indo-gangetic plain**

Variable	Wheat	Rice	Maize
Carbon dioxide (ppm)	0.013***	-0.0004	0.0074
	(0.004)	(0.004)	(0.009)
SIF (($W/m^2/sr/\mu m$)	0.173***	-0.035**	0.225*
	(0.051)	(0.049)	(0.125)
Average temperature (^oC)	0.056*	0.034	0.111
	(0.031)	(0.029)	(0.073)
Annual rainfall (mm)	8.48-05	1.89e-04***	1.71e-04
	(8.18e-05)	(7.83e-05)	(1.88e-04)
Fertilizer use per net cropped area (kg/ha)	-2.37e-05	-4.09e-04***	-0.70e-03**
	(1.45e-04)	(1.38e-04)	(3.33e-04)
Male wage rate (Rupees/day)	-8.3e-05	3.52e-04	5.1e-05
	(2.36e-04)	(2.26e-04)	(5.58e-04)
Ozone (DU)	✓	✓	✓
Nitrogen dioxide ($molecules/cm^2$)	✓	✓	✓
Carbon monoxide (ppbv)	✓	✓	✓
Expected yield (kg/ha)	1.068	10.00***	3.86
	(1.534)	(1.468)	(3.785)
District FE	✓	✓	✓
N	208	208	169
No. of districts	84	84	74
R^2	0.522	0.372	0.161

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.7: **Regression of log riceyield on atmospheric carbon dioxide for districts to the west and east of Lucknow on the Indo-gangetic plain**

Variable	West of Lucknow	East of Lucknow
Carbon dioxide (ppm)	0.009***	-0.005
	(0.004)	(0.009)
SIF (($W/m^2/sr/\mu m$) -0.057	-0.079	
	(0.041)	(0.110)
Average temperature (^oC)	0.021	0.056
	(0.024)	(0.060)
Annual rainfall (mm)	1.04e-04	1.35e-04
	(1.08e-04)	(1.15e-04)
Fertilizer use per net cropped area (kg/ha)	-5.09e-05	-7.66e-04***
	(1.24e-04)	(2.81e-04)
Male wage rate (Rupees/day)	9.26e-05	-8.47e$_0$4 $**$
	(2.17e-04)	(4.02e-04)
Ozone (DU)	✓	✓
Nitrogen dioxide ($molecules/cm^2$)	✓	✓
Carbon monoxide (ppbv)	✓	✓
Expected yield (kg/ha)	4.551**	12.62***
	(1.534)	(1.468)
(3.785)		
District FE	✓	✓
N	122	89
No. of districts	45	39
R^2	0.321	0.594

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table A.8: **Power of regression between rice yield and atmospheric carbon dioxide**

All districts				Indo - Gangetic plain				West of Lucknow			
N	R^2	α	1- β	N	R^2	α	1- β	N	R^2	α	1- β
910	0.2480	0.05	1.00	208	0.3720	0.05	1.00	122	0.3210	0.05	1.00

Table A.9: **Criterion for classification of states**

Criterion	Agriculture led growth	Agriculture lagging states
Urbanization	low[1]	low
GDP per capita	high	low
Contributrion of agriculture to national GDP	high	low

Source: Pingali et al., 2019

Table A.10: **Regression results of agriculture yield on atmospheric carbon dioxide by states**

Variable	Leading states			Lagging states		
	Rice	Wheat	Maize	Rice	Wheat	Maize
Carbon dioxide (ppm)	1.70 (8.01)	-3.19 (13.60)	-11.97 (43.60)	-12.52 (9.57)	34.79*** (7.81)	34.74*** (9.52)
SIF (($W/m^2/sr/\mu m$)	-96.21 (110.8)	18.71 (188.2)	-337.1 (603.3)	249.6* (136.2)	273.9** (111.2)	-54.36 (135.5)
Average temperature (^oC)	12.91 (9.88)	1.824 (16.78)	-67.16 (53.79)	11.92 (56.50)	50.52 (46.11)	-33.60 (56.18)
Annual rainfall (mm)	0.37* (4.55e-05)	0.41 (4.56e-05)	-0.34 (5.13e-05)	0.15 (0.14)	0.24** (0.12)	-0.27* (0.14)
Fertilizer use per net cropped area (kg/ha)	0.42 (0.67)	-0.08 (1.14)	-2.74 (3.66)	-0.47 (0.46)	0.66* (0.37)	-0.73 (0.45)
Male wage rate (Rupees/day)	-0.02 (0.48)	-0.71 (0.81)	-2.01 (2.58)	0.32 (0.41)	-0.11 (0.33)	0.45 (0.41)
Ozone (DU)	-11.67 (8.08)	1.83 (13.71)	25.92 (43.95)	-36.35*** (10.02)	-11.14 (8.18)	-20.51** (9.96)
Nitrogen dioxide ($molecules/cm^2$)	288.3 (213.6)	877.8** (362.6)	1605 (1162)	342.9 (211.6)	-50.67 (172.7)	33.94 (210.4)
Carbon monoxide (ppbv)	16.54 (18.52)	7.11 (31.43)	139.1 (100.8)	-9.09 (15.28)	8.93 (12.47)	-13.92 (15.19)
Expected yield (kg/ha)	2182 (3432)	-1911 (5826)	-13161 (18678)	14766*** (3553)	-10583*** (2900)	-4482 (3534)
District FE	✓	✓	✓	✓	✓	✓
N	152 152	152	604	604	604	
No. of districts	42	42	42	206	206	206
R^2	0.207	0.169	0.061	0.214	0.162	0.194

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Leading states : Andhra Pradesh, Haryana, Himachal Pradesh and Punjab
Lagging states: Bihar, Chattisgarh, Jharkhand, Madhya Pradesh, Odisha, Rajasthan, Uttar Pradesh and West Bengal

Table A.11: **Regression of log yield on atmospheric carbon dioxide**

Variable	Rice	Wheat	Maize
Carbon dioxide (ppm)	-0.008** (0.003)	0.009*** (0.003)	0.004 (0.004)
SIF (($W/m^2/sr/\mu m$)	0.039 (0.048)	0.091** (0.041)	-0.019 (0.054)
Temperature (deviation from India average)	0.008 (0.007)	-0.003 (0.013)	0.0097 (0.008)
Annual rainfall (deviation from national average)	2.75e-04*** (4.58e-05)	1.42e-04*** (4.54e-05)	9.36e-05* (5.16e-05)
Fertilizer use per net cropped area (kg/ha)	1.57e-04 (1.52e-04)	1.33e-04 (1.43e-04)	2.61e-04 (1.67e-04)
Male wage rate (Rupees/day)	2.79e-04* (1.62e-04)	2.33e-04* (1.38e-04)	6.78e-05 (1.74e-04)
Ozone (DU)	-0.018*** (0.003)	-7.64e-05 (0.003)	6.61e-05 (0.004)
Nitrogen dioxide ($molecules/cm^2$)	0.227*** (0.075)	0.035 (0.066)	0.261*** (0.081)
Carbon monoxide (ppbv)	-0.004 15.07***	0.003 3.470***	-0.009 5.485***
Expected yield (kg/ha)	15.07*** (1.279)	3.470*** (1.133)	5.485*** (1.396)
District FE	✓	✓	✓
N	902	818	894
No. of districts	306	278	304
R^2	0.252	0.107	0.123

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

[1]low and high is in comparison to the national averages

Table A.12: **Regression of log yield on atmospheric carbon dioxide**

Variable	Rice	Wheat	Maize
Carbon dioxide (ppm)	-0.009***	0.009***	0.004
	(0.003)	(0.003)	(0.004)
SIF $((W/m^2/sr/\mu m)$	0.041	0.092**	-0.020
	(0.048)	(0.041)	(0.054)
Temperature (deviation from		0.007	-0.003
0.009			
temporal district average)	(0.007)	(0.013)	(0.008)
Annual rainfall (deviation from temporal district average)	2.76e-04***	1.44e-04***	1.03e-04**
	(4.58e-05)	(4.55e-05)	(5.18e-05)
Fertilizer use per net cropped area (kg/ha)	-1.45e-04	-1.26e-04	-2.63e-04
	(1.52e-04)	(1.42e-04)	(1.66e-04)
Male wage rate (Rupees/day)	2.73e-04*	2.32e-04*	6.71e-05
	(1.62e-04)	(1.38e-04)	(1.74e-04)
Ozone (DU)	-0.017***	4.29e-05	0.0004
	(0.003)	(0.003)	(0.004)
Nitrogen dioxide $(molecules/cm^2)$	0.216***	0.029	0.257***
	(0.075)	(0.066)	(0.081)
Carbon monoxide (ppbv)	-0.004	0.003	-0.009
		(0.006)	(0.005)
(0.007)			
Expected yield (kg/ha)	15.07***	3.470***	5.485***
	(1.278)	(1.140)	(1.396)
District FE	✓	✓	✓
N	902	818	894
No. of districts	306	278	304
R^2	0.252	0.107	0.124

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

APPENDIX B

APPENDIX TO CHAPTER 2

Table B.1: **Assets Included In The Asset Index**

Sl No.	Asset	Sl No.	Asset	Sl No.	Asset
1	Stove / gas burner	11	Audio cassette / CD / DVD player	21	Weeding / harvesting machine / thresher
2	Refrigerator	12	Television	22	Motor pump for irrigation / water supply
3	Ceiling fan	13	Wall clock / watch	23	Wheelbarrow / pushcart
4	Table fan	14	Sewing machine	24	Tractor
5	Air cooler	15	Bicylce / cycle rickshaw	25	Spraying machine for water / sprinkler
6	Bed	16	Bullock cart	26	Blacksmith tools
7	Cot	17	Motorcycle / scooter / autorickshaw		
8	Chairs	18	Mobile phone		
9	Table	19	Landline phone		
10	Radio	20	Computer		

B.1 Economic Model

Suppose an agriculture household h is endowed with land $\bar{T}$ and labor $\bar{L}$ whose market prices are r and w respectively. For simplicity I am not considering any other inputs, though including other inputs are straightforward. The price of the output is p. An important assumption here is that input price of borrowing from the market and to the market are same.

For the production problem the households have to choose the amount of inputs ; labor (L) and land (T) that produce the output (Y) which maximizes profit (Π) conditional on the production function and the non-negativity constraints. The farm households thus face the following profit maximization problem

$$\max_{T,L} \ \Pi = \max_{T,L}[pY - wL - rT] \tag{A.i}$$

subject to

$$Y \leq f(L,T) \tag{A.ii}$$

$$T, L \geq 0 \tag{A.iii}$$

The production function Y is concave in inputs the inequality constraints (A.iii) hold strict. We then have the following Lagrangean:

$$\mathscr{L} = pY - wL - rT - \lambda(Y - f(L,T)) \tag{A.iv}$$

The first order and complementary slackness conditions are

$$\frac{\partial \mathscr{L}}{\partial Y} : p - \lambda = 0$$
$$\frac{\partial \mathscr{L}}{\partial L} : w - \lambda \frac{\partial f(L,T)}{\partial L} = 0$$
$$\frac{\partial \mathscr{L}}{\partial T} : r - \lambda \frac{\partial f(L,T)}{\partial T} = 0$$
$$\lambda(Y - f(L,T)) = 0$$

The first order conditions give these optimized function of input demand

$$L^* = L(w, r, p) \tag{A.v}$$

$$T^* = T(w, r, p) \tag{A.vi}$$

The profit maximizing output is thus,

$$Y^* = f(T^*, L^*)$$

$$\Rightarrow Y^* = Y(w, r, p) \tag{A.vii}$$

And maximized profit is a function of all the input prices and output price.

$$\Pi^* = \Pi(w, r, p) \tag{A.viii}$$

The farm revenue is hence

$$TR^* = TR(w, r, p) \tag{A.ix}$$

Having arrived at the maximized profit, the households now can use these profits for their utility maximization under separation between production and consumption. The agricultural households have to choose the amount they would like to consume (C), leisure (l), household labor to be used on own farm (L_f), own land to be cultivated (T_f), labor to be supplied to the market (L_{sm}), land to be rented out to the market (T_{sm}), labor to be bought from the market (L_{dm}) and land to be rented in from the market (T_{dm}) inorder to maximize their utility (U). Π^* is the maximized profit available for households from the production process to utilize for consumption. L^* and T^* is the profit maximizing quantity of inputs the household employs for agricultural production. For simplicity I consider the household consumes goods priced at p. The consumption problem for the farm household is modeled as

$$\max_{C,l,L_f,L_{sm},L_{dm},T_f,T_{sm},T_{dm}} \mathscr{U}(C, l) \tag{A.x}$$

subject to

$$pC \leq \Pi^*(w, r, p) + wL_{sm} + rT_{sm} \tag{A.xi}$$

$$l + L_f + L_{sm} \leq \bar{L} \tag{A.xii}$$

$$T_f + T_{sm} \leq \bar{T} \tag{A.xiii}$$

$$L^* \equiv L_f + L_{dm} \tag{A.xiv}$$

$$T^* \equiv T_f + T_{dm} \tag{A.xv}$$

$$C,\ l \geq 0 \tag{A.xvi}$$

$$L_f,\ L_{sm},\ L_{dm},\ T_f,\ T_{sm},\ T_{dm} \geq 0 \tag{A.xvii}$$

The Lagrangean for the utility maximization problem is

$$\begin{aligned}\mathscr{L} = \mathscr{U}(C, l) - \lambda_1\{pC - \Pi^*(w, r, p) - wL_{sm} - rT_{sm}\}\\ -\lambda_2\{l + L_f + L_{sm} - \bar{L}\} - \lambda_3\{T_f + T_{sm} - \bar{T}\}\\ -\lambda_4\{L^* - L_f - L_{dm}\} - \lambda_5\{T^* - T_f - T_{dm}\}\\ -\mu_1 L_f - \mu_2 L_{sm} - \mu_3 L_{dm} - \mu_4 T_f - \mu_5 T_{sm} - \mu_6 T_{dm}\end{aligned} \tag{A.xviii}$$

First order and slackness conditions of the utility maximization problem are

$$
\begin{aligned}
\frac{\partial \mathscr{L}}{\partial C} : \frac{\partial \mathscr{U}}{\partial C} - \lambda_1 p = 0 \\
\frac{\partial \mathscr{L}}{\partial l} : \frac{\partial \mathscr{U}}{\partial l} - \lambda_2 = 0 \\
\frac{\partial \mathscr{L}}{\partial L_f} : \lambda_4 - \lambda_2 - \mu_1 = 0 \\
\frac{\partial \mathscr{L}}{\partial L_{sm}} : \lambda_1 w - \lambda_2 - \mu_2 = 0 \\
\frac{\partial \mathscr{L}}{\partial L_{dm}} : \lambda_4 - \mu_3 = 0 \\
\frac{\partial \mathscr{L}}{\partial T_f} : \lambda_5 - \lambda_3 - \mu_4 = 0 \\
\frac{\partial \mathscr{L}}{\partial T_{sm}} : \lambda_1 r - \lambda_3 - \mu_5 = 0 \\
\frac{\partial \mathscr{L}}{\partial T_{dm}} : \lambda_5 - \mu_6 = 0 \\
\lambda_1[pC - \Pi^*(w, r, p) - wL_{sm} - rT_{sm}] = 0 \\
\lambda_2[l + L_f + L_{sm}] = 0 \\
\lambda_3[T_f + T_{sm} - \bar{T}] = 0 \\
\lambda_4[L^* - L_f - L_{dm}] = 0 \\
\lambda_5[T^* - T_f - T_{dm}] = 0 \\
\mu_1 L_f = \mu_2 L_{sm} = \mu_3 L_{dm} = \mu_4 T_f = \mu_5 T_{sm} = \mu_6 T_{dm} = 0
\end{aligned}
$$

So we have the solution to the utility maximization problem as

$$C^* = C(w, r, p, \bar{L}, \bar{T}) \tag{A.xix}$$

So when there is separation between production and consumption in agricultural households profits and input use is not a function of the input endowments.

Now, let us assume that there is a failiure of separability between production and consumption. Then both the optimization happen simultaneously and can be modeled using the following problem,

$$\underset{Y,C,l,L_f,L_{sm},L_{dm},T_f,T_{sm},T_{dm}}{Max} \Pi = \underset{Y,C,l,L_f,L_{sm},L_{dm},T_f,T_{sm},T_{dm}}{Max} [pY - wL - rT] \tag{B.i}$$

subject to

$$\bar{\mathscr{U}} \leq \mathscr{U}(C, l) \tag{B.ii}$$

$$Y \leq f(L, T) \tag{B.iii}$$

$$pC \leq pf(L, T) - wL_{dm} - rT_{dm} + wL_{sm} + rT_{sm} \tag{B.iv}$$

$$l + L_f + L_{sm} \leq \bar{L} \tag{B.v}$$

$$T_f + T_{sm} \leq \bar{T} \tag{B.vi}$$

$$L \equiv L_f + L_{dm} \tag{B.vii}$$

$$T \equiv T_f + T_{dm} \tag{B.viii}$$

$$L, T, K, C, l \geq 0 \tag{B.ix}$$

$$L_f, L_{sm}, L_{dm}, T_f, T_{sm}, T_{dm} \geq 0 \tag{B.x}$$

The Lagrangean is

$$\begin{aligned} \mathscr{L} &= pY - wL - rT - \lambda_1\{\bar{\mathscr{U}} - \mathscr{U}(C, l)\} \\ &-\lambda_2\{Y - f(L, T)\} - \lambda_3\{pC - pf(L, T) + w(L_{dm} - L_{sm}) + r(T_{dm} - T_{sm})\} \\ &-\lambda_4\{l + L_f + L_{sm} - \bar{L}\} - \lambda_5\{T_f + T_{sm} - \bar{T}\} \\ &-\lambda_6\{L - L_f - L_{dm}\} - \lambda_7\{T - T_f - T_{dm}\} \\ &-\mu_1 L_f - \mu_2 L_{sm} - \mu_3 L_{dm} - \mu_4 T_f - \mu_5 T_{sm} - \mu_6 T_{dm} \end{aligned} \tag{B.xi}$$

Here the income constraint enters the profit maximization problem in equation (B.iv) and the households choose the level of inputs to maximize income such that utility is atleast a certain level $\bar{\mathscr{U}}$. The Langrangean would give the following

$$\Pi^* = \Pi((w, r, p, \bar{L}, \bar{T}) \tag{B.xii}$$

$$C^* = C(w, r, p, \bar{L}, \bar{T}) \tag{B.xiii}$$

So under non-separable conditions household farm profit is a function of all the input prices, and household labor and land endowments. The farm revenue is

$$TR^* = TR(w, r, p, \bar{L}, \bar{T}) \tag{B.xiv}$$

Farm revenue is a function of the output and input prices and, input endowments. So the comparison between equations (A.ix) and (B.xiv) provides a test for separability between production and consumption in the agricultural households.

Figure B.1: **Map of Chandrapur district**

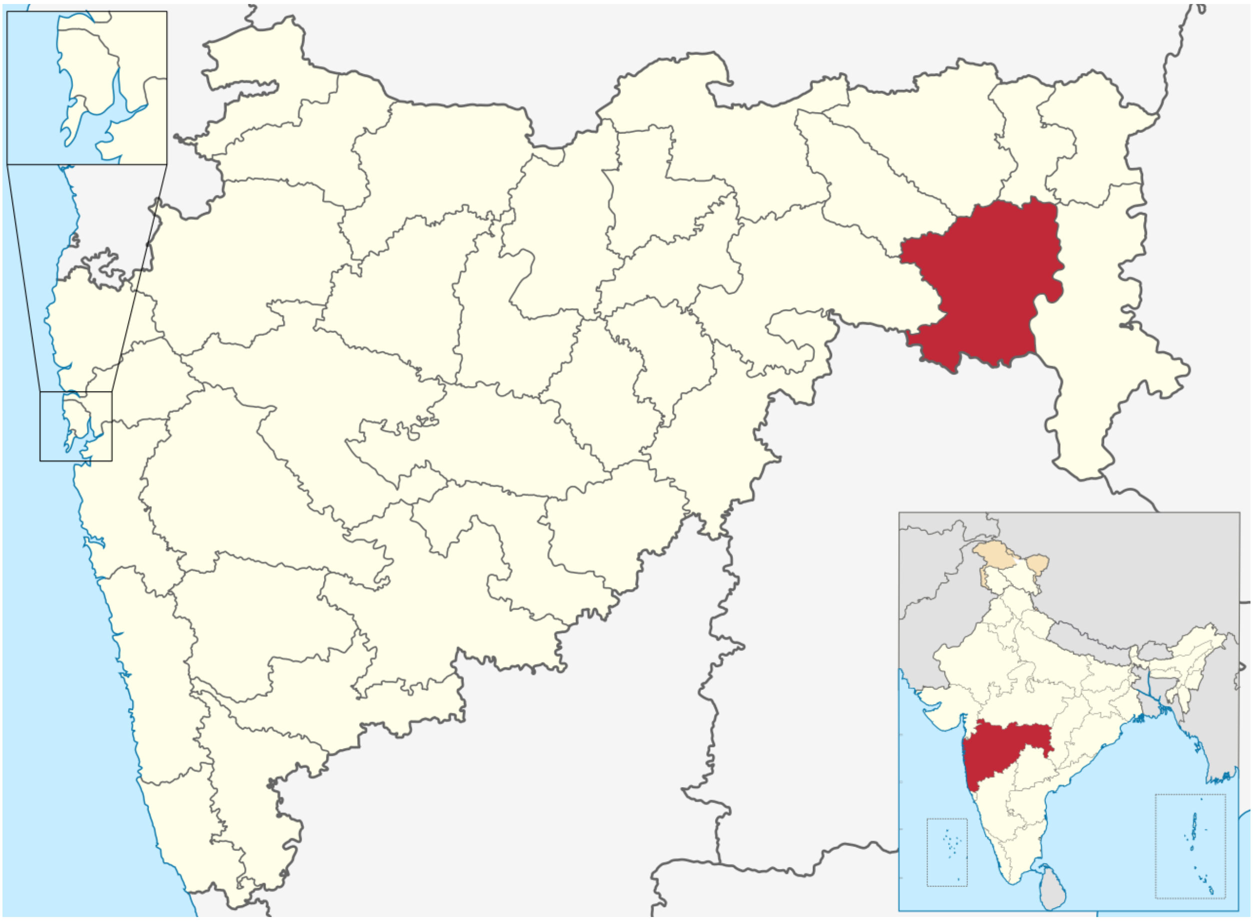


Figure B.2: **Local polynomial relationship between land endowment and agriculture revenue for landholdings less than 5 acres**

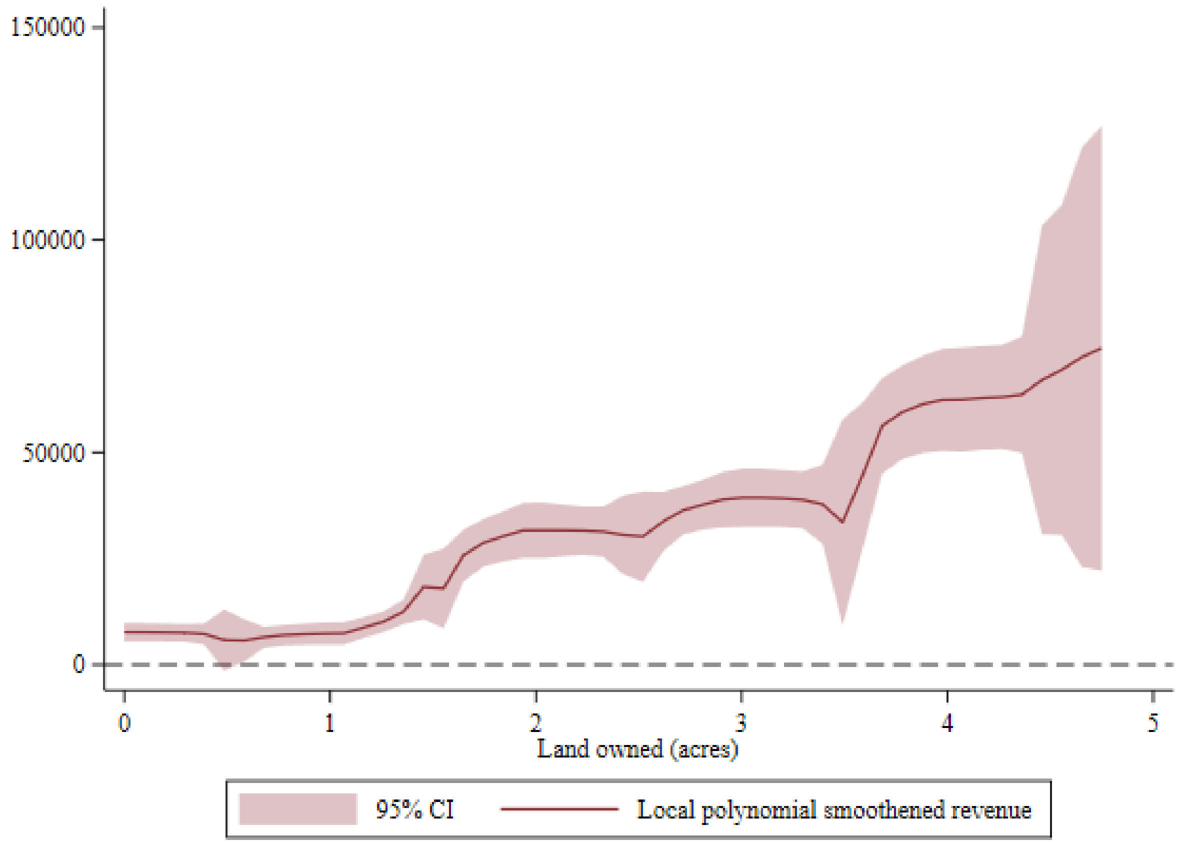


Figure B.3: **Local polynomial relationship between labor endowment and agriculture revenue for landholdings less than 5 acres**

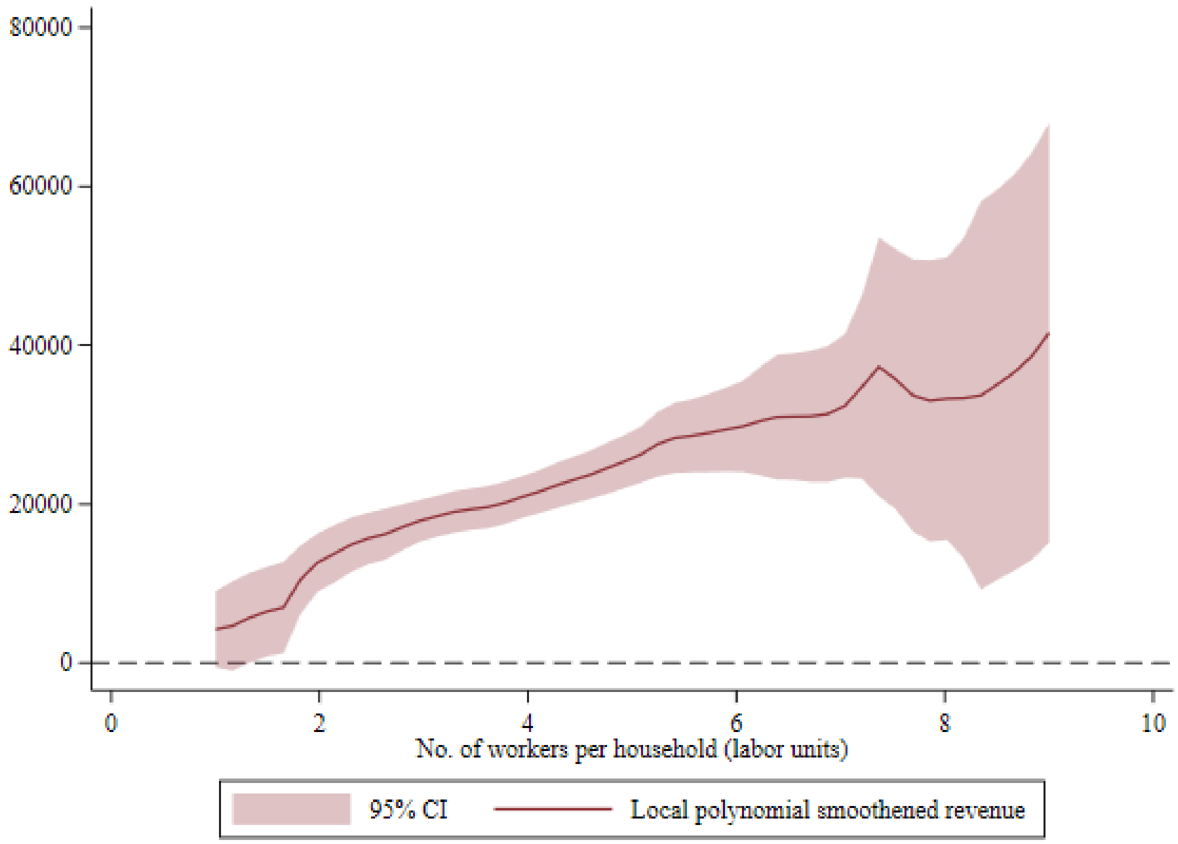


Table B.2: **Preliminary OLS regression results of agriculture revenue on land endowment and labor endowment**

Variable	(1)	(2)	(3)
Mean	6033 (5630)	8904*** (1735)	-1326 (4785)
HH labor (units)	7884*** (1260)		2494*** (1087)
HH land owned (acres)		10223*** (366.2)	10067*** (372.1)
Fixed Effects	Yes	Yes	Yes
N	1884	1884	1884
R^2	0.020	0.293	0.295

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.3: **Panel fixed effects regression results of agriculture revenue on land endowment and labor endowment**

Variable	Overall	Gondpipri	Korpana	Mul
Mean	-27,846***	-22,366***	-19,851***	-20,593*
	(4840)	(5356)	(4778)	(11,004)
HH labor (units)[L]	1508	1513	4222***	1568
	(1012)	(1129)	(1021)	(2117)
HH land owned [T] (acres)	8942***	4616***	3653***	12,108***
	(360)	(426.6)	(522.2)	(650.2)
Wage	324.8**	440.4**	132.9	-152.0
	(137.1)	(172.3)	(132.9)	(-152.0)
Rental income (Rupees)	-0.374**	-0.096	-1.449	-4.027***
	(0.167)	(0.111)	(1.089)	(0.814)
Land rented in	38,845***	23,790***	7987**	72,095***
	(3250)	(3355)	(3878)	(6573)
Asset index	20,311***	15,937***	7104***	21,034***
	(1712)	(1987)	(2026)	(3233)
Fixed Effects	Yes	Yes	Yes	Yes
N	1878	627	626	625
R^2	0.406	0.347	0.177	0.505
F-test (joint significance of T & L)	43.64***	5.83**	0.21	21.49***

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.4: **Panel fixed effects regression results of agriculture revenue on land endowment and labor endowment by land ownership**

Variable	(1) *(Land owned > 2.5 acres)*	(2) *(Land owned ≤ 2.5 acres)*
Mean	-28,729***	-16,907***
	(10,762)	(3411)
HH labor (units) [L]	718.9	1903***
	(2009)	(720.5)
HH land owned [T]	8122***	8501***
acres	(715.4)	(960.7)
Wage	611.5*	200.3**
	(286.1)	(95.15)
Rental income (Rupees)	-2.529***	-0.0711
	(0.700)	(0.0904)
Land rented in	45,517***	31,319***
	(6678)	(2244)
Asset index	26,899***	8845***
	(3012)	(1426)
Fixed Effects	Yes	Yes
N	817	1061
R^2	0.297	0.271
F-test (joint significance of T & L)	65.19***	45.96***

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.5: **Panel fixed effects regression results of agriculture revenue on land and labor endowment by food and cash crops**

	(1) Food crop	(2) Cash crop
HH labor (units) [L]	1969.9*	812.9
(acres)	(1165.2)	(1262.7)
HH land owned [T]	8918.5***	9137.3***
	(444.6)	(452.3)
Wage	525.7***	419.9**
	(157.7)	(178.6)
Rental income (Rupees)	-2.2***	-2.6***
	(0.6)	(0.6)
Land rented in	34418.7***	40294.6***
	(3834.4)	(4038.2)
Asset index	19020.8***	21125.3***
	(1924.6)	(2004.0)
Constant	-32489.7***	-23605.4***
	(5585.9)	(6143.1)
Fixed effects	Yes	Yes
N	1184	1338
R^2	0.423	0.391

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B.6: **Panel fixed effects regression results of agriculture revenue on land and labor endowment by crops grown**

Variable	(1) (No cotton raised)	(2) (Cotton raised)	(3) (No paddy raised)	(4) (Paddy raised)
Mean	-12,964***	-1234	-26,569***	-24,393***
	(2872)	(14,015)	(5653)	(8332)
HH labor (units) [L]	2156***	1408	922.1	4182**
	(608.9)	(2529)	(1184)	(1728)
HH land owned [T] acres	3787***	10,017***	9314***	6405***
	(261.1)	(816.4)	(406.0)	(733.6)
Wage	145.1*	49.74	315.6**	142.7
	(81.81)	(364.6)	(160.2)	(233.6)
Rental income (Rupees)	-0.100	-4.406***	-0.381**	-4.753*
	(0.0872)	(1.082)	(0.175)	(2.770)
Land rented in	11,990***	58,173***	46,713***	12,374**
	(2115)	(7424)	(3860)	(5261)
Asset index	5740***	24,913***	19,938***	17,689***
	(1167)	(3492)	(1974)	(3122)
Fixed effects	Yes	Yes	Yes	Yes
N	1386	492	1489	389
R^2	0.215	0.401	0.428	0.313
F-test (joint significance of L & T)	124.77***	75.72***	272.37***	46.32***

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.7: **Panel fixed effects regression results of agriculture revenue on land endowment and labor endowment by crops grown**

Variable	(1) *(Cotton)*	(2) *(Paddy)*
Mean	-21,607***	-281,85***
	(4,043)	(4,881)
HH labor (units) [L]	1,550*	1,680*
	(847)	(1,012)
HH land owned [T]	3,262***	9,279***
	(419.9)	(384.0)
Wage	59.75	312.8**
	(114.9)	(136.9)
Rental income (Rupees)	-0.278**	-0.385**
	(0.140)	(0.167)
Land rented in	29,746***	38,775***
	(2,779)	(3,247)
Asset index	15,324***	20,143***
	(1,438)	(1,711)
Cotton growing	46,477***	
	(3,697)	
Cotton x Land	5,888***	
	(626.0)	
Paddy growing		2,126
		(4,393)
Paddy x Land		-2,287**
		(970.9)
Fixed Effects	Yes	Yes
N	1,878	1,878
R^2	0.588	0.409

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table B.8: **Robustness check of relationship between agriculture revenue and land and labor input endowments**

Variable	(1)	(2)	(3)	(4)	(5)
	Log revenue	Revenue			
	(Overall)	(Overall)	(Gondpipri)	(Korpana)	(Mul)
Mean	9303***	-37,936***	-47,416***	-3721	-22,055
	(0.154)	(11,039)	(11,841)	(10,390)	(25,453)
HH labor (units) [L]	0.00368	5268	11,728**	-4139	-955.7
	(0.0299)	(4691)	(5037)	(4389)	(10,683)
Labor squared		-435.6	-1121**	845.4*	178.9
		(494.5)	(540.1)	(462.4)	(1111)
HH land owned [T] acres	0.122***	10,942***	6611***	9162***	16,424***
	(0.0105)	(720.1)	(832.8)	(1099)	(1375)
Land squared		-133.0***	-133.1***	-577.3***	-249.9***
		(41.69)	(49.44)	(101.6)	(70.30)
Wage	0.00703*	299.2**	430.0**	73.64	-119.2
	(0.00422)	(137.0)	(171.1)	(130.5)	(284.7)
Rental income (Rupees)	-3.61e-05*	-0.366**	-0.0828	-1.851*	-3.827***
	(1.85e-05)	(0.167)	(0.111)	(1.066)	(0.810)
Land rented in	0.594***	38,506***	23,622***	8212**	71,574***
	(0.0877)	(3244)	(3335)	(3785)	(6519)
Asset index	0.306***	20,173***	16,310***	5938***	20,663***
	(0.0466)	(1713)	(1977)	(1991)	(3209)
Fixed effects	Yes	Yes	Yes	Yes	Yes
N	1099	1878	627	626	625
R^2	0.202	0.410	0.360	0.221	0.515
F-test (joint significance of L & T)	68.16***	116.72***	34.30***	34.75***	71.43***

Standard errors in parentheses
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

APPENDIX C

APPENDIX TO CHAPTER 3

C.1 Utility Maximization Under Non - Separability

Assume non - separation between production and consumption. The agricultural households have the following utility maximization problem

$$\underset{Q_F, Q_{NF}, l, L^f, L^w}{Max} \; U(Q_F, Q_{NF}, l) \tag{1b}$$

subject to

$$p_F Q_F + p_{NF} Q_{NF} + wl \leq wL^m + \bar{R} + p_F^* Y \tag{2b}$$

$$Y \leq F(L, A) \tag{3b}$$

$$L = L^f + L^w \tag{4b}$$

$$l + L^f + L^m \leq \bar{T} \tag{5b}$$

$$p_F = f(p_F^*) \tag{6b}$$

$$Q_F, Q_{NF}, l, L^f, L^w \geq 0 \tag{7b}$$

Here w is the market wage rate, L^m is the labor sold to the market by the household, L^f is the labor employed on own farm, $\bar{R}$ are all other sources of income besides agricultural, such as remittances, etcetera.p_F^* is the price farmers receive for their crops while p_F is the price paid for food and p_{NF} is the price of non-food commodities. Y is the agricultural output. $\bar{T}$ is the total endowment of time available. L^w is the labor rented from the market on the household farm. L is the total labor input employed on the farm by the household and A represents all the other inputs entering production, which I assume as given.

The budget constraint is represented by equation (2b) and equation (3b) is the production function. The production function explicitly enters the consumption problem due to non - separation and thus farm output Y is no more exogenously determined. Here, the households also have to choose the L^w and L^f and thus L (4b) as part of the utility optimization problem. Equation (5b) is the labor endowment constraint of the household. I assume that food prices are a function of the prices the farmers receive for their crops represented by equation (6b). Equation (7b) is the non - negativity constraint.

When separation holds, Y is the profit maximizing output but now that need not be the case as consumer preferences could alter the quantity of Y.

Equation (2b) and (5b) becomes equality constraints since preferences are assumed to be locally non - satiating and homothetic. We also have the production function as convex and non - decreasing in inputs, equation (3b) is binding and production occurs at the boundary of the production function.

Plugging all the equality constraints into the budget constraint gives the new budget constraint

$$f(p_F^*)Q_F + p_{NF}Q_{NF} + w(2l - L^f - \bar{T}) - \bar{R} - p_f^* F(L^f + L^w, A) = 0 \tag{8b}$$

It is reasonable to assume that labor employed on the farm is a function of its characteristics that aides productivity, such as health, age, and so on. Therefore we have

$$L^f = L^f(\alpha^f) \tag{9b}$$

$$L^w = L^w(\alpha^w) \tag{10b}$$

$$So,\ L = L(\alpha^f,\ \alpha^w) \tag{11b}$$

where α^f represents the household labor characteristics and α^w is the market labor characteristics.

Plugging the above result into equation (8b) gives the following budget constraint

$$f(p_F^*)Q_F + p_{NF}Q_{NF} + w(2l - L^f - \bar{T}) - \bar{R} - p_F^* F(L(\alpha^f,\ \alpha^w), A) = 0 \tag{12b}$$

The consumption problem hence becomes

$$\underset{Q_F, Q_{NF}, l, L^f, L^w}{Max}\ U(Q_F, Q_{NF}, l) \tag{1b$'$}$$

subject to

$$f(p_F^*)Q_F + p_{NF}Q_{NF} + w(2l - L^f - \bar{T}) - \bar{R} - p_F^* F(L(\alpha^f,\ \alpha^w), A) = 0 \tag{2b$'$}$$

$$Q_F, Q_{NF}, l, L^f, L^w \geq 0 \tag{7b$'$}$$

The Lagrangean to the optimization problem, where λ is the Lagrange multiplier, is

$$\mathscr{L} = U(Q_F, Q_{NF}, l) - \lambda[f(p_F^*)Q_F + p_{NF}Q_{NF} + w(2l - L^f - \bar{T}) - \bar{R} - p_F^* F(L(\alpha^f,\ \alpha^w), A)] \tag{13b}$$

The Lagrangean equation gives the following first order and complementary slackness conditions

$$dUdQ_F = \lambda g(p_F^*) \tag{14b}$$

$$dUdQ_{NF} = \lambda p_{NF} \tag{15b}$$

$$dUdl = 2\lambda w \tag{16b}$$

$$\lambda w + \lambda p_F^* F'[L(\alpha^f, \alpha^w), A]L'(\alpha^f, \alpha^w)\frac{d\alpha^f}{dL^f} = 0 \tag{17b}$$

$$\lambda p_F^* F'[L(\alpha^f, \alpha^w), A]L'(\alpha^f, \alpha^w)\frac{d\alpha^w}{dL^w} = 0 \tag{18b}$$

$$\lambda[f(p_F^*)Q_F + p_{NF}Q_{NF} + w(2l - L^f - \bar{T}) - \bar{R} - p_F^* F(L(\alpha^f,\ \alpha^w), A)] = 0 \tag{19b}$$

From the first order conditions and the budget constraint we have

$$Q_F = f(p_F^*, p_{NF}, w, \alpha^f, \alpha^w; z) \tag{B}$$

where z represents all other household characteristics. So food consumption is a function of labor characteristics, besides other factors when separability does not hold.

Figure C.1: **Correlation between Fe consumption and DDS (2014)**

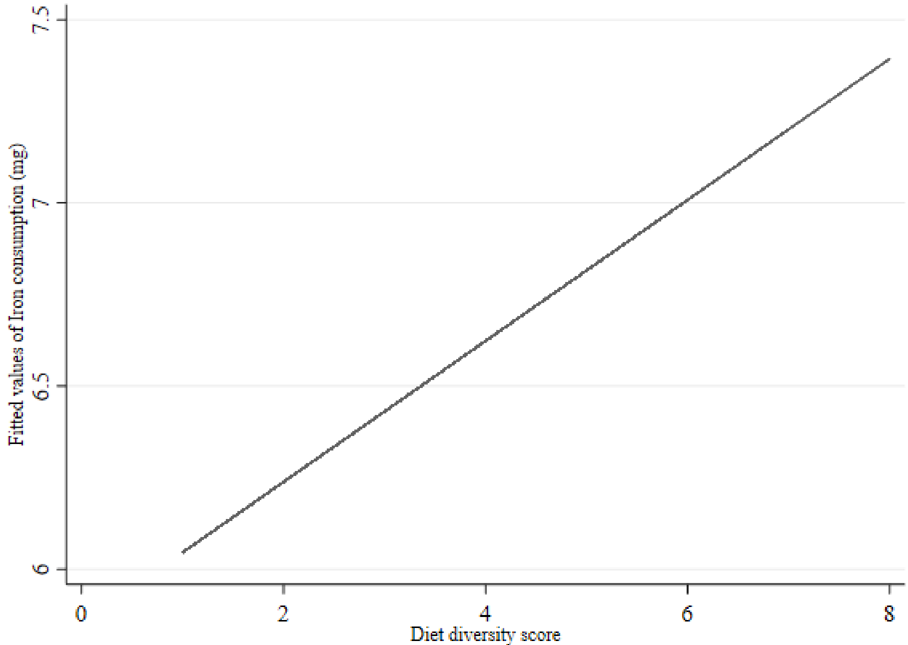


Figure C.2: **Correlation between Fe consumption and DDS (2016)**

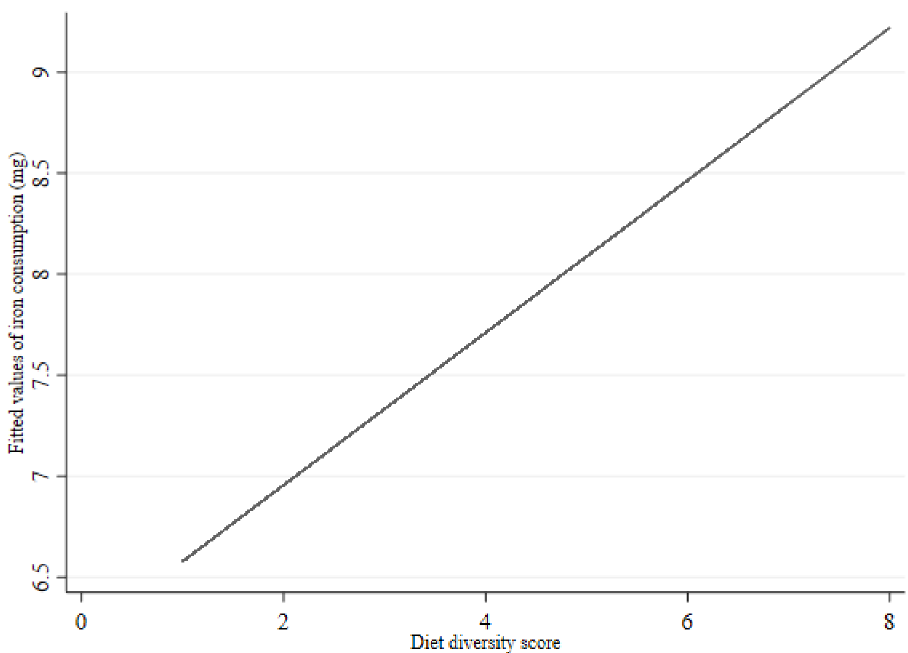
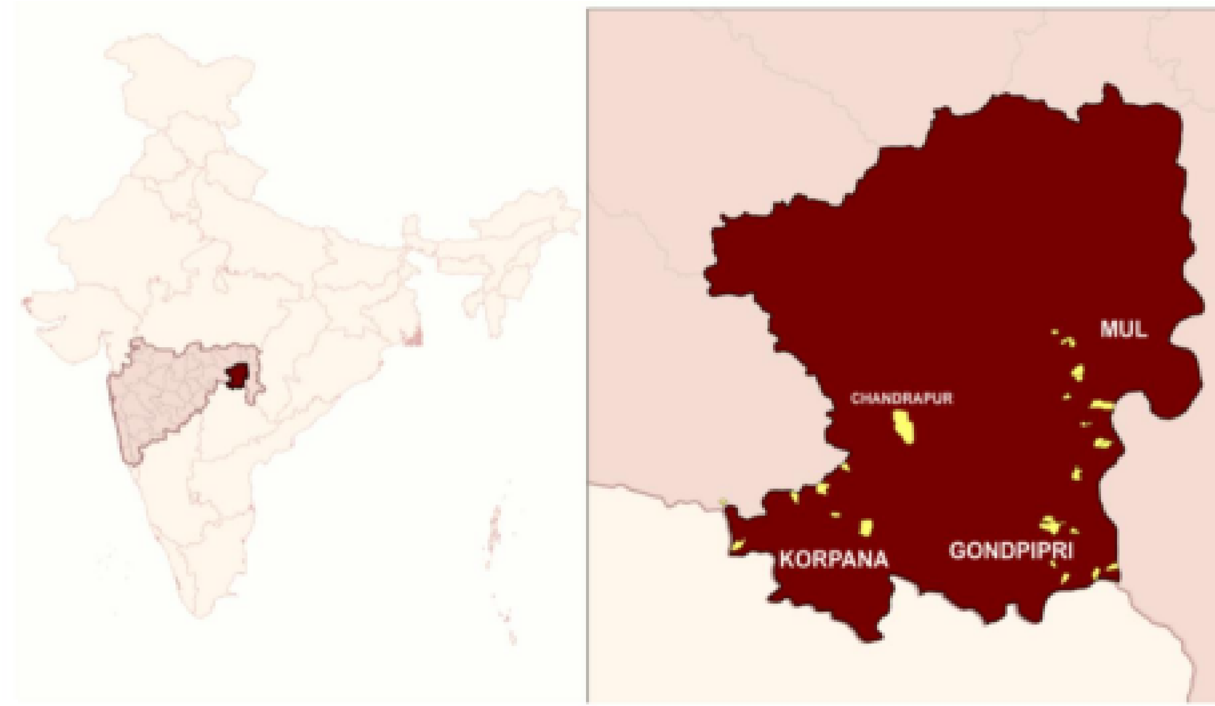


Table C.1: **Assets Included In The Asset Index**

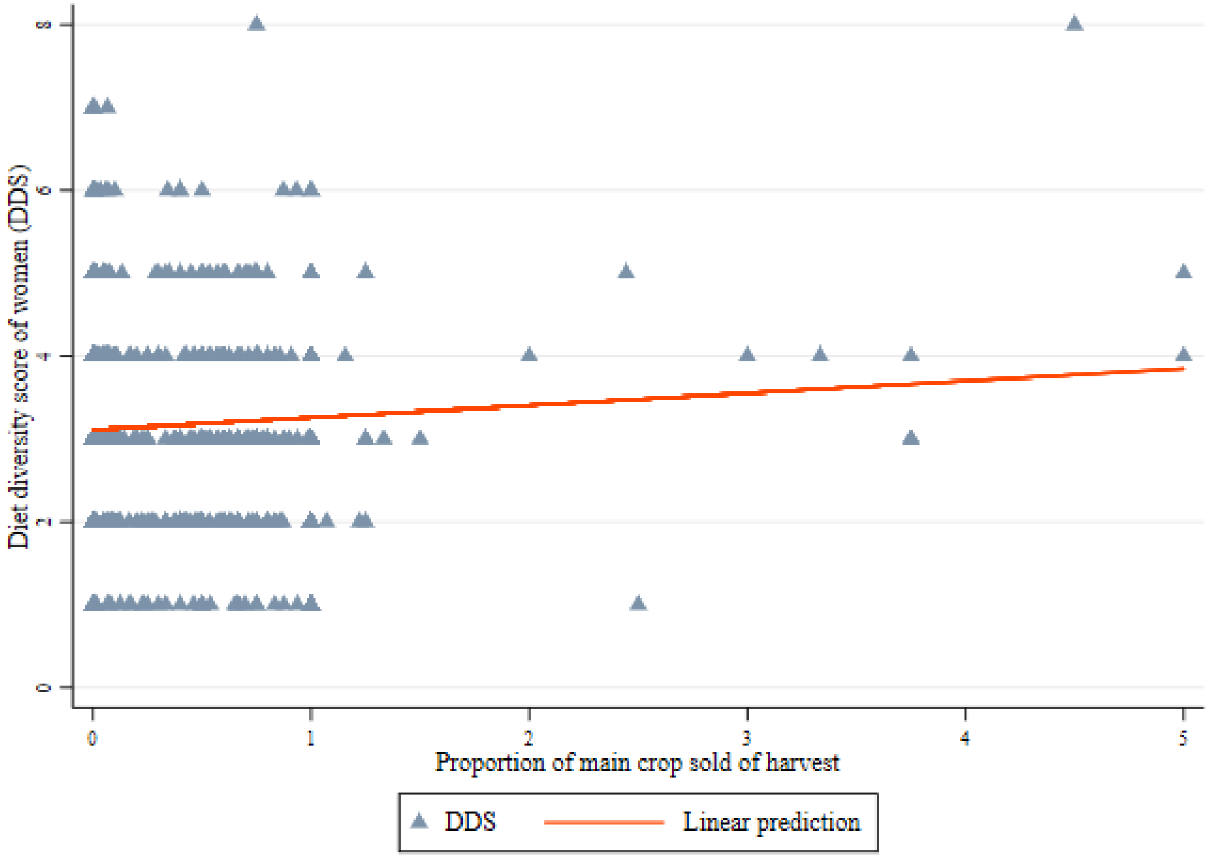
Sl No.	Asset	Sl No.	Asset	Sl No.	Asset
1	Stove / gas burner	11	Audio cassette / CD / DVD player	21	Weeding / harvesting machine / thresher
2	Refrigerator	12	Television	22	Motor pump for irrigation / water supply
3	Ceiling fan	13	Wall clock / watch	23	Wheelbarrow / pushcart
4	Table fan	14	Sewing machine	24	Tractor
5	Air cooler	15	Bicylce / cycle rickshaw	25	Spraying machine for water / sprinkler
6	Bed	16	Bullock cart	26	Blacksmith tools
7	Cot	17	Motorcycle / scooter / autorickshaw		
8	Chairs	18	Mobile phone		
9	Table	19	Landline phone		
10	Radio	20	Computer		

Figure C.3: **Chandrapur District In Maharashtra, India**



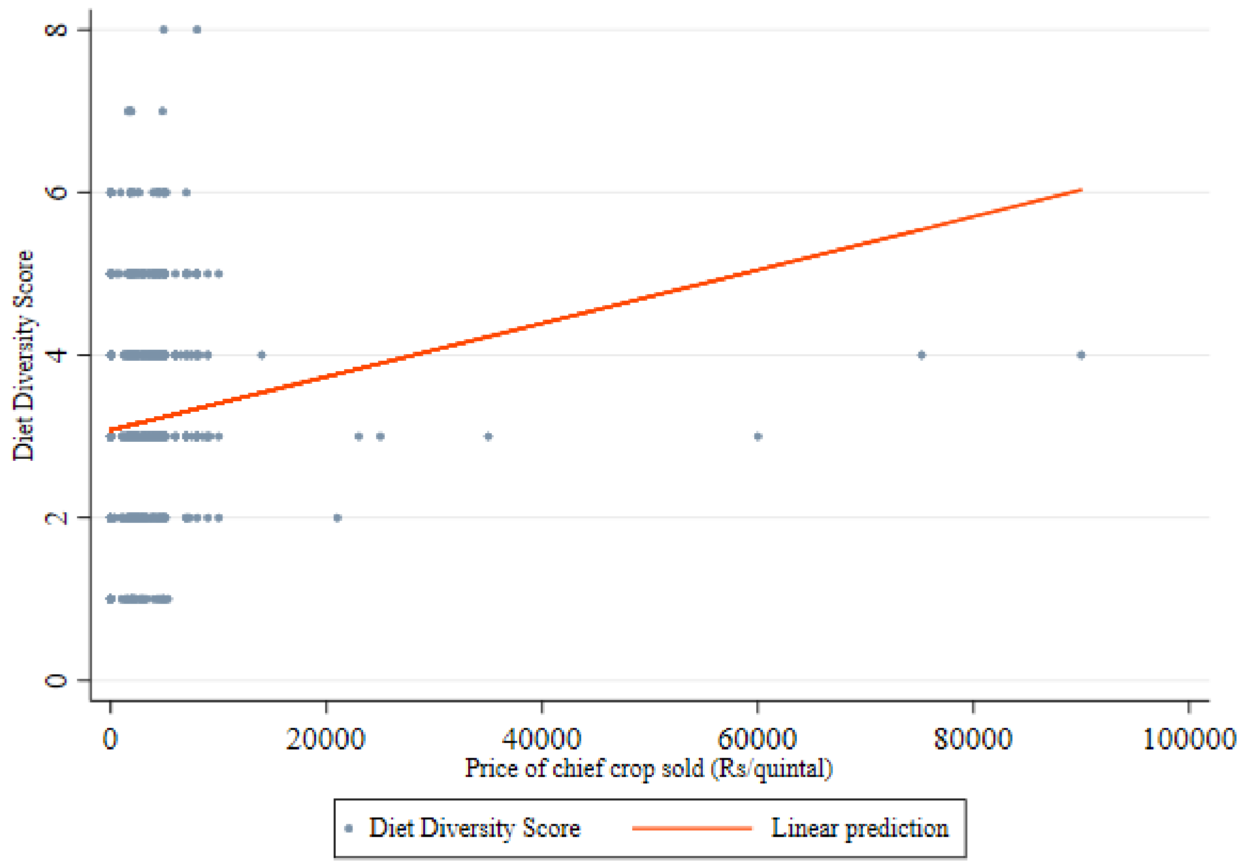
State of Maharashtra and Chandrapur district

Figure C.4: **Predicted Diet Diversity Score Using Market Orientation**



The X-axis measures the market orientation of each household as a proportion of the main crop sold out of the total amount harvested. The Y-axis is the predicted diet diversity score for the women of the household.

Figure C.5: **Predicted Diet Diversity Score Using Price Of Crop Sold**



The X-axis measures the price at which the main crop is sold by the household in rupees per quintal. The Y-axis is the linear predicted value of the diet diversity score for the women of the household.

Table C.2: Relationship Between Diet Diversity Score Of Index Woman And Price Received For Crop

Independent variable	Model 1	Model 2	**Model 3**	Model 4
Price of crop sold (Rs/kg)	0.003***	9.64e-04	**0.002***	0.002*
	(0.004)	(0.239)	**(0.068)**	(0.100)
Wage I [1]		0.107**		0.017
		(0.013)		(0.826)
Wage II		0.044	**-0.073**	-0.045
		(0.312)	**(0.371)**	(0.588)
Wage III		0.014	**0.224****	0.175*
		(0.786)	**(0.010)**	(0.080)
Wage IV		-0.104**		-0.207**
		(0.024)		(0.022)
Monthly remittance income (Rs)		-0.395***	**-0.444*****	-0.402**
		(0.000)	**(0.008)**	(0.016)
Monthly non - food expenditure (Rs)		-3.52e-06	**-4.47e-06**	-2.00e-06
		(0.523)	**(0.734)**	(0.879)
Asset index		.165***	**0.299****	0.253**
		(0.001)	**(0.014)**	(0.038)
HH growing cash crops		0.227***	**0.035**	-0.085
		(0.007)	**(0.910)**	(0.784)
HH growing food crops		-0.097	**0.553****	0.536***
		(0.340)	**(0.044)**	(0.050)
WEAI		-0.008***	**-0.011****	-0.010**
		(0.000)	**(0.012)**	(0.028)
HH Fixed Effects	Yes	No	**Yes**	Yes
Constant	3.08 ***	4.01***	**3.583*****	3.657***
	(0.000)	(0.000)	**(0.000)**	(0.000)
N	1428	1088	**1088**	1088
Number of groups	948	801	**801**	801
R - squared	0.017	0.165	**0.189**	0.205

The values in parentheses are the p-values. * denotes significance at 0.10; ** at 0.05; *** at 0.01

[1]Wages are paid for different agricultural activities differently. Here, the activities are I - planting, II - transplanting, III - manual weeding, IV - harvesting. The wages are collected as step functions with < Rs 100 == 1, Rs 100 - 125 == 2, Rs 125 - 150 == 3, and so on.

Figure C.6: **Price of Crop Sold Coefficient Estimate At 90, 95 & 99 % Confidence Intervals**

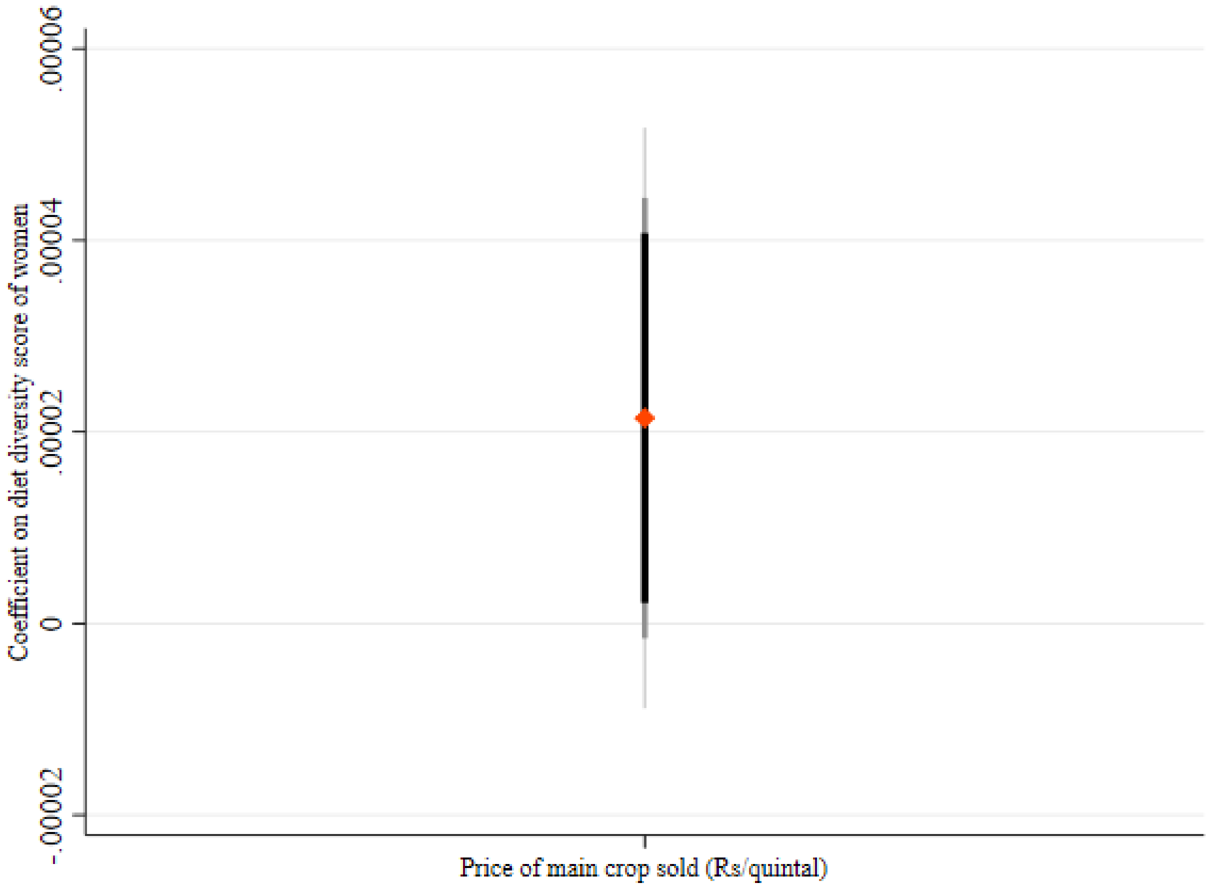


Table C.3: Income - Nutrition Pathway Disaggregated By Land Ownership

Independent variable	Land (≤ 3 *acres*)	Land (> 3 *acres*)
Price of crop sold (Rs/kg)	0.003*	7.43e-06
	(0.064)	(0.767)
Monthly remittance income	-0.156	-0.779***
	(0.589)	(0.003)
Wage transplanting	-0.1	-0.04
	(0.494)	(0.790)
Wage manual weeding	0.255*	0.193
	(0.095)	(0.214)
Monthly non - food expenditure (Rs)	-2.3e-05	1.15e-05
	(0.328)	(0.511)
Asset index	0.209	0.128
	(0.446)	(0.511)
HH growing cash crops	0.335	-0.213
	(0.482)	(0.764)
HH growing food crops	0.732*	0.657
	(0.077)	(0.251)
WEAI	-0.004	-0.018**
	(0.619)	(0.017)
HH Fixed Effects	Yes	Yes
Constant	2.522***	4.89***
	(0.006)	(0.000)
N	643	445
Number of groups	534	337
R - squared	0.194	0.225

The values in parentheses are the p-values. * denotes significance at 0.10; ** at 0.05; *** at 0.01

Figure C.7: **Coefficient Estimates Based On Land Ownership At 90, 95 & 99 % Confidence Intervals**

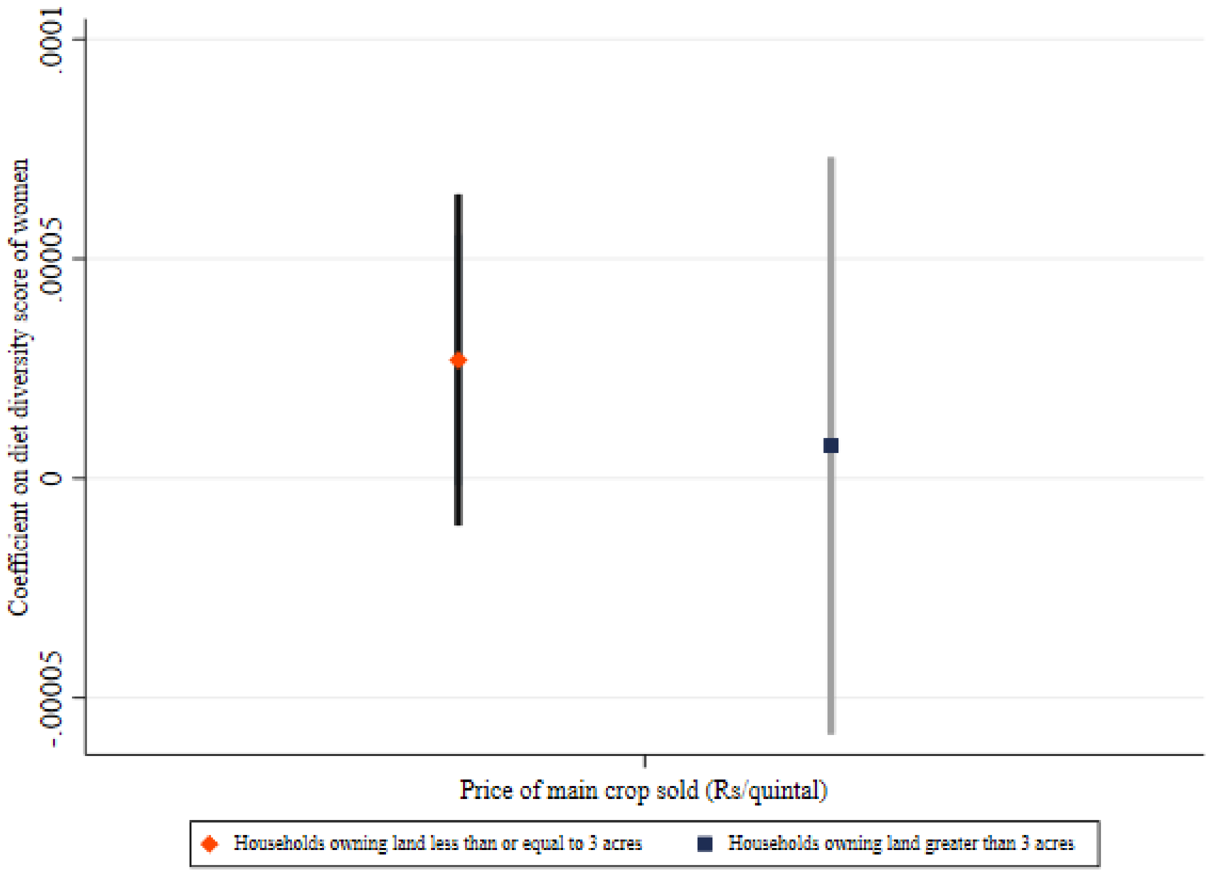


Table C.4: **Multinomial Logistic Regressions with DDS = 3 As Base Outcome**

Independent variable	DDS =1	DDS = 2	DDS = 4	DDS = 5	DDS = 6	DDS = 7	DDS = 8
Price of crop sold (Rs/kg)	-0.025**	-0.014**	6.65e-05	-0.007	-0.008	-0.045	0.044
	(0.043)	(0.018)	(0.647)	(0.232)	(0.539)	(0.319)	(0.328)
Monthly remittance income	0.572*	0.366*	-0.319*	-.367	-1.262***	-1.231	-27.381
	(0.088)	(0.069)	(0.088)	(0.118)	(0.001)	(0.297)	(0.978)
Wage transplanting	-.003	-0.014	0.102	.307**	-.091	-.117	-.591
	(0.986)	(0.891)	(0.305)	(0.019)	(0.681)	(0.919)	(0.433)
Wage manual weeding	-0.419**	-0.63	0.171*	-.234*	.104	-.666	1.258
	(0.025)	(0.562)	(0.100)	(0.086)	(0.631)	(0.558)	(0.182)
Monthly non - food expenditure (Rs)	-4.93e-08	1.3e-05	-3.50e-06	3.55e-06	-4.2e-05	2.1e-05	-6.5e-05
	(0.998)	(0.262)	(0.812)	(0.836)	(0.424)	0.540	(0.782)
Asset index	-0.097	-0.222*	0.048	.179	.378*	.957**	1.017
	(0.638)	(0.079)	(0.664)	(0.177)	(0.098)	(0.046)	(0.325)
HH growing cash crops	-0.445	0.058	.109	.888***	-.323	.063	29.922
	(0.309)	(0.808)	(0.559)	(0.003)	(0.559)	(0.966)	(0.986)
HH growing food crops	0.279	0.524**	.323	-.037	-.604	19.058	14.139
	(0.425)	(0.034)	(0.205)	(0.910)	(0.218)	(0.999)	(0.998)
WEAI	0.012	0.002	-.009*	-.019***	-.009	.003	-.124
	(0.167)	(0.713)	(0.072)	(0.006)	(0.484)	(0.928)	(0.218)
Constant	-2.331**	-0.873	.106	.163	.510	-21.876	-20.384
	(0.016)	(0.150)	(0.857)	(0.823)	(0.662)	(0.999)	(0.997)

N : 1088. The values in parentheses are p values. *** p < 0.01, ** < 0.05, * < 0.10

Table C.5: **Regressions Between Iron Availability And Income**

Independent variable	
Price of crop sold (Rs/kg)	-2.52e-04
	(4.93e-04)
Monthly remittance income	-0.007
	(0.745)
Wage transplanting	-0.046
	(0.361)
Wage manual weeding	0.169
	(0.375)
Monthly non - food expenditure (Rs)	-2.31e-04
	(5.55e-04) height
Asset index	1.578***
	(0.543)
HH growing cash crops	-0.516
	(1.372)
HH growing food crops	0.679
	(1.169)
WEAI	-0.042**
	(0.02)
Constant	7.266***
	(2.307)
HH FE	height

N : 1000

R^2 : 0.011

The values in parentheses are p values. *** p < 0.01, ** < 0.05, * < 0.10

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