Three Topics in Applied Economics

by

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A dissertation submitted to the Graduate Faculty of
Auburn University
in partial fulfillment of the
requirements for the Degree of
Doctor of Philosophy

Auburn, Alabama
December 8, 2021

Keywords: Financial Literacy, Financial Inclusion, Poverty, Production, Beginning Farmers and Ranchers, Barriers to Entry

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Abstract

This dissertation consists of three different chapters. The first chapter sheds the light on the association between financial literacy and financial inclusion; financial literacy and poverty in India during the period 2016 and 2017. The second chapter analyses the impact of National Food Security Mission on the production and yield of rice in India. The last chapter determines the factors that affect the entry and survival of beginning farmers, young, and women farmers and ranchers.

Chapter 1 investigates the relationship between financial literacy and poverty; and financial literacy and financial inclusion in respect of India during the period 2016 and 2017 by employing the probit model and fixed effects model at the individual level and the district level, respectively. To control simultaneous biasness, numeracy (measure of basic math skill) as an instrument for financial literacy has been employed. The marginal effects at median of IV-Probit model reveal that financial literacy seems to be positively associated with the likelihood of having an account in bank, but the result is less clear about the likelihood of being above poverty line.

The aim of Chapter 2 examines whether the implementation of National Food Security Mission (NFSM) led to increase the production and yield of rice or not. In the recent time, India has experienced a fall in the yield and production of rice due to water logging, salinization etc. In aspect of demand, it is expected that India's population will reach to 1.4 billion by year 2020 and the demand of rice will also rise. To lessen the gap between demand and supply of rice, National Development Council (NDC) launched National Food Security Mission (NFSM) to increase the production and yield of rice. Therefore, this study examines the impact of NFSM on the production and yield of rice at the district level in India by employing Propensity Score

Matching procedure. The results show that adoption of NFSM had a significant impact on increasing the production of rice, however, not on the yield of rice.

Chapter 3 reviews the determinants that affect the entry and survival of beginning, young and women farmers and ranchers by employing fixed effect model at the county level in United States for the period 1997-2017. The results suggest that entry of BFRs increase with number of farm operations, lower farm productivity, availability of more and small size of farms, farmland prices, benefits from insurance and availability of part time farming opportunities. Results also indicate that the high capital intensity nature of farming is a predictable obstruction for the entry of BFRs. The availability of non-real estate increases the net entry, while real estate decreases the net entry and survival of BFRs.

Acknowledgments

First and foremost, this dissertation is the result of guidance from Dr. Valentina M. Hartarska, Alumni Professor at Department of Agricultural Economics and Rural Sociology. It would have not been possible without her supervision, efforts, and generosity. She has gone out of the way to help me draft the essays.

I am incredibly grateful to Dr. Denis A. Nadolnyak for serving as co-advisor. His critical comments on the essays helped me to delve deep into the economic theories. My deep appreciation also goes to my Dr. Ruiqing Miao and Dr. Jitka Hilliard for their support and constructive advice all along. I am incredibly grateful to Department of Agricultural and Rural Sociology for financial support.

My sincere thanks to Dr. George Flowers, Professor, Dean of Graduate School for providing me with Graduate Fellowship during the first two years of my study at Department of Economics at Auburn. My special thanks to Dr. Ashutosh Mishra, Professor, Department of Mechanical Engineering for providing moral support during tough times.

I am also thankful to my parents who helped me to reach from a patriarchal agricultural household in rural India to Auburn University, Alabama in USA. I belong to a family where land size is less than one hectare but their vision and moral to educate the girl child is extraordinary. Especially, I am thankful to my brother, Amit Sehrawat, as, without his valuable guidance during the initial stages of admission and strong support throughout the Ph.D. program, it would have not been a successful journey. Their support has helped me to become the First Ph.D. in my family.

Finally, I am incredibly grateful to friends in Auburn and whole Auburn family for the culture, society, diversity, traditions, and the American Dream.

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List of Abbreviations

AFCL	Agriculture Finance Corporation Limited
ATE	Average Treatment Effect
ATT	Average Treatment of the Treated
BEA	Bureau of Economic Analysis
BFRs	Beginning Farmers and Ranchers
BLS	Bureau of Labor Statistics
COA	Census of Agriculture
DFSMEC	District Food Security Mission Executive Mission
ERS	Economic Research Service
FCS	Farm Credit System
FDIC	Federal Deposit Insurance Corporation
FEMA	Federal Emergency Management Agency
GC	General Council
GDP	Gross Domestic Product
NABARD	National Bank for Agriculture and Rural Development
NASS	National Agriculture Statistics Service
NDC	National Development Council
NFSA	National Food Security Act
NFSM	National Food Security Mission
NOAA	National Oceanic and Atmospheric Administration
NSP	National State Domestic Product

OECD	The Organization for Economic Co-operation and Development
OGD	Open Government Data
PPI	Progress Out of Poverty Index
PSM	Propensity Security Mission
SFSMEC	State Food Security Mission Executive Mission
SRI	System of Rice Intensification

Chapter 1 Impact of Financial Literacy on Poverty and Financial Inclusion: Evidence from India

Introduction

In the last two decades, empirical research on financial literacy in both developed and developing countries has gained momentum (see, e. g., Atkinson et al., 2007; Buckland 2010; Vieira 2012). The Organization for Economic Co-operation and Development (OECD) defines financial literacy as "a combination of awareness, knowledge, skill, attitude and behavior necessary to make sound financial decisions and ultimately achieve individual financial wellbeing" (INFE 2011). A person is financially literate if he/she has an understanding of three or more financial concepts out of four: numeracy (interest rate), compound interest rate, inflation and risk diversification (S&P Rating Literacy Survey).

Financial illiteracy is widespread among different sections of the population i.e. women, elderly, minorities and people with lower education (S&P Rating Literacy Survey; Lusardi and Mitchell 2006). It is an important tool for developing innovative financial products like mobile money (refers to transfer funds between accounts, paying bills via mobile), e-wallet, credit, microinsurance, saving, etc. These innovative products have positive impact on people' financial well-being (Aggarwala et al., 2014), strengthening microinsurance market (Biener, Eling, and Schmit, 2014) and economic growth (Ghosh and Vinod, 2017). The Standard & Poor's literacy survey, however, reveals that only 33% of the adult population across the world is financially literate.

India is the second most populous country in the world with approximately 1.35 billion inhabitants in 2018 (United Nations Department of Economic and Social Affairs 2018). However, barely 17% of the adult population in India is familiar with basic financial concepts for making sound financial decisions (Financial Inclusion Insight Survey 2016). The low level of financial literacy places a barrier on India’s economic growth (Ghosh and Vinod, 2017). The 2017 Global Findex Database, however, reveals that India is the home to the second largest unbanked adult population (approximately 191 million) in the world. The Planning Commission Draft Ninth Five Year Plan (1997-2002) estimated that the percentage of people below the poverty line has declined from 54.9 in 1973-74 to 26.9 in 1999-2000. However, the World Bank Report (2015) reveals that even though the extreme poverty rate in India is relatively low at 13.4%, this represents a significant proportion of poor people i.e. approximately 176 million people. With the widespread use of innovative financial products, financial literacy has become important. Financial literacy has the potential to help people to use more of financial products and to exit from poverty trap by making better financial decisions.

In this context, existing literature reveals that most of the empirical research on financial literacy has focused on either evaluating financial literacy levels among different demographic and socio-economic groups (e.g., Lusardi et al. 2009, Lusardi and Mitcell 2011; Rooji, Lusardi and Alessie, 2011) or measuring the impact of financial literacy on agent’s financial behavior such as retirement, investing in stock market, buying home, liability choice, insurance policies (Vieira, 2012; Grohmann, 2018; Baidoo et al., 2008; Brown and Graf 2012; Aggarwal et al., 2015). For e.g., Aggarwal et al. (2015) finds that one-point increase in financial literacy would correspondingly increase the number of goals of investment, liability choice and insurance policies. Several studies have also investigated the impact of financial literacy on wealth accumulation and household savings (e.g., Hastings and Mitchell, 2011; Beckmann, 2013; Brown and Graf, 2012; Lsuradi and Michell, 2011).

In the literature pertaining to financial literacy and financial inclusion, the link between financial literacy and financial inclusion has also been studied. Grohmann, Kluhs and Menkhoff

(2018) studied whether financial literacy improves financial inclusion at the country level in 2014. Their results suggested that one percentage point increase in financial literacy would increase the account ownership by 0.511 percentage points and use of debit cards by 0.518 percentage points. Baidoo et al. (2018) found that the probability of saving increases by 2.3 percentage points if one additional fundamental financial literacy question was answered correctly in Ghana. Berry, Karlan and Pradhan (2018) evaluated the impact of financial literacy education programs (Aflatoun and Honest Money Box program) in Ghana on saving behavior and found that program had significant impact on self-reported saving at the school but had no significant impact on aggregate saving.

Few studies have also focused on the endogeneity of financial literacy. Berhman et al. (2012) analyzed the relationship between financial literacy and wealth accumulation in Chile by using observed personal characteristics as an instrument to avoid the problem of biasness created by measurement error and unobserved factors. The result suggested that financial literacy had a positive significant impact on wealth accumulation by employing an IV estimator. Grohmann (2018) used childhood roots as an instrument to analyze the impact of financial literacy on financial behavior (i.e. saving decision and borrowing decision) of middle-class people in emerging Asian countries. Christiansen et al. (2008) explored the impact of economists on decision relating to stock market participation by using opening of new university as an instrument to deal with endogeneity arising from unobserved variables. Jappelli and Padula (2013) looked at the impact of financial literacy on wealth measured by real and financial assets and used the stock of financial literacy in early life as an instrument to avoid the reverse causality between financial literacy and wealth accumulation. Despite the presence of literature on the link between financial literacy and financial inclusion, the topic has not been studied for the case of India. Therefore, the first main purpose of this paper is to study the association between financial literacy and financial inclusion in India.

In the literature pertaining to poverty, the headcount rate for rural poverty declined from 1987 to 1999 (for e.g., Deaton and Drèze 2002; Kijima and Lanjouw 2005; Panagariya and More 2014). Researchers have explored the impact of financial inclusion on poverty, but the results are mixed. Some scholars found the impact of financial depth i.e. private credit (measured by the ratio of credit and GDP) on poverty reduction to be significant (Jalilian & Kirkpatrick, 2005; Beck, Kunt & Levine, 2007; Akhter and Daly 2009; Chibba 2009; Beck, Levine, and Levkov, 2010; Bruhn and Love, 2013). However, Honohan (2008) could not establish a strong relationship between use of financial services (i.e. having an account in bank) and poverty alleviation. To the best of my knowledge, the relationship between financial literacy and poverty has not been explore adequately. Therefore, I try to address this gap by studying the direct link between financial literacy and poverty.

The objective of the paper is to test two hypotheses using household-level and district-level data for India. First, financial literacy is associated with improved financial inclusion as measured by having a saving account in the bank. Second, financial literacy is associated with a higher probability of being above poverty line (defined as household earnings above $1.25 per day). The hypotheses are tested at both the individual (household) and district level. In addition, both the hypothesis are also tested by using numeracy as an instrument at both the individual and district level to deal with the problem of financial literacy being endogenous. Numeracy is a measure of basic mathematical skills and has the following components: counting, addition, subtraction, multiplication and division. Therefore, this paper aims to fill the gap in the literature by empirically exploring (1) the link between financial literacy and financial inclusion; and (2) the relationship between financial literacy and poverty in India.

To test the hypothesis, I have used the probit model at the individual level and fixed effects model at the district level to analyze the effect of financial literacy on financial inclusion and poverty. The marginal effects at median of IV-Probit model reveal that financial literacy seems to be positively associated with the likelihood of having an account in bank, but the result is less clear about the likelihood of being above poverty line. At the individual level, more financial literate people are more likely to be above poverty lines. However, Indian districts with higher level of financial literacy of its people do not seem to have higher proportion of people above poverty line.

The remainder of the paper is organized as follows. Section 2 describes the source of the data and descriptive summary for the explanatory variables and outcomes. Section 3 represents the empirical framework to analyze the impact. Section 4 and 5 presents the results of the regression and the conclusion, respectively.

Data

I have employed the data from Financial Inclusion Insight (FII) Survey Programs, Intermedia and from Reserve Bank of India's official website for the year 2016 and 2017. FII survey targeted the adult population i.e. people aged 15 and older. The data can be accessed by filling the application of data request on their official website. The survey was conducted all over India, except one state (Jammu and Kashmir) and two union territories (Andaman-Nicobar islands and Lakshadweep). The seven North-Eastern states (Arunchal Pradesh, Manipur, Meghalaya, Mizoram, Sikkim, Nagaland and Tripura) are considered as one cluster for sampling purposes. FII Survey provides the information on the financial literacy, bank account ownership, non-bank financial institutions, loan, financial behavior, poverty, financial literacy, numeracy, marital status, education, literacy, household characteristics, assets, etc. I have also used data on statistics on bank branches in district, inflation rate, Net State Domestic Product (NSP) per capita, government expenditure on education and length of district roads from Reserve Bank of India's official website.

In the sampling frame, each town was classified into five classes and village was classified into three classes based on the population size. Town Class 1 had more than 4 million population, Town Class 2 had 1 to 4 million people, Town Class 3 had 0.1 to 1 million people, Town Class 4 had 0.05 to 0.1 million people and Town Class 5 had less than 0.05 million people. Village Class 1 had more than 3,000 population, Village Class 2 had between 1,000 and 3,000 population and Village Class 3 had less than 1,000 population. The sample was a stratified multistage sample. In the first stage, towns and villages were selected as primary selection unit with probability proportional to population size and, excluded villages with less than 50 households. In the second stage, a ward was selected in the sampled town and a pooling station was selected in each sampled ward. In the fourth stage, 10 households were selected using the random walk methodology in both urban and rural areas. In the last stage, one adult household was selected from the selected households using the Krish grid (which ensured that each adult household has the equal probability of getting selected).

In the sample, poverty line is defined by using Grameen Foundation's Progress out of Poverty Index (PPI). This approach is based on 10 indicators that are highly correlated with poverty to determine whether the household's per capita consumption is above $1.25 or not. The indicators are mentioned in Appendix. It is an easy and low-cost method to measure poverty. The indicators are pervasive in nature and applicable throughout India.

<Table 1.1 here>

Table 1.1 represents the descriptive statistics at the individual level and the district level. My sample size consists of 92,672 individuals with 518 districts. Column 2 and 3 represents mean and standard deviation, respectively at the individual level. While, Column 5 and 6 represents mean and standard deviation, respectively at the district level. Approximately, 17 percent people have answered four or more financial literacy questions correctly at both individual and district level. In the sample, 53% respondents are female and just 7% of females answered four or more financial literacy-based questions correctly. Approximately, 23 percent, 36 percent, 8 percent and 7 percent have completed the primary school (represents class 1 to 8), secondary school (represents class 9 to 10), senior secondary school (represents class 10 to 12) and under-graduation at the individual level, respectively. While, 23 percent, 35 percent, 7 percent and 5 percent have completed the primary school, secondary school, senior secondary school and under-graduation at the district level, respectively. Approximately, 68 percent and 80 percent people lived in rural area at the individual level and district level, respectively. At both levels, the average age of the respondents and household size are approximately 38 years old and 4.6 people, respectively. The average inflation rate was around 4.2%. Approximately, half of the respondents and three-fourth of them were head and married, respectively. The average number of branches are 385 and 350 at the individual level and at the district level, respectively. The average of bank branches per 100,000 persons are 14.209 and 17.73 at the individual level and district level, respectively.

Approximately, 17% of the respondents are earning above $1.25 per day at the individual level as well as the district level. Around 39% and 35% of the people have the ownership of saving account in bank at the individual level and at the district level, respectively.

Empirical Model

The index for financial literacy is constructed by following the approach of S&P Rating Literacy Survey. According to S&P Rating Literacy Survey, a person is said to be financially literate if he/she has an understanding of three or more financial concepts out of four: numeracy (simple interest rate), compound interest rate, inflation and risk diversification. The index for financial literacy is constructed by following questions:

Numeracy (Simple Interest Rate): "If a person has Rs. 1,000 in a saving account and the bank adds 10 percent interest rate per year. After 5 year, how much will be there in the account if no money is withdrawn from the account?"

Compound Interest Rate: "If a person has some money in the bank and gets 15 percent interest rate per year. Will the bank give more, less or same money in the second year as compared to the first year?"

Inflation: "Suppose the price of the things double in the next 10 years and income doubles. Will you buy more, same or less than what you buy today?"

Risk Diversification: "A person should invest into one or into multiple business or investments?"

If a person answers three or more questions correctly, then the indicator value for financial literacy is 1, otherwise it takes the value of 0. These questions measure the level of financial knowledge, awareness, skill, attitude and behavior to make well-behaved financial decisions

(OECD). These questions are common for all the studies and all over the world with a little variation. For e.g., Lusardi and Mitchell (2011) created the index based on 3 questions, instead of 4 questions. They excluded the numeracy from the set of financial literacy questions.

First, the relationship between financial literacy and financial inclusion is examined by the following probit model at the individual level:

$$Pr(FI_i=1)=\phi(\boldsymbol{\beta}_1 FL_i + \boldsymbol{\beta}_2 Access_i + \boldsymbol{\beta}_3 X_{3i} + u_i) \qquad \textbf{(1)}$$

where, FI_i represents whether an individual 'i' is financially included or not, FL represents whether 'i' individual is financially literate or not, X_{3i} represents other covariates like married, rural, household size, education level, education expenditure per 100,000 individuals, inflation rate etc. and ϕ stands for standard normal cumulative distribution function. The variable 'access' is measured by the number of bank branches in a district. Financial inclusion is measured by whether a person has a saving account in a bank or not. Saving account is different from checking account because saving accounts offers interest rate on the amount deposited in the bank. While, checking account does not provide the facility of interest rate. Moreover, saving account encourages people to save and checking account is meant for daily basis transactions. Zinsa and Weill (2016) states that owning a bank account that allows borrowing, saving or using as payment services in formal financial institution is considered as financial inclusion with respect to a person.

Second, the relationship between financial literacy and being above poverty line is studied at the individual level. The following probit model is used to measure the impact at the individual level:

$$Pr(Poverty_i = 1) = \phi(\boldsymbol{\beta}_1 FL_i + \boldsymbol{\beta}_2 S.A._i + \boldsymbol{\beta}_3 Access_i + \boldsymbol{\beta}_4 X_{4i} + u_i) \qquad \textbf{(2)}$$

where, $Poverty_i$ represents whether an individual 'i' is above poverty line or not, FL represents whether 'i' individual is financially literate or not, $S.A._i$ represents percentage of ownership of a saving account in district 'd' in which individual 'i' resides, X_{3i} represents other covariates like head, household size, education level, female, graduate, education expenditure per 100,000 individuals, inflation rate etc. and ϕ stands for standard normal cumulative distribution function. A person is considered to be above poverty line, if he/she is earning above \$1.25 per day. If a person is earning above \$1.25 per day, it takes the value of 1 and zero, otherwise. I have reported the marginal effects at median in the results.

I have employed fixed effect model to examine the effect of differences in financial literacy on the outcome variables at the district level. The individual level data does not allow to control for unobservable fixed effects since different respondents answered in 2016 and 2017. By employing the fixed effect with the district level data, unobservable differences across districts can be controlled. This helps to explore variations in change in poverty and financial inclusion. The following equation explores the fixed effect model at the district level:

$$\ddot{Y}_{d,t} = \alpha_d + \boldsymbol{\beta}_1 \ddot{FL}_{d,t} + \boldsymbol{\beta}_2 \ddot{Access}_{d,t} + \boldsymbol{\beta}_3 \ddot{X}_{3d,t} + \ddot{u}_{d,t} \qquad \textbf{(3)}$$

where, $\ddot{Z}_{d,t} = Z_{d,t} - \bar{Z}_t$ for any $Z \in \{Y, FL, Access, X, u\}$. α_d represents the district effects, $Y_{d,t}$ represents the average of outcome variables for 'd' district at time 't', $FL_{d,t}$ represents the average number of financial literate individuals for 'd' district at time 't', $X_{3d,t}$ represents average of other covariates for 'd' district level at time 't'. The outcome variable measures the average number of people above the poverty line in a district 'd' at time 't' and average number of people having a saving account in bank in a district 'd' at time 't'. However, an extra variable i.e. $(S.A.)_{d,t}$ (represents percent of people own a saving account in a district 'd' at time 't') is included to analyze the relationship between financial literacy and poverty. This variable tries to control for omit biasness for poverty.

The relationship between financial literacy and the outcome variables may suffer from simultaneous causality. In order to deal with simultaneous causality, an instrument variable approach is applied. The variable ‘numeracy’ (a measure of basic math skills) is used as an instrument for financial literacy. Numeracy consists of following components: counting, addition, multiplication and division. I believe that numeracy is a good instrument for financial literacy because of the following two reasons. First, numeracy and financial literacy are highly correlated because financial literacy related questions are basically based on the basic math i.e. addition, subtraction, multiplication and division. Numeracy skills consist of counting, addition, multiplication and division and are a prerequisite for financial literacy. So, a person needs to have good understanding of primary mathematics to correctly answer the financial literacy-based questions. For example, to answer the inflation-based question, a person needs to know counting, addition and division. Counting, addition and division are components of basic numeracy. Therefore, if a person has good numeracy skills, then he/she would also have a good understanding of financial literacy concepts. Second, I also believe that numeracy does not directly affect outcome variables (i.e. financial inclusion and poverty). Having good skills in numeracy does not help a person to have saving account ownership in the bank (saving account is a measure of access and supply side) and being above the poverty line. Moreover, a person needs to have an access to bank for opening an account in the bank. Therefore, numeracy affects the outcome variables only through the channel of financial literacy. Grohmann (2018) and Sekita (2011) used numeracy as an instrument to control for endogeneity of financial literacy.

The following equation encounters with simultaneous problem for outcome variable i.e. financial inclusion at the individual level:

$$FL_i = \alpha_1 Numeracy_i + \alpha_2 Access_i + \alpha_3 X_{3i} + e_i \qquad \textbf{(4)}$$

where, numeracy is a binary variable. If a person is numerate, it takes the value of 1 and zero, otherwise.

The following equation deals with simultaneous causality for financial inclusion at the district level:

$$\ddot{FL}_{d,t} = \alpha_1 \ddot{Numeracy}_{d,t} + \alpha_2 \ddot{Access}_{d,t} + \alpha_3 \ddot{X}_{3d,t} + \ddot{e}_{d,t} \qquad \textbf{(5)}$$

where, $\ddot{Z}_{d,t} = Z_{d,t} - \bar{Z}_t$ for any $Z \in \{FL, Numeracy, Access, X, e\}$.

The association between poverty and financial literacy suffers from an additional endogeneity because variable '*S.A.*" is related with financial literacy. Length of district road is taken as an instrument for variable 'percent of people own a saving account in a district.' Length of district road is not a weak instrument because of following two reasons. First, saving account and length of district road are highly correlated because paved roads make an easy access for individuals to approach a bank and get an account opened in bank. Mandira and Pais (2011) suggested that a good network of roads would encourage the bank/government to open new branches, especially in the rural and less populated areas. Secondly, length of district road is not directly related to poverty because paved roads reduce poverty and unemployment in the same fiscal year in which they are constructed by offering more employment opportunities. After few years, however, the impact of paved roads on poverty alleviation disappear. So, existing length of district road is not directly related with poverty.

The following equations deal with the endogeneity problem of financial literacy and percentage of ownership of a saving account in district 'd' in which individual 'i' resides (i.e.

$S.A._i$) by employing numeracy and length of district roads as instruments, respectively, for being above poverty line at the individual level:

$$FL_i = \alpha_1\, Numeracy_i + \alpha_2 (Length)_i + \alpha_3\, (Access_i) + \alpha_4 X_{4i} + e_i \qquad \textbf{(6a)}$$

$$(S.A.)_i = \alpha_1\, Numeracy_i + \alpha_2 (Length)_i + \alpha_3\, (Access_i) + \alpha_4 X_{4i} + e_i \qquad \textbf{(6b)}$$

where, length represents the length of road in district 'd' in which individual 'i' operates. It is measured in kilometers.

The following equation tries to control for endogeneity for outcome variable i.e. being above poverty line at the district level:

$$\boxed{\ddot{FL}}_{d,t} = \alpha_1 \boxed{Num\ddot{e}racy}_{d,t} + \alpha_2 \boxed{(Le\ddot{n}ght}_{)d,t} + \alpha_3 \boxed{Ac\ddot{c}ess}_{d,t} + \alpha_4 \boxed{\ddot{X}}_{4d,t} + \boxed{\ddot{e}}_{d,t}$$

(7a)

$$\boxed{S.\ddot{}A.}_{d,t} = \alpha_1 \boxed{Num\ddot{e}racy}_{d,t} + \alpha_2 \boxed{(Le\ddot{n}ght}_{)d,t} + \alpha_3 \boxed{Ac\ddot{c}ess}_{d,t} + \alpha_4 \boxed{\ddot{X}}_{4d,t} + \boxed{\ddot{e}}_{d,t} \qquad \textbf{(7b)}$$

where, $\boxed{\ddot{Z}}_{d,t} = Z_{d,t} - \boxed{\bar{Z}}$ for any $Z \in \{FL, Numeracy, Length\ of\ road, Access, X, e\}$.

Result

This section represents the main results for regressing the financial literacy on financial inclusion and poverty at the individual level and at the district level.

<Table 1.2 here>

Table 1.2 reports marginal effects at median of regressing the financial literacy on financial inclusion at the individual level for Probit model and IV-Probit model. Column 1 represents the marginal effect at median of regressing financial literacy on saving with bank using Probit model. The marginal effect at median of financial literacy is 0.064 suggesting that the probability of ownership of saving account is 0.064 higher for financial literate individuals as compared to those who are not financial literate, when all other variables are at their marginal effect at median value. This finding about the impact of financial literacy on having saving account in bank is in consistent with existing literature (e.g. Grohmann, 2018; Brown and Graff, 2012; Baidoo et al. 2018). The marginal impact at median of education, NSP per capita, household size, age, head are positive and significant at 1 percent level of significance. The estimate of female suggests that probability of owning a saving account is 0.027 lower for females as compared to males. Ghosh and Vinod (2017) found that male headed households are significantly more likely to have access to formal saving institutions in comparison to households with female headed. The marginal impact of rural at median suggests that people who live in rural are more likely to be financially excluded. The marginal effect at median for government education per 100,000 people is also significant. The coefficient of inflation suggests that it is not associated with ownership of account.

Column 2 explores link between financial literacy and a saving account ownership in bank using numeracy as an instrument. Stock-Yogo F-stat for weak instrument is 16.38 that is above from the thumb rule i.e. 10. From Stock-Yogo result, it can be concluded that numeracy is not a weak instrument. The probability of owning a saving account is 0.65 higher for financial literate individuals. The marginal effect of financial literacy at median is quite large with the use of instrument as compared to marginal effect of financial literacy at median in Column 1. However, the impact of education, except secondary school and female have become insignificant. This is in consistent with Grohmann, Kluhs and Menkhoff (2018) found that completion of senior secondary and graduate education is not likely to impact the decision of saving at formal institution. The rest of the covariates, except rural remain positively significant at 1% level of significance. In addition, the marginal effect of branches per 100,000 people remains insignificant.

<Table 1.3 here>

Column 1 and 2 in Table 1.3 reports marginal effects at median of regressing the financial literacy on poverty at the individual level for Probit model and IV-Probit model, respectively. The main variable of interest 'financial literacy' is not associated with probability of being above poverty level. The marginal effect at median on secondary school and senior secondary school take value of .014 and 0.024, respectively. The probability for being above poverty line is .014 and 0.02 greater for the individuals who completed their secondary school and senior secondary school, respectively, when other variables are at their median value. However, the marginal impact of graduation at median is insignificant. The marginal effect of rural at median suggests that individuals who live in rural areas are more likely to be below the poverty line. However, head is having insignificant impact on the probability of being above poverty line. In addition, the marginal effect of female and percent of ownership of saving account in district at median are also insignificant. The negative sign of Log NSP per capita might suggest that there is an increase in the income of only rich or middle-class families, not of the poor families. The marginal effect at median of government education expenditure per 100,000 persons implies that one unit increase in education expenditure per 100,000 persons is associated with 0.06 increase in the likelihood of being above poverty line. The marginal effect at median of age and branch per 100,000 persons is negatively significant at 1 percent but very small.

In Table 1.3, Column 2 represents the marginal effect at median for the probability of being above poverty line using IV-Probit model. The first stage regression model represents that one unit increase in numeracy increases the financial literacy by 0.147 percent point. Stock-Yogo F-stat for weak instrument is approximately 19.93 that is above from the thumb rule i.e. 10.

Therefore, numeracy and length of road are not weak instruments. As compared to Column 1, the marginal effect of financial literacy at median becomes large as well as significant. The probability of being above poverty line is 0.230 higher for financially literate individuals, when other variables are at their median value by employing instruments. The marginal impact at median of percentage of ownership of saving account in district suggest that it is negatively related with probability of being above poverty line. However, the marginal effect at median is too small. The marginal effect at median of education, branch, NSP per capita and head are not significantly associated with the probability of being above poverty. As compared to the marginal effect at median of Column 1, the marginal effect of government education expenditure at median does not change much.

In the poverty model, financial literacy might have indirect effect on likelihood on being above the poverty line. Table A1.8 explores the indirect effect of financial literacy on likelihood on being above poverty line through percentage of ownership of saving account in district. Column 1 and 2 explore the indirect link between financial literacy and poverty with the use of instrument and without the use of instrument, respectively. In both Columns, the coefficient of indirect effect is insignificant which states that no indirect link exists between financial literacy and poverty. From this, it can be suggested that banking the unbanked poor people would not be an effective strategy to alleviate or reduce poverty.

<Table 1.4 here>

Table 1.4 explores the link between financial literacy and financial inclusion at the district level. Specification 1 explores link between financial literacy and a saving account ownership in bank using fixed effects model. The point estimate of financial literacy is significantly associated with ownership of a saving account in bank, other things being constant.

This point estimate implies that one unit increase in average number of financial literate people lead to increase in the average rate of saving account by 0.30. The point estimates of log NSP per capita suggests that one percent increase in NSP per capita significantly increases the average rate of a saving account ownership in bank by 0.11 at 1% significance level. Coefficient of female and age are negatively significant. The estimate of head and inflation are positively associated with ownership of account.. The coefficients of education except graduate suggest that they are not associated with ownership of account. In addition, other covariates do not seem to have any relationship with ownership of saving account.

Column 2 explores the relationship between financial literacy and ownership of saving account by using an instrument numericity (average for the district) at district level. The F-stat for weak instrument is 16.88. This leads to the conclusion that numeracy is not a weak instrument. The impact of financial literacy becomes large on the average rate ownership of saving account in bank at the same significant level as compared to Column 1. This finding about the impact of financial literacy on financial inclusion is in consistent with existing literature (e.g., Grohmann; Grohmann, Kluhs and Menkhoff, 2018). The use of instrument enlarges the association between financial literacy and account ownership. The coefficient of branch per 100,000 indicates that one more opening of branch per 100,000 led to increase in the average rate of ownership of account in bank by 0.063. The coefficient of NSP per capita remains significant at the same level of significance. The estimate of married suggests that the married people are not likely to have an account. The coefficients of education except secondary remain insignificant. Grohmann (2018) found the impact of secondary and tertiary education on financial inclusion is insignificant and suggested that GDP variable is likely to eliminate the impact of education. The point estimate of age becomes negatively significant at 1 percent significant level and female's coefficient becomes more negatively insignificant. In addition, the marginal impact of head and inflation decreases.

<Table 1.5 here>

Table 1.5 presents the results of regressing by financial literacy on being above poverty line at the district level. Column 1 represents the link between financial literacy and above poverty line using fixed effect model. The point estimate of financial literate is insignificantly different from zero suggesting no impact. However, the coefficient of secondary school is positive and significant at 5% level of significance, respectively. In addition, rural and married seem to be weakly associated with poverty. Other controls such as inflation, branch per 100,000, Net State Product per capita are not likely to have any significant effect on the likelihood of being above the poverty line.

Specification 2 explores link between financial literacy and being above the poverty line using numeracy and length of district road as an instrument for financial literacy and ownership of account, respectively. The relation between financial literacy and being above the poverty line is insignificant. The coefficients of primary school, secondary school and rural become insignificant. It can be concluded that financial literacy is not associated with poverty at the district level. In addition, other covariates remain insignificant. In Appendix Table A1.9, I analyzed the indirect relation between financial literacy and poverty at the district level. The coefficient of financial literacy is insignificant which represents that financial literacy is not indirectly related to poverty through ownership of saving account.

In Appendix Table A1.1, the link between outcome variables and four indicators of financial literacy are also explored. Column 1 represents the marginal impact of all the four indicators at median indicate that they are significantly positively associated with financial inclusion at the individual level. For example, the marginal effect of simple interest rate at median indicates that the probability of ownership of saving account is 0.03 higher for those who knew the concept of simple interest rate, when all their variables are at their median value. Column 2 represents the marginal impact of all indicators at median for being above poverty line at the individual level. Simple interest rate and risk diversification are positively related to the likelihood on being above poverty line, but compound interest rate is negatively related to it at the individual level. Column 3 represents the link between financial inclusion and four dichotomous indicators of financial literacy at the district level. All the indicators, except risk diversification rate are positively related to ownership of an account at the district level. Column 4 represents the result for being above the poverty line at the district level. The estimates of dichotomous indicator suggest that there is no association between poverty and indicators of financial literacy at the district level.

Conclusion

This paper contributes to the literature on financial literacy, poverty and financial inclusion. The effect of financial literacy on financial inclusion and being above the poverty line is analyzed by employing probit model at the individual level, as well and by using fixed effect model at the district level to control for unobservable characteristics, using 2016 and 2017 survey data for India. This paper also deals with simultaneous biasness by using numeracy as an instrument at both the individual and district level. At the individual level, the marginal effects at median for probit model show that financial literacy is positively associated with the likelihood of having an account in bank and no relation with likelihood of being above poverty line. However, the marginal effects at the median for IV-Probit reveal that the probability of being above poverty line and having the ownership of a saving account is 0.08 and 0.63 for financial literate individual, respectively.

At the district level, the financial literacy is not associated with being above poverty but is positively associated with ownership of a saving account in the bank. In addition, the fixed effect model with instrument also shows similar results. However, the education is not associated with being above poverty line , when simultaneous biasness is controlled. This is in consistent with Grohmann et al. (2018).

Financial literacy is an important tool for making adequate financial decisions in the growing complex and integrated economy. When people or institutions make ill financial decisions, it is bad for individuals as well as for the whole economy. Having the basic knowledge about finance, would help people to make better decisions about saving, buying insurance, investing in stocks, avoiding moneylenders who provide loan at higher interest rate, planning retirement saving in a wiser way, using credit cards wisely, managing debts wisely, avoiding financial traps etc. The financial skills might also lead to increase in the usage of accounts, increase the demand for finances and might help poor people to exist from poverty by having access to loans and credit at lower interest rate. However, financial literacy is not sufficient to combat poverty, as poverty is a complex phenomenon. Yet, better financial literacy could be tool contributing toward making better financial decision which in the future can affect poverty.

Table 1.1 : Descriptive Statistics

	Individual			District		
	Obs	Mean	Std.Dev.	Obs	Mean	Std.Dev.
	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variables						
Above poverty	92672	.173	.378	860	.177	.164
Saving Account in Bank	82705	.389	.488	860	.35	.217
Independent Variables						
Financial Literacy	92672	.171	.377	860	.17	.135
Numeracy	92672	.932	.252	860	.93	.104
Length of district road	92672	36963.62	28908.37	860	32771.83	26838.33
Branch	92672	384.723	466.482	860	285.85	409.359
Branch per 100,000 persons	92672	14.209	28.289	860	17.735	89.812
NSP per capita	92672	11.429	.667	860	11.432	.674
Primary School	92672	.231	.421	860	.238	.13
Secondary School	92672	.368	.482	860	.36	.167
Senior Secondary School	92672	.087	.283	860	.073	.062
Graduate	92672	.071	.257	860	.059	.055
Rural	92672	.676	.468	860	.795	.332
Female	92672	.532	.499	860	.527	.109
Age	92672	37.911	15.023	860	38.036	3.224
Head	92672	.503	.5	860	.5	.165
Household size	92672	4.595	1.989	860	4.555	.961
Married	92672	.753	.431	860	.761	.085
Inflation	92672	4.2	1.622	860	4.214	1.615
Education expenditure per 100,000 persons	92672	.135	.174	860	.158	.18

Notes: Primary School represents class 1 to 8, secondary school represents class 9 to 10, senior secondary school represents class 11 to 12 and graduate represents under graduation.

Table 1.2: Impact of Financial Literacy on Account Ownership at Individual Level

Variables	Ownership of Saving Account (Probit Model) (1)	Ownership of Saving Account (IV-Probit Model) (2)
Financial Literacy	0.064***	0.655***
	(0.004)	(0.023)
Branch	0.028***	0.016***
	(0.004)	(0.004)
Branch per 100,000 persons	-0.001***	-0.000***
	(0.000)	(0.000)
NSP per capita	0.012***	0.022***
	(0.002)	(0.002)
Secondary School	0.042***	-0.010**
	(0.003)	(0.004)
Senior Secondary School	0.106***	-0.004
	(0.012)	(0.012)
Graduate	0.062***	0.002
	(0.013)	(0.012)
Rural	-0.035***	-0.019***
	(0.004)	(0.003)
Female	-0.027***	0.003
	(0.003)	(0.003)
Age	0.001***	0.001***
	(0.000)	(0.000)
Head	0.056***	0.038***
	(0.003)	(0.003)
Household size	0.054***	0.031***
	(0.004)	(0.004)
Married	0.025***	0.009***
	(0.001)	(0.001)
Inflation	-0.012	0.007
	(0.010)	(0.009)
Education expenditure per 100,000 persons	0.064***	0.655***
	(0.004)	(0.023)
Observations	82,705	82,705

Notes: The table reports marginal effects at median for ownership of saving account results at individual level with standard errors in parentheses. Column (1) shows marginal effects at median for ownership of saving account using Probit model and Column (2) shows marginal effects at median for ownership of saving account using IV-Probit model. Numeracy acts as an instrument in Column 2. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively

Table 1.3: Impact of Financial Literacy on Poverty at Individual Level

Variables	Poverty (Probit Model) (1)	Poverty (IV-Probit Model) (2)
Financial Literacy	0.003	0.230***
	(0.003)	(0.031)
% of Ownership of saving account in district	-0.000	-0.002***
	(0.000)	(0.000)
Branch	-0.008**	0.003
	(0.003)	(0.004)
Branch per 100,000 persons	-0.001***	-0.001***
	(0.000)	(0.000)
NSP per capita	-0.006***	-0.001
	(0.002)	(0.002)
Secondary School	0.014***	-0.003
	(0.003)	(0.003)
Senior Secondary School	0.024**	-0.006
	(0.009)	(0.010)
Graduate	0.012	-0.002
	(0.010)	(0.010)
Rural	-0.017***	-0.017***
	(0.003)	(0.003)
Female	-0.001	0.008***
	(0.002)	(0.003)
Age	-0.001***	-0.001***
	(0.000)	(0.000)
Head	-0.001	0.000
	(0.002)	(0.002)
Married	0.010***	0.007**
	(0.003)	(0.003)
Inflation	-0.001	-0.002***
	(0.001)	(0.001)
Education expenditure per 100,000 persons	0.061***	0.053***
	(0.007)	(0.007)
Observations	92,672	92,672
Psuedo R^2		

Notes: The table reports marginal effects at median for poverty results at individual level with standard errors in parentheses. Column (1) shows marginal effects at median for being above poverty line using Probit model and Column (2) shows marginal effects at median for being above poverty line using IV-Probit model. Numeracy acts as an instrument in Column 2. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 1.4: Impact of Financial Literacy on Account Ownership: Fixed Effect Model Using at the District Level

Variables	Ownership of Saving Account (Without Instrument) (1)	Ownership of Saving Account (With Instrument) (2)
Financial Literacy	0.304***	1.166***
	(0.079)	(0.418)
Branch	-0.746	-0.806
	(0.851)	(0.615)
Branch per 100,000 persons	0.042*	0.063***
	(0.024)	(0.020)
NSP per capita	0.117***	0.162***
	(0.026)	(0.029)
Secondary School	-0.141	-0.221***
	(0.095)	(0.079)
Senior Secondary School	-0.103	-0.015
	(0.495)	(0.360)
Graduate	0.978*	0.646
	(0.552)	(0.429)
Rural	-0.055	-0.054*
	(0.039)	(0.028)
Female	-0.231**	-0.208***
	(0.110)	(0.080)
Age	-0.006*	-0.008***
	(0.003)	(0.003)
Head	0.209***	0.131*
	(0.078)	(0.067)
Married	0.104	0.174
	(0.141)	(0.107)
Inflation	0.024***	0.014**
	(0.007)	(0.007)
Education expenditure per 100,000 persons	-0.124	-0.096
	(0.213)	(0.154)
Constant	-1.165**	-2.039***
	(0.567)	(0.586)
Observations	860	860
R-squared	0.78	0.70

Notes: The table reports results for ownership of saving account at the district level with standard errors in parentheses. Column (1) shows fixed effect model results for the proportion of people that having saving account in the bank without the use of instrument and Column (2) results for the proportion of people that having saving account in the bank with the use of instrument. Numeracy acts as an instrument in Column 2. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table 1.5: Impact of Financial Literacy on Poverty: Fixed Effect Model at District Level

Variables	**Poverty (Without Instrument) (1)**	**Poverty (With Instrument) (2)**
Financial Literacy	-0.068	-5.137
	(0.067)	(6.861)
Branch	0.001	0.049
	(0.000)	(0.066)
% of Account Ownership in district	0.613	4.463
	(0.714)	(5.993)
Branch per 100,000 persons	-0.025	-0.317
	(0.020)	(0.403)
NSP per capita	0.018	-0.736
	(0.023)	(1.023)
Secondary School	0.168**	1.182
	(0.080)	(1.406)
Senior Secondary School	-0.203	-0.076
	(0.414)	(1.704)
Graduate	0.429	-2.902
	(0.465)	(5.064)
Rural	0.062*	0.322
	(0.033)	(0.380)
Female	0.020	1.040
	(0.093)	(1.451)
Age	0.002	0.040
	(0.003)	(0.054)
Head	-0.011	-0.693
	(0.066)	(1.004)
Married	-0.220*	-1.015
	(0.118)	(1.175)
Inflation	0.009	-0.065
	(0.006)	(0.108)
Education expenditure per 100,000 persons	0.105	0.585
	(0.179)	(0.985)
Constant	0.104	9.376
	(0.478)	(12.657)
Observations	860	860
R-squared	0.667	0.567

Notes: The table reports results for being above poverty line at the district level with standard errors in parentheses. Column (1) shows fixed effect model results for the proportion of people that are above the poverty line without the use of instrument and Column (2) results for the proportion of people that that are above the poverty line with the use of instrument. Numeracy acts as an instrument in Column 2. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

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Appendix

Table A1.1 Impact of Sub-Components of Financial Literacy on Financial Inclusion and Poverty

Variables	Account Ownership (At Individual Level) (1)	Poverty (At Individual Level) (2)	Account Ownership (At District Level) (3)	Poverty (At District Level) (4)
Simple Interest Rate	0.032***	0.012***	0.094*	-0.045
	(0.00)	(0.00)	(0.06)	(0.05)
Compound Interest Rate	0.023***	-0.009***	0.126**	0.061
	(0.00)	(0.00)	(0.06)	(0.05)
Inflation	0.040***	0.002	0.122**	-0.045
	(0.00)	(0.00)	(0.06)	(0.05)
Risk Diversification	0.034***	0.010***	0.114	0.011
	(0.00)	(0.00)	(0.08)	(0.07)
% of Saving Account Ownership in District		0.000		0.000
		(0.00)		(0.00)
Branch	0.025***	-0.008**	-0.778	0.672
	(0.00)	(0.00)	(0.85)	(0.72)
Branch per 100,000 people	-0.001***	-0.000***	0.043*	-0.026
	0.00	0.00	(0.02)	(0.02)
NSP per capita	0.010***	-0.006***	0.121***	0.027
	(0.00)	(0.00)	(0.03)	(0.02)
Secondary School	0.033***	0.013***	-0.186*	0.163**
	(0.00)	(0.00)	(0.10)	(0.08)
Senior Secondary School	0.092***	0.023**	-0.083	-0.196
	(0.01)	(0.01)	(0.49)	(0.42)
Graduate	0.059***	0.013	0.969*	0.414
	(0.01)	(0.01)	(0.55)	(0.47)
Rural	-0.033***	-0.016***	-0.055	0.062*
	(0.00)	(0.00)	(0.04)	(0.03)
Female	-0.021***	0	-0.248**	0.02
	(0.00)	(0.00)	(0.11)	(0.09)
Age	0.001***	-0.001***	-0.005	0.001
	0.00	0.00	(0.00)	(0.00)
head	0.053***	-0.001	0.225***	-0.024
	(0.00)	(0.00)	(0.08)	(0.07)
Married	0.049***	0.010***	0.108	-0.219*
	(0.00)	(0.00)	(0.14)	(0.12)

Inflation Rate	0.025***	-0.001*	0.027***	0.008
	(0.00)	(0.00)	(0.01)	(0.01)
Education exp. per 100,000 people	-0.011	0.061***	-0.242	0.122
	(0.01)	(0.01)	(0.21)	(0.18)
Constant			-1.333**	0.037
			(0.57)	(0.49)
Observations	82,705	92,672	860	860
Pseudo R^2	0.033	0.005	0.79	0.668

Notes: The table reports results for the impact of dichotomous indicator on ownership of saving account at the individual level with standard errors in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table A1.2: First stage regression for IV results: The Impact of Numeracy on Financial Literacy at the Individual Level (Financial Inclusion Model)

Variables	Financial Literacy
Numeracy	0.147***
	(0.005)
Branch	0.000*
	(0.000)
Branch per 100,000 persons	-0.000***
	(0.000)
NSP per capita	-0.018***
	(0.002)
Secondary School	0.057***
	(0.003)
Senior Secondary School	0.121***
	(0.010)
Graduate	0.064***
	(0.011)
Rural	-0.005*
	(0.003)
Female	-0.028***
	(0.002)
Age	-0.000
	(0.000)
Head	0.003
	(0.002)
Married	0.007**
	(0.003)
Inflation	0.013***
	(0.001)
Education expenditure per 100,000 persons	-0.022***
	(0.008)
Observations	92,672
R-squared	0.039
F- test of first stage regression	787.44
F-test for weak instruments	16.38

Notes: This table reports the first stage regression of the IV regressions using equation (4) shown in this paper with standard errors in parentheses. The F-statistics reports the F-stat for the first stage regression. The F-test for weak instruments denotes passing the Stock-Yogo test at 15%. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively

Table A1.3: First stage regression for IV results: The Impact of Numeracy on Financial Literacy at the Individual Level (Poverty Model)

Variables	Financial Literacy
Numeracy	0.147***
	(0.005)
Length of road	-0.000
	(0.000)
Branch	0.000*
	(0.000)
Branch per 100,000 persons	-0.000***
	(0.000)
NSP per capita	-0.018***
	(0.002)
Secondary School	0.057***
	(0.003)
Senior Secondary School	0.121***
	(0.010)
Graduate	0.064***
	(0.011)
Rural	-0.005*
	(0.003)
Female	-0.028***
	(0.002)
Age	-0.000
	(0.000)
Head	0.003
	(0.002)
Married	0.007**
	(0.003)
Inflation	0.013***
	(0.001)
Education expenditure per 100,000 persons	-0.022***
	(0.008)
Constant	0.167***
	(0.023)
Observations	92,672
R-squared	0.038
F- test of first stage regression	393.77
F-test for weak instruments	19.93

Notes: This table reports the first stage regression of the IV regressions using equation (6a) shown in this paper with standard errors in parentheses. The F-statistics reports the F-stat for the first stage regression. The F-test for weak instruments denotes passing the Stock-Yogo test at 15%. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively

Table A1.4: First stage regression for IV results: The Impact of Length of Road on Percent of Account Ownership in District at the Individual Level (Poverty Model)

Variables	% of Saving Account Ownership in District
Numeracy	0.136***
	(0.007)
Length of road	0.000***
	(0.000)
Branch	0.000***
	(0.000)
Branch per 100,000 persons	-0.000***
	(0.000)
NSP per capita	0.003
	(0.003)
Secondary School	0.038***
	(0.004)
Senior Secondary School	0.115***
	(0.013)
Graduate	0.074***
	(0.014)
Rural	-0.038***
	(0.004)
Female	-0.027***
	(0.003)
Age	0.002***
	(0.000)
Head	0.061***
	(0.003)
Married	0.054***
	(0.004)
Inflation	0.030***
	(0.001)
Education expenditure per 100,000 persons	-0.058***
	(0.011)
Constant	-0.054*
	(0.031)
Observations	92,672
R-squared	0.048
F- test of first stage regression	1160.23
F-test for weak instruments	19.93

Notes: This table reports the first stage regression of the IV regressions using equation (6b) shown in this paper with standard errors in parentheses. The F-statistics reports the F-stat for the first stage regression. The F-test for weak instruments denotes passing the Stock-Yogo test at 15%. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively

Table A1.5: First stage regression for IV results: The Impact of Numeracy on Financial Literacy at the District Level (Financial Inclusion Model)

Variables	Financial Literacy
Numeracy	1.166***
	(0.418)
Branch	-0.806
	(0.615)
Branch per 100,000 persons	0.063***
	(0.020)
NSP per capita	0.162***
	(0.029)
Secondary School	-0.015
	(0.360)
Senior Secondary School	0.646
	(0.429)
Graduate	-0.054*
	(0.028)
Rural	-0.208***
	(0.080)
Female	-0.008***
	(0.003)
Age	0.131*
	(0.067)
Head	0.174
	(0.107)
Married	0.014**
	(0.007)
Inflation	-0.096
	(0.154)
Education expenditure per 100,000 persons	1.166***
	(0.418)
Constant	-2.039***
	(0.586)
Observations	860
R-squared	0.70
F- test for weak instruments	16.381

Notes: This table reports the first stage regression of the IV regressions using equation (4) shown in this paper with standard errors in parentheses. The F-test for weak instruments denotes passing the Stock-Yogo test at 15%. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively

Table A1.6: First stage regression for IV results: The Impact of Numeracy on Financial Literacy at the District Level (Poverty Model)

Variables	Financial Literacy
Numeracy	0.197**
	(0.080)
Length of district road	0.000
	(0.000)
Branch	0.075
	(0.596)
Branch per 100,000 persons	-0.021
	(0.017)
NSP per capita	-0.051***
	(0.018)
Secondary School	0.010
	(0.346)
Senior Secondary School	0.243
	(0.387)
Graduate	-0.008
	(0.027)
Rural	-0.046
	(0.078)
Female	0.003
	(0.002)
Age	0.085
	(0.054)
Head	-0.065
	(0.098)
Married	0.013***
	(0.005)
Inflation	-0.124
	(0.156)
Education expenditure per 100,000 persons	0.197**
	(0.080)
Constant	0.753*
	(0.406)
Observations	860
R-squared	0.662
F-test for weak instruments	7.03

Notes: This table reports the first stage regression of the IV regressions using equation (7a) shown in this paper with standard errors in parentheses. The F-test for weak instruments denotes passing the Stock-Yogo test at 15%. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively

Table A1.7: First stage regression for IV results: The Impact of Length of Road on Percent Ownership of Saving Account in District at the District Level (Poverty Model)

Variables	**% of Account Ownership in District**
Numeracy	23.079**
	(11.706)
Length of district road	0.000
	(0.000)
Branch	-77.691
	(87.351)
Branch per 100,000 persons	4.061
	(2.506)
NSP per capita	10.198***
	(2.649)
Secondary School	-3.073
	(50.663)
Senior Secondary School	97.440*
	(56.723)
Graduate	-6.285
	(3.992)
Rural	-25.126**
	(11.363)
Female	-0.497
	(0.351)
Age	23.241***
	(7.880)
Head	9.777
	(14.328)
Married	2.861***
	(0.712)
Inflation	-19.645
	(22.920)
Education expenditure per 100,000 persons	-77.691
	(87.351)
Constant	-117.124**
	(59.465)
Observations	860
R-squared	0.78
F-test for weak instruments	7.03

Notes: This table reports the first stage regression of the IV regressions using equation (7b) shown in this paper with standard errors in parentheses. The F-test for weak instruments denotes passing the Stock-Yogo test at 15%. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively

Table A1.8: The Indirect Effect of Financial Literacy on Poverty at Individual Level

VARIABLES	Poverty (Without instrument) (1)	Poverty (With instrument) (2)
Financial Literacy		
Total	0.003	0.170***
	(0.003)	(.031)
Indirect	-0.000	-0.003
	(0.000)	(9.834)
Direct	0.003	0.253***
	(0.003)	(0.038)
Observations	92,672	92,672

Notes: This table reports the indirect effect of financial literacy on poverty at the district model with standard errors in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table A1.9: The Indirect Effect of Financial Literacy on Poverty At the District Level

Variables	Poverty (Without Instrument) (1)	Poverty (With Instrument) (2)
Financial Literacy		
Total Effect	0.089	0.230
	(0.041)	(0.132)
Indirect Effect	-0.005	-1.305
	(0.005)	(1.145)
Direct Effect	0.096	1.535
	(0.041)	(1.149)
Observations	860	860

Notes: This table reports the indirect effect of financial literacy on poverty at the district model with standard errors in parentheses. ***, ** and * denote significance at the 1%, 5% and 10% levels, respectively.

Table A1.10 Construction of Poverty Probability Index

The following questions are used to construct Poverty Probability Index (PPI) for India:

1. How many household members are there in the house?
2. What is the general education level of the female head/spouse?
3. Does the household possess a refrigerator?
4. Does the household possess a stove/gas burner?
5. Does the household possess a pressure cooker/pressure pan?
6. Does the household possess a television?
7. Does the household possess an electric fan?
8. Does the household possess an almirah/dressing table?
9. Does the household possess a chair, stool, bench or table?
10. Does the household possess a motorcycle, scooter, motor car or jeep?

Chapter 2 Impact of National Food Security Mission on Rice Productivity and Yield at the District Level: Evidence from India

Introduction

Agriculture is the backbone of India that contributes approximately 50 percent to the employment sector and approximately 14 percent to the GDP of India (Economic Survey 2012-13, Government of India). Rice is the most important food grains in India and staple food for more than two third of India's population. Approximately, fifty million families depend on rice for its main source of income and occupation (Babu). Hence, it is a preeminent crop for food security in India (Barah, 2005). Moreover, it is also a staple food for half of the population in the world (Sinha and Talahati, 2007; Vijaykumar et al. 2006).

The largest proportion of rice is grown during the Kharif/monsoon season (i.e. from June to October) because the climatic conditions like hot and humid temperature, heavy rainfall are favorable during these months to grow rice. India has the largest area for rice cultivation i.e. approximately 44 million hectares in 2014 but ranks second in terms of production and consumption of rice in the world. In addition, India also ranks first in terms of export of rice since 2011 (Directorate of Economics and Statistics). FAO (2015) report suggests that India exported approximately 42.5 million tonnes of rice to the world. However, China occupies first position as a producer of rice but second position in aspect of area for rice cultivation.

After Independence, India had a deficit of food grains and faced frequent droughts and famines. The estimates from Directorate of Economics and Statistics indicated that the production of rice was quite low i.e., approximately 20.5 million tonnes in 1950-53. Therefore, India adopted Green Revolution technology in mid-1960 to achieve self-sufficiency in terms of food grains and lessen poverty and malnutrition. Though, Green Revolution was more prominent in Punjab, Haryana and Western Uttar Pradesh than other parts of India. Research indicated that there was an increase in rice yield by using more of water, hybrid seeds and chemical fertilizers until 1980s. However, excess use of water and chemical fertilizers increased alkalinity and salinity of soil and waterlogging. This led to stagnancy in rice yield until the end of 20^{th} century and declined in the beginning of 21^{st} century (Greenlands 1997; Yadav et al 1998; Kumar and Yadav 2001). Janaiah, Otsuka and Hossain (2005) also showed that the rate of increase in TFP growth in rice yield was slower during 1996-2000 as compared to rate of growth in TFP during 1970-1980. Gujja and Thiyagarajan (2009) found that stagnancy of rice yield led to fall in the supply of rice, in turn doubled the global price during the period 2001-2007. In addition, Chand et al. (2012) suggested that the growth rate in TFP was slower in East India as compared to South India. The compound growth rate of production was 1.95 percent in 1970, then increased to 4.04 percent in 1980 and then decreased to 1.68 percent in 1990 (Barah, 2005).

Among the demand constraints, UN DESA 2015 report stated that India would be the most populous country in the world by 2025. In 2014, FAO reported that the percentage of poor people has declined to 17 percent in 2012. But, this is still a big problem in India because rice is staple food and primary source of the nutrients for poor people. In addition, it is also expected that world's population might reach to 10 billion by 2050 and the demand for rice will be rising as compared to other crops. Moreover, to meet the demand of growing population (especially of poor people) is a gigantic task. Hence, the production of rice, pulses and other food grains need to be increased to ease the demand constraint. Among the supply constraints, increase in industrialization and urbanization; growing population and water scarcity are decreasing the availability of land for cultivation. Increase in alkalinity and salinization of soil, water logging, land degradation and change in climate are among other factors that are leading to fall in the yield of rice. Therefore, there is a need to increase the production and yield of rice by using the less land, less fresh water and less inputs. To deal with these hurdles, Government of India launched National Food Security Mission (NFSM) in August 2007 to increase the production of rice, wheat and pulses in a sustainable manner.

NFSM has following three components i.e. wheat, rice and pulses. The objective of this mission was to increase the production of rice by 10 million tonnes, wheat by 8 million tonnes and pulses by 2 million tonnes in a sustainable manner during the period 2007-12. In addition, the program also emphasized to restore the soil fertility, productivity, creating employment opportunities and adopt strategy to increase profits in agriculture. Intially, NFSM-Rice was being implemented in 133 districts of 12 states; NFSM-Wheat was implemented in 142 districts of 9 states and NFSM-pulses was implemented in 468 districts of 16 states. To ensure the implementation of NFSM, Government of India released approximately Rs. 4,883 crore during 2007-08 to 2011-12 to the selected districts and spent around Rs. 3,381 crore until 31st March, 2011 (Economic Survey, 2011-12). This mission was continued during 12th Five Year Plan i.e. 2012-2017. Coarse cereals and commercial crops were also included under NFSM program. By the end of 12th Five Year Plan, NFSM-Rice, NFSM-Wheat, NFSM-Pulses and NFSM-Coarse cereals were implemented in 194 districts, 126 districts, 638 districts and 265 districts, respectively.

In literature, the impact of NFSM on the pulse crop in different states has been evaluated. National Bank for Agriculture and Rural Development (NABARD) conducted an evaluation study for pulses in Rajasthan and found that production and productivity grew by 134 and 49 percent, respectively in NFSM districts. However, production and productivity decreased by 101 percent and 68 percent, respectively in Non-NFSM districts. Shah (2012) conducted a study to analyze the impact of NFSM on pulse in a NFSM district (i.e. Amravati) and a non-NFSM district (i.e. Beed) of Maharashtra. Their results indicate that there was a significant rise in the yield of pigeon pea crop and gram crop in Amravati as compared to Beed. Narain et al. (2016) suggested that the productivity level of chickpea of trained farmers under NFSM was 26.67 percent higher than untrained farmers in Hamirpur of Uttar Pradesh. Pasala and Rudra (2017) found that the growth rate of area, production and productivity were 0.0039, 0.026 and 0.022, respectively in Andhra Pradesh. Maharjan and Grover (2018) found a significant increase in the production of chickpea by 15.11%, 8.42% and 5.91% in Bihar, Odisha and West Bengal, respectively. In contrast, Naik and Naik and Nethrayini (2019) did not find any significant rise in the growth rate of productivity of pigeon-pea and found negative growth rate of productivity for chickpea crop in NFSM districts of Karnataka.

Researchers have also studied the impact of NFSM on rice production and farmers' livelihood. Sivagnanam and Murugan (2015) found that the rice production increased from 17.24 percent in 2007-08 to 32.84 percent in 2012-13 in NFSM districts of Tamil Nadu. Sivagnanam, Murugan and Thenkovan (2019) suggested that the net income of NFSM farmers was 22.64 percent more as compared to non-beneficiaries in 2012. Pardhi, Meena and Shrivastava (2014) found yield of rice increased by 10.94 quintal per hectare and 9.48 quintal per hectare for small farmers and medium farmers, respectively in Bhandara district (selected as NFSM) of Maharashtra during 11^{th} Five Year Plan. Agricultural Finance Corporation Limited (AFCL) suggested that there was about two and five times increase in the yield of rice in NFSM districts during 2007-08 and 2008-09, respectively.

The literature has also evaluated the factors that influence the participation of farmers in NFSM. Sivagnanam et al., (2015) analyzed the factors that influence the participation of farmers and constraints faced by the farmers in Tamil Nadu. The ratio of irrigated land to operational land, education and size of family depending on agriculture are positively associated with the participation of farmers in NFSM program. Similar results have also been suggested by Manjunatha and Kumar (2015) in Karnataka. In addition, they also suggest that availability of credit is also having a positive influence on the participation of farmers. However, this study is not fully explored because the factors that have potential to influence the farmer's decision for participation are not studied for most of the states or for whole India.

In literature, researchers have also argued that farmers are not aware about the program (Sivagnanam, Murugan and Thenkovan, 2019; Manjunatha and Kumar, 2015). Even if farmers were aware about the program but they faced the problems of taking advantage of the assistances under NFSM. The field survey conducted by Manjunatha and Kumar (2015) in Karnataka suggested that a long gap for receiving subsidy after the first purchase of equipment, lack of technical advises, biasness towards big farmers etc., and many other problems discouraged the participation of farmers. The survey on constraints faced by beneficiaries conducted by Nagarethinam and Anjugam (2020) suggested that all the beneficiaries of NFSM program received the subsidy for just one hectare of land, approximately 92% did not receive the sanctioned amount on the time and more than half of them lacked technical understanding. In support, other researchers have also suggested that farmers in Tamil Nadu and Chattisgarh (Sivagnanam et al., 2019; Singh et al., 2020) faced the similar constraints.

Previous work have mainly focused on the growth trends in production, area and yield in the literature. Even to analyze the impact between NFSM districts and non-NFSM districts, authors just compare the growth rate in production, area and yield in NFSM and non-NFSM districts without using any appropriate econometric strategy. However, none of the studies have analyzed the impact of NFSM on the production and yield of rice for whole India by using Propensity Score Matching approach. The rice productivity grew by 230% during the period 1950-2006 in India (Directorate of Economics and Statistics, 2008). The yield of rice was 1.05 tonnes per hectares in 1970, then increased to 3.62 tonnes per hectare in 1980 and then again decreased to 1.32 tonnes per hectare in 1990 (Barah, 2005). In addition, the rice productivity of India is still 0.5 tons/ha below than the world's average rice productivity (Varma, 2016). Therefore, it is important to analyze whether the adoption of NFSM program led to increase in the production and yield of rice or not.

This paper tries to test two hypotheses at the district level for India. First, implementation of NFSM program led to increase in the production of rice in the selected NFSM-districts post year 2007. Second, implementation of NFSM led to increase in the yield of rice in the selected NFSM-districts post year 2007. The present study, therefore, tries to analyze the impact of NFSM on production and yield of rice in India by using Propensity Score Matching (PSM) Method. My results indicate that the impact of NFSM on the production of rice is positive and significant, indicating that the average production of rice is higher in NFSM districts in the range of 70,643 tones to 80,238 tones. However, the impact of NFSM on the yield of rice is significantly negative, indicating that the yield of rice is higher in non-NFSM districts.

The rest of the paper is organized as follows: Section 1 discusses the background of NFSM in India. Section 2 and 3 discusses about the source of data and the methodology adopted to analyze the impact of NFSM on the production and yield of rice, respectively. Section 4 presents the result and Section 5 gives the conclusion.

Background

UN-DESA (2015) reported that India's population would be approximately 1.4 billion by 2022 and the demand for rice will also grow. The findings of Population Foundation of India show that the anticipated demand of rice would be 121.2 million tonnes by the end of 2030. Dev and Sharma (2010) also suggested that approximately one-third of India's population is under extreme poverty line and half of children are malnourished. Kumar et al., (2014) estimated that the yield of the rice should be 3.3 tonnes per hectare to meet the demand of rice. On the supply side, the yield of rice has fallen in the recent years. Ray et. al suggested that the yield of rice and wheat have stagnated in 36 % and 70% in growing areas, respectively. Murugan and Sivagnanam (2020) indicated that the production of rice reduced to 1.7% during 1990s from 4% during 1980. Therefore, the National Development Council (NDC) launched National Food Security Mission in India to bridge the gap between demand and supply on 29th May, 2007 by expanding area under cultivating and also decreasing the gap between potential and exiting yield of potential crops.

The main objectives of NFSM program were to create food security, increase the production, restore the soil fertility at the individual level, creating more employment opportunities, adopting strategies to increase the farm profits and encouraging farmers to adopt the use of improved seeds. In short, NFSM was created to reduce the demand-supply gap. To ensure the implementation of the NFSM-Rice, several measures like demonstrations on improved packaged of practices, System of Rice Intensification, hybrid rice technology; incentive for micronutrients, multi-crop planters, farm mechanization etc. were undertaken.

NFSM-Rice was implemented in 11 districts of Andhra Pradesh, 13 districts of Assam, 18 districts of Bihar, 10 districts of Chhattisgarh, 5 districts of Jharkhand, 7 districts of

Karnataka, 6 districts of Maharashtra, 9 districts of Madhya Pradesh, 15 districts of Orissa, 5 districts of Tamil Nadu, 26 districts of Uttar Pradesh and 8 districts of West Bengal. Under NFSM-Rice, those districts were selected that had an area of more than 50,000 hectares under rice and the productivity was less than the average productivity of State. To ensure the implementation of NFSM-Rice, Government of India released approximately Rs. 1,772 crores during 2007-08 to 2011-12 to the selected districts (Economic Survey, 2011-12).

A three-tier monitoring approach is followed to evaluate the implementation of NFSM at the National Level, State Level and District Level. General Council (GC) at the National Level, State Food Security Mission Executive Committee (SFSMEC) at the State Level and District Food Security Mission Executive Committee (DFSMEC) at the District Level were formed to ensure the implementation of the mission. GC has the responsibility of forming policies in order to ensure the implementation and to evaluate the progress and the development of the mission. DFSMEC plays an important role to ensure, monitor and implementation of NFSM interventions. The mission was funded by Central Government till 2014-15. From 2015-16, the mission is 60 percent sponsored by Central Government and 40 percent sponsored by State Government except North Eastern and 3 Himalayan states. In the North Eastern and 3 Himalayan states, 90 percent of the mission is sponsored by Central Government and rest of the mission is sponsored by the State Government. The Central Government release the funds directly to SFSMEC and SFSMEC allocate funds to DFSMEC based on the performance of the missions in the district. The funds are released in the installments after submitting the progress reports of NFSM and utilization certificate to the Ministry of Agriculture.

NFSM was continued in 12th Five Year Plan (2012-17) with the objective to increase the additional production of food grains by 25 million tonnes. In addition, the coarse cereals and commercial crops were also included in the mission. The government increased the allocation of funds to Rs. 12,350 crores for implementation of NFSM during 12th Five Year Plan. By the end of 12th Five Year Plan, NFSM-Rice was implemented in 194 districts of 25 states (Annual Report 2017-18, Department of Agriculture, Cooperation & Farmers Welfare). The production of wheat, rice and pulses increased by 22.57 million tonnes, 16.79 and 8.75 million tonnes, respectively from 2006-07 to 2016-17. By the end of 2017, India had a surplus of approximately 285 million tonnes of foodgrains. Beyond the 12th Plan, the mission is being continued with new additional target of 13 million tonnes of foodgrains form 20017-18 to 2019-20. Now, NFSM is carried in identified districts of 29 states in the country.

Data

To analyze the impact of NFSM at the district level for rice from year 2003 to 2012, I have employed the data from various sources. In India, 87% of rice is mainly grown in Kharif season (also known as autumn or monsoon). It is sown in June-July and harvested in November-December in most of the states. Just 13% of the rice is cultivated in Rabi season (from November-December to May-June) in some of the southern and eastern states of India like Assam, West Bengal, Tamil Nadu etc., because of the favorable climatic conditions in these states. Therefore, I am focusing only on the production of rice during Kharif season because the climatic conditions are favorable during this time to cultivate rice and most of the farmers depend on the monsoon rains to grow rice.

The data on outcome variables i.e. yield and production at the district level is employed from District Wise Crop Production Statistics, Ministry of Agriculture. The variables production and yield are measured in the terms of tonnes and tonnes per hectare, respectively. There are 475 districts in each year. The data on availability of credit outstanding to agriculture at the district level and consumption of fertilizer at the state level is employed from Reserve Bank of India's official website. The availability of credit is denominated in thousands. The consumption of fertilizer is expressed in terms of kilogram per hectare. The fertilizer has 3 components: Nitrogen, Potassium and Phosphorus. Since rainfall is important to produce rice, the data on annual rainfall is collected from Open Government Data (OGD) Platform, India. OGD Platform collects the data from India Meteorological Department. The data on rainfall is collected at the 36 sub-division level and is in terms of millimeters. Web Land Use Statistics under Ministry of Agriculture provides the data on the net sown area at the district level. Net sown area is defined as the total area sown under the crops and orchards and area i.e. sown more than once is also counted as once.

The summary statistics of all the variables is represented in Table 2.1. Column 2 represents the mean with standard error in parenthesis for whole sample. Column 3 and 4 represents mean for treatment (NFSM districts) and control (non-NFSM districts) group, respectively and Column 5 represents the difference in mean of independent and dependent variables between non-NFSM districts and NFSM districts. We observe that mean of production and yield in overall sample is approximately 132,605 tonnes and 2.05 tones per hectare, respectively. The average production of rice is higher by approximately 111,000 tones in NFSM-Rice districts. On the contrary, the average yield of rice is higher by 0.27 tones per hectare in non-NFSM-Rice districts. From the descriptive table 2.1, we also observe that log of net sown area and consumption of fertilizer is statistically higher in NFSM-Rice districts. In addition, there is no statistically significant difference in the mean of availability of credit for agriculture (measured in millions), rainfall and minimum support price between treatment and control groups.

Empirical Approach

I could not employ the difference – in – difference strategy to analyze the impact of NFSM on the rice production and yield because the selection of districts under NFSM-Rice was not random. Instead, NFSM-districts were selected based on two criteria. First, a district needed to have an area of more than 50,000 hectares under rice to become NFSM-district. Second, the productivity of the district had to be less than the average productivity of the state. Hence, NFSM-districts do not only differ in the status of treatment but also based on their selection. Moreover, the comparison of the mean estimates' outcome of treatment and control group provided by difference-in-difference strategy would be biased. Therefore, I have employed propensity score matching (PSM) developed by Rosenbaum and Rubin (1983) to analyze the impact of NFSM on rice production and yield to avoid the potential biasness. PSM strategy helps to create a control group that has same attributes as the treatment group. This strategy estimates the average effect of the NFSM-policy and reduces the biasness of the treatment effect.

Suppose the treatment is denoted by variable 'T', where T =1 states that NFSM policy was adopted in that district and T equals to zero indicates that NFSM was not adopted in the district. Defining Y_1 as the change in the production and yield of rice in a specific district if that district adopted NFSM policy and Y_0, otherwise if district did not adopt NFSM policy. The impact of NFSM policy cannot be described as the mean difference of Y_1 and Y_0 because either Y_1 or Y_0 can be observed for each district and the assignment of the policy is not random. Therefore, PSM approach is adopted matches non-NFSM districts with NFSM districts based on the probability of having NFSM program. The probability of having NFSM program, $P(T=1|X) \in (0,1)$, is estimated by using the observed covariates X. To evaluate the impact of NFSM policy, we estimate Average Treatment of the Treated (ATT) that is defined as the expected difference in the mean of outcome variables between NFSM counties and matched counterfactual non-NFSM districts constructed on the base of the same propensity score matching.

$$\boxed{ATT = E[Y_1|T = 1] - E[Y_0|T = 1]}$$

$$=\boxed{E\{E(Y_1|T = 1, P(T = 1|X))|T = 1 - E(Y_1|T = 0, P(T = 1|X))|T = 1\}}$$

Where, $\boxed{E[Y_0|T = 1]}$ stands for expected change in the outcome in NFSM districts and $\boxed{E(Y_1|T = 0, P(T = 1|X))|T = 1\}}$ stands for mean of the corresponding constructed matched non-NFSM counterfactual group. We have also estimated Average Treatment Effect (ATE) of NFSM program. ATE is defined as the difference in the average of the outcome variable between treatment and control groups.

$$ATE = E[Y_1 - Y_0]$$

If the selection of NFSM-districts would have been random, then the value of ATE and ATT would have been same. Since, the selection of districts under NFSM districts was not random, the value of ATE is different from ATT and is defined as the sum of ATT and selection bias.

The validity of PSM strategy is based on two conditions. First, there should not be any unobservable variable in the set of independent variables that has the potential to affect the treatment group. I believe that this assumption is satisfied because my all the variables such as net sown area, rainfall etc., that affect treatment group are observable. The second assumption is the presence of common support (also known as overlap condition). Formally, it can be stated as $0 < P(\text{Treatment} = 1 \mid X) < 1$ that means the probability for both receiving treatment and not receiving treatment for each independent covariate should lie between 0 and 1 to find proper matches. In Appendix, the figure represents pre-matching (figure a) and post-matching (figure b) kernel density of the treatment and control group. In the pre-matching kernel density figure, it is evident that the difference between two groups is significant. However, there was no significant difference between two groups after the matching was conducted. This indicates that assumption of common support is satisfied. If both the assumptions are satisfied, then PSM strategy can be used as a proxy to evaluate the impact of NFSM on the production and yield of the rice (Smith & Todd, 2005).

In addition, I have also conducted the balancing test to test whether the distribution of observed variables with the same propensity score is similar or not irrespective of the treatment status. The figure A2.1 and A2.2 represents the kernel distribution of propensity scores demonstrating common support for production and yield, respectively. In appendix, the result of balancing hypothesis test representing the variables' characteristics pre and post matching have also been presented. The results show that p-values were not significantly different after matching. The median biasness is also reduced and lies between after the matching. This indicates that PSM approach has reduced a significant amount of biasness. Moreover, the low value of pseudo R^2 also indicates that NFSM districts and non-NFSM are similar to each other in characteristics after matching. This suggests that the balancing hypothesis was satisfied.

Results

I have employed logit model to predict the conditional probability of participating in NFSM program for production and yield of rice. Table 2.2 and 2.3 represents the logit estimates for production and yield of rice, respectively. The results indicate that the districts with higher net sown area, higher consumption of fertilizer and with higher rainfall are more likely to participate in NFSM program. However, the districts with higher minimum support price are less likely to enroll in NFSM program. In addition, availability of credit to the agriculture sector is not likely to have any impact on participation in NFSM program.

The average treatment effects of the treated (ATET) for the outcome variables i.e. production and yield of rice for unmatched, nearest neighbor, Mahalanobis and Kernel procedures are represented. ATT represents the average effect of NFSM on production and yield of rice for those districts that adopted NFSM program. Nearest neighbor (NN) matching estimates the ATT by matching observation of the control group whose propensity scores are nearest to the treated group and dropping those observations in the group which do not have matches. At the last, Kernal matching criteria matches all the units of the treatment group with a weighted average of all the units in the control group. The weighted average is calculated by bandwidth parameter, kernel function and propensity score.

Table 2.4 represents the results for ATT for the production of rice. First, we observe that the mean of production of unmatched criteria is equal to the mean in Nearest Neighboring, Kernel neighboring and Mahalanobis specification in the treated group. However, the mean of production is smallest in unmatched category and highest in Mahalanobis category among matching category. Second, production in the unmatched criteria is significantly different between treatment and control group. The positive significant difference in the mean of the treatment and control group represents gain in the production of rice by approximately 105,890.59 tonnes. Third, the production is positively statistically significantly different between treatment and control group across all the matching criteria. The coefficient of ATT represents that average effect of NFSM-Rice on the production of rice between lies b 39,428 tones to 71,614 tones on average in those districts that adopted NFSM as compared to non-NFSM districts. The highest effect of ATT is represented in the Kernel matching procedure (71,613.51 tones). In addition, the lowest ATT effect is in Mahalanobis matching criteria (39,427.31 tonnes) and is approximately half of the ATT effect in Kernel matching.

Table 2.4 also represents the ATT effect for yield of rice. First, the mean of the yield in treatment group is same across all the specifications. However, the mean of the yield in the control group is lower in the unmatched procedure than the matched procedures. In contrast to the effect of ATT on the production of rice, the effect of ATT on yield of rice is negatively significant different in the unmatched specification and across all the specifications and that represents the loss in the yield. In other words, the yield of rice of was lower in NFSM districts as compared to Non-NFSM districts by about 0.3 tones per acre to 0.46 tones per acre. In addition, ATT effect is lowest in Mahalanobis procedure (0.29 tones per acre) as compared to other matched specifications and is approximately half of ATT in other matched specifications. Moreover, the effect of ATT in the unmatched specification does not differ much as compared to Mahalanobis specification.

The coefficients of ATT for production and yield suggest that NFSM program was successful in increasing the production of rice significantly in the NFSM adopted districts, however, it was unsuccessful to increase the yield of rice. This can be concluded that the increase in production was not ample to increase the yield of rice. The reasons could be that the beneficiaries of NFSM program faced many constraints to avail all the benefits of NFSM program (Sivagnanam, Murugan and Thenkovan, 2019; Manjunatha and Kumar, 2015; Nagarethinam and Anjugam, 2020; Sivagnanam et al., 2019; Singh et al., 2020).

Table 2.5 summarizes the average treatment effect (ATE) for production and yield of rice. ATE represents the estimated effect of NFSM program on the production and yield of rice for districts that did and did not adopt NFSM program. The coefficient of ATE for the production of rice in NFSM districts lies between 72,260 tones and 80,240 tones. It represents that the adoption of NFSM program increases the production between 72,260 tones and 80,240 tones on an average. For yield of rice under all matching strategies, ATE lies between -0.36 tones per acre and -0.49 tones per acre. This also suggests that adoption of NFSM program did not increase the yield of rice. At the last, the coefficient of ATE and ATT differ from each other which implicate that selection biasness is corrected by employing PSM approach.

These results are in consistent with those who have evaluated the impact of NFSM on the production of chickpeas, pulses and rice (Shah 2012; Narain et al., 2016; Sivagnanam and Murugan 2015; Pardhi, Meena and Shrivastava 2014). However, the results cannot be compared to these studies because they did not adopt any proper econometric strategy to study the impact of NFSM. In India, System of Rice Intensification (SRI) was adopted to increase the production of rice. SRI is a sustainable approach to increase the production by using less water, by changing the input requirements i.e. soil, water and nutrients (Uphoff, 2003). Some organic farmers in Pondicherry, Tamil Nadu in 2000, first adopted this approach (Prasad, 2007). ICRISAT (2008) reported that SRI is practiced in approximately 216 districts. Gujja and Thiyagarajan (2009) suggested that SRI cultivation is practiced in 1 million hectares in India. Under SRI cultivation, there was an increase in yield (Palanisami et al., 2013; Sinha and Talati 2007; Barah 2009). However, farmers hesitate to adopt SRI because of their poor knowledge about water management, unsuitable soil nutrients, labor intensive technology etc. (Varma 2019; Palanisami et al., 2013). Nirmala et al., (2015) also suggested that SRI is adopted at a very slow pace because it is knowledge intensive strategy to adopt. In 2007, SRI also became a part of NFSM to increase the production and yield of rice.

Conclusion

Rice occupies an important place in farming in India because it is cultivated on approximately 44 million hectare of land and contributes 15% to India's GDP. In the aspect of consumption, Gathrone-Hardy et al., (2016) suggest that 31% of the calorie intake is from rice in India. In addition, the yield of rice also fell down to 1.32 tonnes per hectare in 1990 from 3.62 tonnes per hectare because of water logging, salinization and other environment problems. Barah (2005) suggested that 6 million hectare of rice land is vulnerable to waterlogging and salinization. Therefore, the fall in the yield of rice is worrisome. Hence, it is important to analyze whether NFSM would help India to overcome over this problem or not. So, this paper tries to evaluate the impact of NFSM on the production and yield of rice in India by using Propensity Score Matching strategy.

Based on the matching procedure, the results indicate that the gain in average production lies between 18% and 30% in NFSM adopted districts. However, the results indicate the loss in yield of rice and lies between 16% and 25% based on the matching procedure. The reasons could be the strategies adopted under NFSM to increase the production. The strategies are demonstrations on improved packaged of practices, System of Rice Intensification, hybrid rice technology; incentive for micronutrients, multi-crop planters, farm mechanization etc. By the end of 2011-12, India produced approximately 105 million tonnes of rice (Directorate of Economics and Statistics).

Researchers also suggested that farmers have faced constraints to avail the benefits under NFSM program. Some equipment like pump sets, rotators are available only to the big farmers, not to marginal or small farmers. Moreover, the distribution of these equipment is decided by the political parties. Many farmers are also not aware about NFSM program in India (Sivagnnam, Murugan and Thenkovan 2019). There is lack of coordination between Department of Agriculture and other departments that make sure the implementation and success of NFSM program and lack of coordination also led to failure of some of the planned activities. In addition, demonstrations of SRI or hybrid seeds are not taking place adequately. NFSM is not just a program to ensure the increase in the production and yield of the foodgrains. It will also help India to achieve the food security because rice contributes approximately 31 percent of calorie intake in India (Gathorne et al. 2016).

In 2013, Government of India also launched National Food Security Act (NFSA) to achieve food security. Under NFSA, 75% of the rural population and 50 percent of the urban policy receive 5 kg. of foodgrains at subsidized price. Therefore, NFSM has the potential to increase the productivity and yield of rice and would also help to achieve food security. There is also a need to deal with above stated constraints for increasing production, improving soil fertility and enhancing the farm profits. Moreover, increasing the production of rice in eastern states of India will also help those states to combat the poverty.

Tables

Table 2.1: Descriptive Statistics of the variables

Variables	**All**	**Treatment**	**Control**	**Difference (T-C)**	**p-value**
Independent Variables					
production	132605.60	224623.00	113799.60	110823.40***	0.00
Yield	2.05	1.83	2.10	-0.27***	0.00
Dependent Variables					
Log Net Sown Area	10.55	10.92	10.48	0.44***	0.00
Log Rainfall	6.88	6.85	6.88	-0.03	0.09
Log Fertilizer Consumption	4.40	4.87	4.32	0.55***	0.00
Availability of Credit, in millions	4.96	5.37	4.88	0.50	0.25
Minimum Support Price	828.5	828.5	828.5	0.00	1.00

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

Table 2.2: Logit Results for Production of Rice

Variables	Coefficient	Standard Error	z	P>z
Log Net Sown Area	0.057***	0.019	3.02	0.003
Availability Credit, Million	-0.008	0.007	-1.08	0.278
Log Fertilizer	0.727***	0.074	9.87	0.00
Log Rainfall	0.609***	0.118	5.15	0.00
MSP	-0.001***	0.000	-2.83	0.005
Constant	-9.038***	0.979	-9.23	0.00

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

Table 2.3: Logit Results for Yield of Rice

	Coefficient	S.E.	z	P>z
Log Net Sown Area	0.06***	0.02	3.00	0.003
Availability Credit, Million	-0.01	0.01	-1.06	0.288
Log Fertilizer	0.73***	0.07	9.88	0.000
Log Rainfall	0.61***	0.12	5.19	0.000
MSP	0.00***	0.00	-2.84	0.005
Constant	-9.07***	0.98	-9.26	0.000

Table 2.4: Average Treatment Effect of the treated For Production and Yield of Rice

			Group Means by Treatment				
		All	Treatment	Control	Difference	%	t-stat
	N	3,419	2,785	634			
Unmatched	Production		224,825.26	118,934.67	105,890.59***	47%	12.83
	Yield		1.844	2.101	-0.256***	14%	-5.62
	N	3,420	2,785	635			
Nearest Neighbor	Production		224,666.92	156,802.17	67,864.75***	30%	5.61
	Yield		1.843	2.308	-0.465***	25%	-7.27
	N	3,429	2,794	635			
Mahalanobis	Production		224,825.26	185,397.95	39,427.31***	18%	3.63
	Yield		1.844	2.134	-0.290***	16%	-6.55
	N	3,429	2,794	635			
Kernel	Production		224,825.26	153,211.75	71,613.51***	32%	8.85
	Yield		1.844	2.284	-0.440***	24%	-11.34

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

Table 2.5: Average Treatment Effect for Production and Yield of Rice

		Mean Difference
Nearest Neighbor	Production	73,225.47***
	Yield	-0.49***
Mahalanobis	Production	72,260.34***
	Yield	-0.36***
Kernel	Production	80,238.22
	Yield	-0.47***

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

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Appendix

Table A2.1 Balance Test

		Treated Mean	Control Mean	% Bias	% Bias Reduction	t-value	p>t	V(T)/V(C)
Log Net Sown	U	10.78	10.307	15.3		3.51	0	1.07
Area	M	10.78	10.851	-2.3	84.9	-0.42	0.673	1.20*
Availability	U	5.3734	4.736	8.7		2.08	0.038	1.36*
Credit	M	5.3734	5.49	-1.6	81.8	-0.29	0.771	1.62*
Log Fertilizer	U	4.879	4.411	52.5		9.78	0	012*
	M	4.879	4.899	-2.3	95.6	-0.84	0.401	0.83*
Log Rainfall	U	6.858	6.845	3.4		0.67	0.501	0.34*
	M	6.858	6.844	3.6	-5.6	0.73	0.463	0.51*
MSP	U	856.09	861.49	-2.2		-0.5	0.617	0.99
	M	856.09	869.25	-5.4	-143.6	0.98	0.325	1.12

Sample	Ps R^2	LR chi^2	p>chi^2	Mean Bias	Med Bias	B	R	%Var
Unmatched	0.053	175.01	0.00	16.4	8.7	61.1*	0.21*	60
Matched	0.001	1.67	0.893	3	2.3	7.2	0.8	80

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

Figure A2.1: Kernel Distribution of Propensity Score Demonstrating Common Support for Production

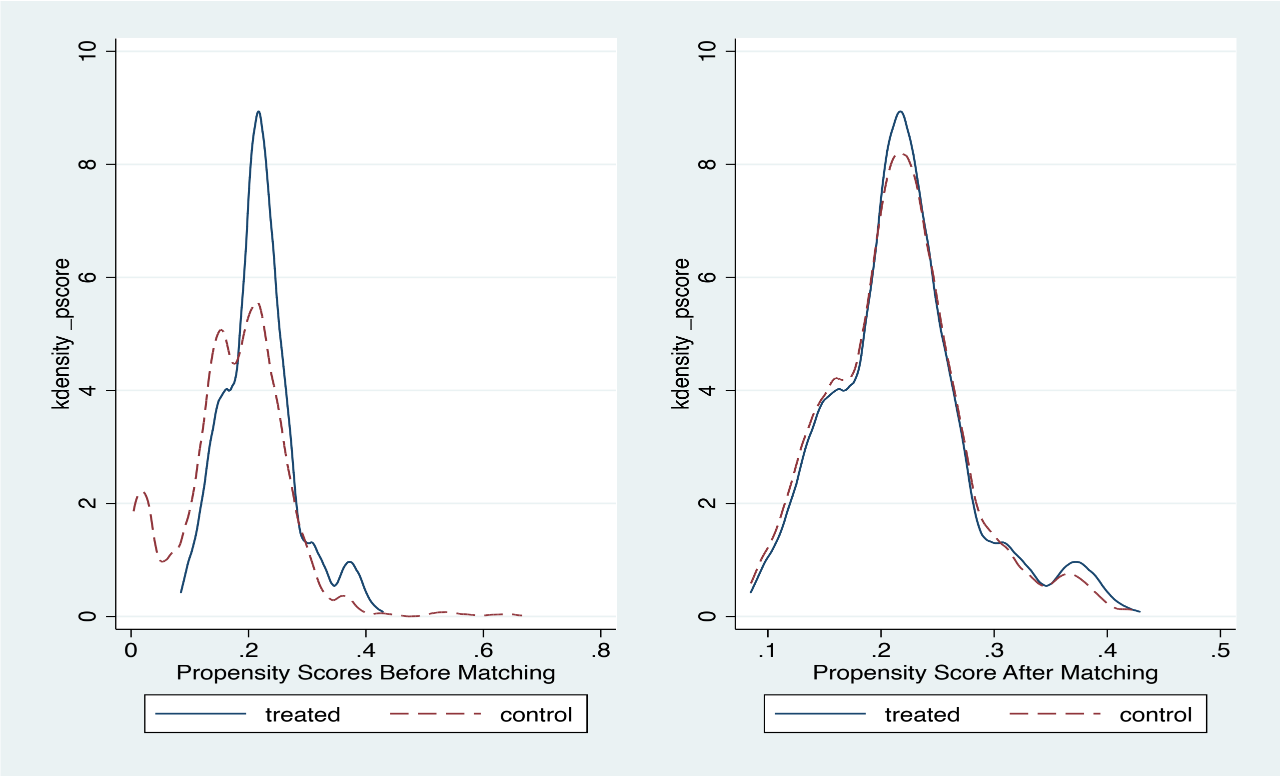
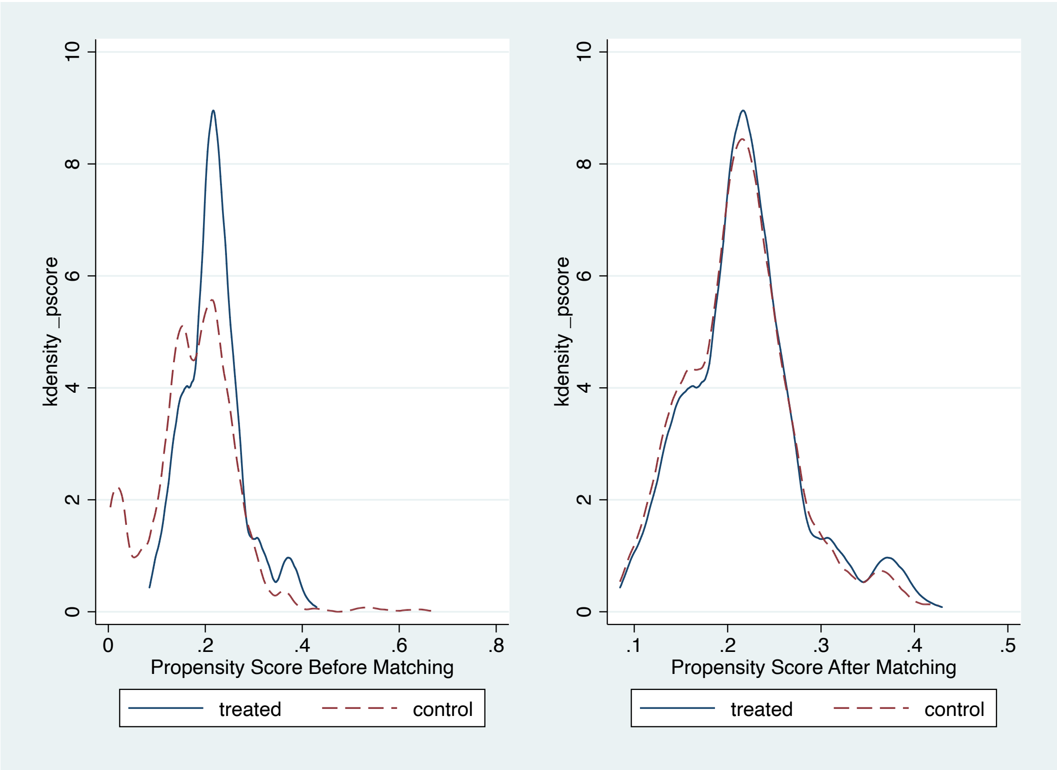


Figure A2.2 : Kernel Distribution of Propensity Score Demonstrating Common Support for Yield



Chapter 3 Beginning Farmers' Entry and Exit: Evidence from County Level Data

Introduction

Beginning farmers and ranchers (BFRs) are playing an increasingly important role in the US agriculture and hold the promise of increasing its productivity and efficiency. While most specialize in traditional industries like row crops and beef cattle, many make an outsized contribution to growing new markets such as controlled-environment farming, organic farming, vineyards, and specialty crops (Freedgood and Dempsey, 2014; Key and Lyons, 2019). Identifying the drivers of BFR entry and exit is particularly important because the majority of established farmers are nearing retirement and large farm ownership transfers are expected in the near future. For example, for every farmer under 35, there are about five farmers who are over 65.[1] While data show that less than a third of new entrants survive (Katchova & Ahearn, 2017), the existent literature provides limited guidance on what factors contribute to the net entry of BFRs and thus to the growth of the farming sector. In this paper, we address gaps in the literature by identifying the factors that affect net entry by BFRs.

Most published work evaluating the entry-exit dynamics and success of beginning farmers relies on data prior to 2017, the year of the latest Census of Agriculture (Ahearn, 2013; Ahearn & Newton, 2009; Freedgood & Dempsey, 2014; Kauffman, 2013; Pouliot, 2011, Nadolnyak *et al.*, 2019). The main research questions revolve around challenges to acquire appropriate farmland (*e.g.*, Freedgood & Dempsey, 2014), high prices of assets and variable input costs (*e.g.*, Kauffman, 2013), and how farmers learn to successfully operate a farmstead (Trede & Whitaker, 2000). BFRs are also at a greater risk of financial stress and vulnerable to agricultural downturns that negatively affect their profitability, liquidity, and solvency, although not their repayment capacity (Katchova and Dinterman, 2018).

Data from the most recent Census of Agriculture show significant changes pertaining to BFRs' assets and composition, which necessitates a fresh look at what factors help BFRs to succeed. For example, in 2017, equal shares of BFRs and regular farmers owned cropland (61%), while in previous years much fewer BFRs owned their land. [2] Moreover, analysis of ARMS data for the period 2013-2017 shows that fewer BFRs were committed to full-time farming with only 23% (versus 42% of all producers) not working off-farm between 2013-2017 (Key and Lyons, 2019). [3]

In this paper, we follow Goetz and Debertin's (2001) framework and use regression analysis with county level data where the dependent variables are changes in the number of BFRs and other farmer categories defined as log differences (identical to percentage differences in this setup) in their numbers between Census of Agriculture years that are reflective of their entry and survival. We evaluate how barriers to entry and economic environment, access to and use of credit, and climate variables affect net entry by estimating fixed effects regressions with standard errors clustered at the county. Results show higher net entry in counties with more and smaller size farms and with lower farm productivity. This may indicate that the BFR group has the potential to improve the overall productivity in such counties if they are able to grow and prosper since they will be adding their contribution to areas in smaller, less productive areas. Results also indicate that the capital-intensive nature of farming is a strong barrier to entry. BFRs are more likely to do well in counties where agriculture is important for the economy and there are benefits from using insurance, as well as from more off-farm work opportunities, in line with Key and Lyons (2009), Travlos (2019), and Mishra *et al.* (2010). Net entry is unaffected by government payments and on- or off-farm income but net entry is responsive to farmland and output prices, which is in line with Goetz and Debertin (2001) and Kropp and

Katchova (2011). We observe substitutability between farming and alternative self-employment in counties with more entrepreneurial environments. Net entry increases with availability of non-real estate loans but decreases with real estate credit. Thus, access to credit remains essential for BFRs to acquire the assets needed to reach optimal scale, which is consistent with Katchova and Dinterman (2018), Key and Roberts (2006), and Gale (2003).

The rest of the paper is organized as follows. We briefly overview the relevant literature in Section 2 and describe the method and data in Section 3. The results are discussed in Section 4, and Section 5 concludes.

Literature Review

This work is related to the economic literature on young and beginning farmers, barriers to entry, and credit constraints, as well as to research on the impact of economic, environmental, and climate variables on entry and exit decisions by BFRs and other farmer cohorts.

Economic literature is abundant with research on barriers to entry. There are several definitions of an entry barrier, ranging from an advantage of established sellers reflected in persistent prices above competitive levels (Bain, 1956) to "a rent that is derived from incumbency" (Gilbert, 1989). The most all-encompassing definition is probably "anything that prevents and entrepreneur from instantaneously creating a new firm in a market" (Carlton and Perloff, 1994). Particular types of entry barriers relevant to farming include economies of scale (and scope) and other cost advantages (better access to resources such as labor, water, and soil), as well as network effects (demand-side economies of scale) that favor larger established producers. Related to that are high sunk costs and higher capital intensity of the incumbents that new entrants with higher financing needs lack, both of which have been observed in agricultural production. In this regard, financial constraints and limited access to credit faced by potential entrants may be viewed as a barrier (Griffin *et al.*, 2020). Additionally, exclusivity of agreements with key distributors and suppliers including market integration may disadvantage new entrants. [4] In addition to entry barriers, there are also barriers to exit. These barriers include costs related to closure that may induce farmers to postpone or forego exit, trade-specific skills and knowledge of the business that increase the opportunity cost of exiting, and uncertainty.

Traditionally, research on entry and exit in economics has been concerned with how they are linked to industry growth and how barriers to entry affect the persistency of profits or losses. Recent empirical research on non-farm industries shifted focus to the effects of entry barriers on productivity growth and innovation adoption. This research finds that entry and exit happen in most industries simultaneously and that entering and exiting firms account for a significant share of the total industry output important (Bartelsman et al., 2004). That is why studying the entry-exit dynamics is important.

The entry and exit dynamics in farming are more complicated than firm dynamics because farming is usually a family business that is often also perceived as a lifestyle and requires long-term planning for a life cycle, making entry and exit decisions dependent on age and other producer demographics (Hoppe and Korb, 2006). Overall, the literature on farm entry is linked to that on exit and is rather dated and fragmented, with a few notable exceptions. For example, research has focused on individual commodities like dairy farms in Pennsylvania and Maryland (Stokes, 2006) or farmers overseas (Kimhi and Lopez, 1999). Williamson (2017) shows significant age-related difference in growth trajectories of surviving BFRs between 1999 and 2014. Nadolnyak *et al.* (2019) identified the economic, demographic, and weather related factors that affect exit of BFRs, while Griffin *et al*. (2019) evaluated the factors that affect exit of retirement age farmers.

Recently, Katchova and Ahearn (2017) provided improved estimates for annual entry and exit rates for beginning and established farmers and farmers older than 65 over the period 1997-2012 using the Census of Agriculture (COA) data. They show that both annual entry and exit rates were higher for beginning farmers as compared to established farmers but do not identify factors that have the potential to influence entry and exit from farming. Our work contributes to this line of research by focusing on identifying differences across farmer cohorts and inviting further questions.

The net BFR entry is related to farm assets ownership acquisition and transfer, which is driven mostly by the tax implications of individual choices (Boehlje, and Eisgruber, 1972; Tauer, 2006; Leonard *et al.*, 2017; Mishra and Chang, 2011). The choice of a successor also depends on geographic location and government policies, in addition to demographic factors such as operator education, age, off-farm employment, and expected household wealth (Mishra *et al.*, 2010).

In terms of demographic differences, younger farmers (below 35 years) have consistently higher entry and exit rates relative to mid-age farmers (35-65 years) for each 5-year period between 1997 and 2012 (Katchova and Ahearn, 2017).[5] In terms of exit, minority and female BFRs were more likely to exit during the 1992-2012 period, while family farms were found to be less likely to exit (Hoppe and Korb, 2006; Nadolynak *et al.*, 2019). The probability of exit also increases after a certain age for farmers in Canada and Israel (Kimhi and Bollman, 1999). Other demographic factors and social attributes also affect farmers' exit decisions (Kuehne, 2012; Fisher and Burton, 2014; Nadolnyak *et al.*, 2019).

The size of the operation, which reflects productivity and scale economies, also influences farmers' decision to enter or exit farming. While exit is less likely by larger farms (Hoppe and Korb, 2006), lower productivity associated with smaller and less efficient dairy farms has been linked to higher probability of exit (Dong *et al.*, 2016). Ownership of large assets is associated with lower exit probability of BFRs (Nadolynak *et al.*, 2019) and of retirement age farmers (Griffin *et al.*, 2019). In contrast, flow economic variables like income and off-farm work do not seem to affect exit of BFRs (Nadolnyak *et al.,* 2019)

Government support programs, including subsidized insurance, are important for the success of BFRs but do not always meet their goals. For example, Goetz and Debertin (2001) found that federal government program increased the probability of exit in the subset of counties that were already losing farmers. Nadolnyak *et al.* (2019) find that reliance on government payments also increases the probability of exit by BFRs. In contrast, Mishra *et al.* (2010) show that high intensity of government payment reduces exit for all farmers. Government payments were found to have a small impact on the remaining in the farm business for the period 1987-1997 (Key and Roberts, 2006), as well as to have no effect on entry and exit (Debertin, 2001; Griffin *et al.*, 2019). Travlos (2019) finds that the participation of BFRs in crop insurance programs included in the Agricultural Act of 2014, in Farm Service Agency loan programs, and in the Conservation Reserve Program's Transition Incentive Program was beneficial for BFRs. However, BFRs in Missouri were unable to take full advantage of these opportunities because of the lengthy application processes, limited program awareness, understaffed programs, and rigid eligibility requirements (Travlos, 2019).

Government programs specifically targeting credit also have had mixed results. The "Aggie" bonds in 1980 and other support programs in 1992 did not help BFRs to significantly improve their repayment capacity and did not increase entry (Kropp and Katchova, 2011; Williamson and Katchova, 2013). However, Williamson and Katchova (2013) suggest that these programs helped beginning farmers to become full owners of the land. Kropp and Katchova (2011) find that, while government payments were helpful to established farmers, they did not help improve BFRs' term debt coverage.

Access to off-farm work and other income seems important to new entrants (Key and Lyons, 2109) as they reflect farmers' opportunity cost and offer income diversification opportunities. The empirical evidence is mixed. While there is evidence of association between exit decisions and off-farm work in the general farming population (Goetz and Debertin, 2001; Mishra *et al.*, 2010) and among retirement age farmers (Griffin et al., 2019), off-farm work does not seem to affect exit for BFRs (Nadolnyak *et al*., 2019).

The literature has highlighted the importance of access to credit as a factor that has the potential to drive farmer entry and exit. Access to loans is critical for production in agriculture because farming is both fixed and working capital intensive and requires large outlays for fixed capital in the initial years of operation. Therefore, access to capital is an important barrier to entry. BFRs and young farmers have less access to credit from the banks and government agencies because of their limited experience, smaller land and other assets, lack of collateral, and lower net worth (Katchova and Dinterman, 2018; Gale, 2003). Prior to 2017, young and beginning farmers were more likely to rent rather than own farmland suggesting that they faced credit constraints (Ahearn and Newton, 2019; Katchova and Dinterman, 2018; Williamson, 2017). Ifft *et al*., (2014) found that highly leveraged farms (such as many BFRs) generate significantly higher output and young farmers have continued to use credit at similar rates over the preceding 20 years while Griffin *et al*., (2020) find that BFRs suffer larger losses of productivity attributable to credit constrains. Access to commercial credit remains an important barrier to entry for BFRs and young farmers (Gale 2003; Hartarska and Nadolnyak, 2012). Commercial bank lending practices (even specialized credit programs targeting beginning farmers) are not sufficiently helping beginning farmers to acquire land ownership, forcing them to rely on alternatives such as leasing (Kaufmann, 2013).

The high level of commodity price volatility is not likely to subside in the near future and this might accelerate the exit rate (Newman and McGroarty, 2017). However, in contrast to this idea, Nadolynak *et al.*, (2019) find that one standard deviation increase of price volatility is associated with decrease in BFRs' exit by 16%. Thus, there is a need to further evaluate the relationship between price movements and BFRs' entry and exit.

The literature pertaining to the impact of climate on agriculture is vast and of great interest (*e.g*., Mendelsohn *et al.*, 1994; Schlenker *et al.*, 2006; Deschenes and Greenstone 2007; Schlenker and Roberts, 2009; Schauberger *et al.*, 2017). For example, Lee *et al.*, (2017) find a negative impact of precipitation on farm labor supply and a non-linear relationship with temperature. Climate is an important variable in farming and its variability might increase the hazard of BFRs' exit because they are generally less experienced, have lower net worth, less access to resources, and higher cost of adapting to climate change. For example, Nadolnyak *et al.*, (2019) find that climate variability has only a small impact on BFRs' exit with droughts having the strongest impact. This may be explained by reduction in vulnerability to climate fluctuations via risk management tools such as government programs, disaster assistance, insurance, lending by specialized financial institutions, adoption of irrigation, etc. (Nadolnyak and Hartarska, 2012; Nadolnyak *et al*., 2017). While climate (as opposed to weather) may not directly impact farmers' incomes, there is evidence that climate extremes may have an indirect impact. It is reflected in observed delinquencies in the portfolio of agricultural lenders related to the El Nino cycles but loan restructuring and portfolio diversification within FCS institutions and commercial agricultural banks mitigate the climate risks (Nadolnyak and Hartarska, 2010 and 2013; Hartarska *et al.*, 2016).

Methods and Data

The empirical model of entry and exit is rooted in the constrained intertemporal utility maximization framework originally proposed by Kimhi and Bollman in 1999 (also used in Pietola *et al*., 2003; Goetz and Debertin, 2001; Blundell and MacCurdy, 1999; Towe *et al.*, 2008; Yagi and Garrod, 2018). In this framework, the difference between the value functions of continuing to farm or exiting is interpreted as a tendency to exit that is a function of variables that affect farmer's utility such on- and off-farm income, farmer and farm attributes, and local economic and institutional factors. The same framework is useful to model entry, in which case the tendency to enter will depend on the same variables as an individual is comparing on- and off-farm utility and income such as farmer and farm attributes and local economic and institutional factors. [6] Because we work with county level data, this tendency, or hazard, of entering or exiting is proxied by net entry/exit on county level measured as log difference between the number of BFRs in 5 and 10-year Census intervals as in Goetz and Debertin (2001). Thus, we focus on entry and exit from the industry's perspective through an empirical framework that lends itself to identifying the factors associated with BFRs' dynamics. The empirical model is informed by the literature on barriers to entry. Specifically, we estimate

$$N_{it} = c_0 + \textit{Barriers to Entry'}_{it}\,\alpha + \textit{Credit'}_{it}\,\beta + \textit{Econ\&Environment'}_{it}\,\gamma + \textit{Climate'}_{it}\,\lambda + f_i + e_{it}$$

where N_{it} is the net entry/exit into farming in county *i* in Census interval *t*, f_i is a county specific fixed effect, and e_{it} is the error term. The explanatory variables are grouped in four vectors*: Barriers to Entry, Credit, Economic Environment factors, and Climate related* factors. The model is estimated using fixed effects panel method with standard errors clustered at the county level.

The dependent variable N_{it} *(Net entry)* is measured as a log difference of BFRs over 10 and 5 year intervals. Like Goetz and Debertin (2001), we use 10 year lags (two Census intervals) as the measure of pure entry as, by definition, a BFR cannot remain a BFR 10 years after starting to farm. We also use the numbers of BFRs with less than 5 and 3 years of experience to get a better insight into what happens to the newest BFRs. In addition to BFRs, we compute net entry of young (less than 35 years of age) farmers that may capture the choice of farming relative to other occupations available in rural areas. Net entry by women farmers is also used as a dependent variable because women are entering farming at rates higher than men, according to data from 2012 and 2017. Finally, we use net entry by retirement age farmers to capture possible determinants to entry or exit (negative net entry) by retirement age farmers.

The independent variables capturing barriers to entry include average *Farm size* expected to decrease net entry if there are economies of scale/scope or other advantages to large farming operations. *Farm productivity* (sales-to-assets ratio) is also expected to be negatively associated with net entry. Other barriers to entry and (dis)incentives include *Net Cash Income per Operation* and *Non-farm Income Per Operation, Farmland Price*, as well as *Government Payments* and *Indemnity payments* per acre, and the number of farmers that *Work Off-Farm* for more than 200 days in a Census year.

The variables in the *Credit* vector include two measures of access to credit: the number of bank branches per square mile (*Bank per sq. mile*) and the Farm Credit System branches per square mile (*FCS per sq. mile*). Together, these two major creditors supply about 80% of the credit to the agricultural sector. Availability and use of credit is captured by the value of *Real* and *Non-real Estate Debt*.

The control variables in *Economic Environment* include percentage of state agricultural GDP in state GDP (*Agricultural GDP*) that reflects the prevalence of the agricultural sector, which may encourage BFR entry. The agricultural price index (*Ag. Price Index*) reflects economic environment in the farm sector and is computed as a ratio of the total output to total input price indexes from the ERS Agricultural Productivity in the U.S. dataset. The *Unemployment rate* reflects local economic conditions and may also be associated with labor supply and potential residents who may become farmers. The share of non-farm proprietors in the working population (*Non-Farm Proprietor*) proxies competitiveness and entrepreneurship potential of the local economy, which may impact net entry in several ways. *Metro* county designation reflects competitive pressures from development, whereas a *Disaster Declared County* dummy indicates whether a county experienced a negative shock that could affect net entry. *Cropland* in acres and number of *Farm Operations* serve as scaling variables to control for the size of the county.

Finally, the *Climate* vector contains the level and squared mean annual temperature and precipitation that may affect net entry. Recent literature finds that climate and climate variability may affect profitability and labor supply in various ways and thus impact entry and exit (Wheeler *et al.*, 2020; Mase *et al.*, 2017; Wheeler *et al.*, 2013; Nadolnyak *et al.*, 2019; Lee *et al.*, 2017, among many others).

We assemble the dataset from several sources including and corresponding to the Census of Agriculture (COA) Quick Stats county level surveys spanning the period from 1997 to 2017. Additional data come from the Bureau of Labor Statistics (BLS), Census Bureau, Bureau of Economic Analysis (BEA), USDA Farm Income and Wealth Statistics, Federal Deposit Insurance Corporation, National Agricultural Service Statistics (NASS), Federal Emergency Management Agencu (FEMA), SHELDUS, USDA's Economic Research Service (ERS), and the National Oceanic and Atmospheric Administration (NOAA).

<<<<<[Table 3.1]>>>>>

The summary statistics are presented in Table 3.1. Data for the dependent variables come from the Quick Stats (COA) and include the number of (principal) BFR (operators with less than 10 years of experience and BFRs with less than 5 and 3 years of experience), young operators (aged 35 years or less), female operators, principal operators older than 65 years, and the total number of principal operators.[7] These variables are used to compute the log difference measuring the net entry (growth rate) of these cohorts. Data from the COA include the number of operators who worked off-farm for more than 200 hours to proxy for part-time farming, cropland in acres, total number of farm operations, net cash farm income, average farm size, and farm sales and assets. The *Net Cash Farm Income* is the income from operations (excluding government payment and insurance payment) divided by the number of farms in the county. The farm *Productivity* variable is computed by dividing total sales by the value of total assets. The average farm size is defined as the cropland area operated divided by the number of farm operations.

We use data from the Bureau of Economic Analysis for the share of Agriculture to the state GDP, the number of non-farm proprietors per county, and government payments to farmers for each county. The *Government Payment per Operations* variable is total government payments (in millions) divided by the number of farm operations (from the COA data). County unemployment data come from the Bureau of Labor Statistics. The number of *Non-farm proprietors* measures the entrepreneurial potential in a county and is computed as a share of non-farm proprietors to the working population, obtained from the US Census.[8]

Data on access to finance come from the Federal Deposit Insurance Corporation and the Farm Credit Service. The USDA's Farm Income and Wealth Statistics provides the data on real estate debt, non-real estate debt, and on the components of real and non-real estate debt. State level data on average farmland price come from the USDA's national Agricultural Statistical Service. Data on disaster county designation and the indemnity payments are collected from the SHELDUS.[9] *Disaster county* is a dummy that takes the value of one if a county was announced to be a disaster during the past 5 Census years. The variable *Indemnity Payment* is county level indemnity payment divided by acres of cropland Data on county annual mean temperature and precipitation (also squared) come from the National Oceanic and Atmospheric Administration.

Results

Table 3.2 contains the results from the fixed effects regressions with standard errors clustered at county level. In the first two columns, the dependent variables are BFR net entry computed as log differences in the numbers of BFRs over 10 and 5 year intervals for BFRs with farming experience of less than 10 and 5 years, respectively. The dependent variable in the third column is the share of BFRs with less than 3 years of experience.[10,11] Columns 4-6 contain results from regressions where the dependent variables are the net entry by retirement age farmers (age

>65 years), young farmers (age <35 years), and female farmers. These categories are used to help understand better the difference between BFRs and young farmers because these categories do not necessarily overlap. This can also shed light on what motivates exit by retirement age farmers because this indirectly affects the BFRs ability to enter.[12] We are interested in the net entry by female farmers because recent data have shown that women enter farming in proportions higher than men and, therefore, it is important to understand what factors may be associated with women farmers net entry rates.

<<<<<[Table 3.2]>>>>>

The results show that net entry is influenced by several barriers to entry. First, we find that net entry in all regressions is negatively associated with the average county *Farm Size*, indicating that economies of scale and fixed costs are an important barrier to entry in the industry. Larger farms that are likely incumbent, more efficient, and more connected through the supply chain possibly influencing new entrants' transaction costs and ability to access markets. The coefficients' magnitudes are similar for BFRs, young, and women farmers (-0.026, -0.025 and -0.023) but are double that for BFRs with less than 5 years of experience (-0.038) indicating that newest entrants are even more sensitive to the average farm size. The negative and much smaller coefficient (-0.014) for operators over 65 indicates a tendency of operators of larger and supposedly incumbent farms to stay in business longer (retire later), consistent with Griffin *et al.* (2019) but with the added qualification that this delay in retirement is more likely to happen in counties with smaller size farming units. These results are consistent with the positive coefficient estimated on the number of operations in a county – net entry increases with the number of farm operations. Together with the positive association with smaller farm size, this suggests that BFRs seek opportunities to overcome barriers to entry and are more successful in counties with more and smaller farms, which confirms that fixed capital needs are an important entry barrier and is supporting of policies to improve access to credit for financing asset acquisition.

The farm productivity indicator (sales to assets ratio) is negatively associated with entry of BFRs measured over 10 year intervals, indicating that BFRs are likely more successful in counties with lower average productivity. If the new BFRs survive and succeed in those counties, their average productivity may increase. In contrast, young farmers' net entry seem to be higher in counties with higher average farm productivity. .

Farmland price also has a positive association with BFRs' net entry (over 10 year period). The results indicate that a 1% increase in farmland prices is associated with an increase in net entry by 13.8% but with only half of that (7%) in retirement age farmers and only 3.9% in female operators. Net entry by young farmers has the opposite association with the farmland prices, with net entry decreasing by 14.9% when farmland prices increase by 1%. The share of newest entrants in the BFR group (with less than 3 years of experience) is also negatively associated with farmland prices. This is largely consistent with studies showing that most new farmers do not inherit farmland and face challenges acquiring it (Katchova and Ahearn, 2016). While, in the past, descendants usually took over family farms, beginning around the late 1980s, most agricultural land in the U.S. was purchased from a non-relative (Ahearn, 2013; Rogers and Wunderlich, 1993). For the entire farming population, USDA estimates that a quarter of farmland transfers is between non-relatives and that the farmland prices matter.

Another consistent result is that all categories of BFRs, as well as young farmers, have higher growth in counties that have more opportunities for off-farm work. The number of farmers that worked off-farm for more than 200 days is positively associated with net entry of all BFR types and young farmers. The coefficient is the largest for the newest BFRs as share of all

BFRs (0.327). The estimates for young farmers and BFR with less than 5 years of experience are practically the same (0.085 and 0.08 respectively), and times larger than those for all BFRs (0.023) indicating that opportunities for income diversification or supplement are attractive to beginning farmers, particularly in the early stages of their farming business. The coefficient estimate is negative for the net entry of retirement age farmers, suggesting that counties with more off-farm work opportunities are the ones with more retiring older farmers.

Consistent with Nadolnyak *et al*. (2019), net entry by BFRs and young farmers is not associated with the average income from farming nor with non-farm income. It is also not associated with government payments. The only exception is the positive coefficient of non-farm income for the newest BFRs (less than 3 years of experience), once again confirming the importance of income diversification in the early stages of farming. In contrast, retirement age farmers and female farmers are less likely to grow in numbers in counties with higher average farming income (coefficients of -0.045 and -0.066, respectively). The net entry of women farmers is higher are also less likely to survive in counties with higher average non-farm earnings. This is consistent with the finding that women contribute to farming not only as operators but also by working off farm (Witt et al., 2019).

The estimates of the average indemnity per acre indicate that net entry is higher in counties with higher value of the average indemnity payments per acre. Average indemnity payments per acre are positively related to either insurance uptake (insured acres) or higher incidence of insurable outcomes, or both. The argument behind adverse selection suggests that, in counties subject to relatively higher insurable risks, indemnity payments may also be positively related to the use of insurance. The finding that the net inflow of BFRs and young operators is higher in counties with higher use of insurance suggests that these producer categories may be benefitting from insurance as a risk management tool. Interestingly, female farmers are more likely to do better in counties with fewer indemnity payments, which is consistent with the observations that women tend to succeed in niche markets and counties suitable for these enterprises are likely less suitable for growing output that is readily eligible for subsidized insurance.

The results regarding the access to and availability of credit are somewhat surprising. Access to credit is defined as access to infrastructure or availability of commercial bank or the Farm Credit System (FCS) branches, while availability of credit is captured by the total values of Farm Real Estate and Farm Non-Real Estate Debt. There is a considerable body of literature finding that access to banking infrastructure (accessible branches) remains important for credit to small size businesses and farmers in particular (Jones and Pratap, 2020; Stam and Dixon, 2004). We find, however, that net entry of BFRs with less than three and five years of experience is lower in counties with higher density of commercial bank branches (coefficients of -16.28 and -2.62) and female farmers (-1.73). We also find that retirement age farmers are less likely to exit if they have better access to the FCS branches, consistent with the idea that incumbents have advantages in terms of access to agricultural credit.

In line with the idea that incumbents have the advantage of sunk costs that acts as an effective barrier to entry (McAfee *et al.*, 2004), we find that net entry is negatively associated with the available real estate credit (mostly offered through FCS institutions) in all regressions. Real estate debt typically finances capital investment, which amplifies the role of revenue volatility and the higher risk of default. At the same time, the non-real estate credit offered by the majority of agricultural and non-agricultural banks is consistently positive for all farmer cohorts. Non-real estate debt is mostly seasonal loans to finance working operating capital and should, at least in theory, increase productivity and efficiency and, thus, net entry of BFRs with access to this type of credit.

<<<<<[Table 3.3]>>>>>

Table 3.3 contains a more detailed summary of estimated coefficients for each subgroup of credit. The regressions are equivalent to those in Table 3.2 but the real and non-real estate debts are broken into their subgroups. Each type of credit is included in a stepwise fashion and thus the estimated coefficients are interpretable only relative to all other sources of credit.[13] These estimates show negative association between the net entry and commercial bank real estate, FSA real estate, Life insurance real estate, and FSA non-real estate loans for the group of BRS with less than 5 years of experience, farmers of retirement age, and young farmers. The fact that the results differ for newer BFRs suggests that the BFRs who survive the first 5 years are able to reverse the negative association with these sources of farm credit. The rest of credit types are positively associated with net entry except for the individual real-estate credit for women.

Going back to Table 3.2, the estimates of the control variables are largely consistent with the literature. Agricultural GDP ratio has a small and significant positive impact on the net entry, indicating that counties with relatively larger agricultural economies attract BFRs (Griffin *et al.*, 2019; Nadolnyak *et al.*, 2019). A 1% increase in the ratio is associated with approximately 0.04% and 0.2% increase in net entry of BFRs with <10 and <5 years of experience. Unemployment rate has a negative association with net entry of BFRs with <5 years of experience and women and a positive association with net entry by BFRs with <10 years of experience. Unemployment is usually associated with higher labor supply but is also indicative of the health of local economy, which might explain the conflicting and insignificant estimates. The entrepreneurial potential of a county is measured by the ratio of non-farm proprietors to total working age population and is only negatively associated with the net entry by young farmers. This indicates some level of substitutability between choosing farming and alternative entrepreneurial activities by young entrepreneurs.

As expected, the agricultural output/input price index is positively associated with net entry, consistent with Goetz and Debertin (2001). Only retirement-age farmers' exit is positively associated with the declaration of a county as a disaster zone suggesting that incumbents benefit more from all kind of programs possibly including disaster payments. The metro/non-metro county classification is negatively associated with net entry by female farmers only suggesting that women may not be choosing urban agriculture. Finally, the estimated coefficients on the climate variables indicate that lack of precipitation marginally affects vulnerable producers (BFRs), while annual mean temperature increases the entry of BFRs' net entry at a decreasing rate and increases net exit of retirement age farmers.[14]

Conclusions

Beginning farmers and ranchers (BFRs) are playing an increasingly important role in the US agriculture and hold the promise of increasing its productivity and efficiency. Understanding the drivers of their entry in the business is particularly important because the majority of established farmers are nearing their retirement age and large farm ownership transfers are expected in the near future. We contribute to the farm entry and exit literature by identifying several important factors that affect BFR dynamics.

Our analysis is motivated by Goetz and Debertin (2001) who use changes in the number of farmers between Agricultural Census rounds to study farm entry and exit dynamics. We define net entry as log difference in farmer numbers between the Census of Agriculture rounds.

We then evaluate how net entry is affected by barriers to entry and economic environment, access to credit, and climate variables by estimating fixed effects regressions with standard errors clustered at the county level using county level data from 1997 to 2017. To better understand the differences and interdependencies between the dynamics of different farmer cohorts, we use net entry of BFRs with various numbers of years in farming (less than 10, 5, and 3 years), as well as entry/exit of young, retirement age, and women farmers. The explanatory variables come from several sources matching the Census county level data and include Census of Agriculture (COA) Quick Stats, BLS, BEA, USDA Farm Income and Wealth Statistics, FDIC, FEMA, NOAA and others.

The results show that new farmers face effective entry barriers. In particular, we find that net entry by BFRs is negatively associated with the average farm size in a county but positively associated with the number of farm operations, which indicates that economies of scale and fixed costs are an important barrier to entry, confirming the significance of capital requirements and possibly network effects. BFRs' net entry rate decreases and young farmer net entry increases with average county farm productivity suggesting local competition as another entry barrier, as well as important differences between BFR and young farmers. Farmland prices are positively associated with BFR entry and negatively with the young farmer entry but the causality and the tradeoff between price and farmland quality is hard to establish. Both BFRs and young farmers have higher growth rates in counties with more operators farming part-time indicating that opportunities for income diversification are attractive to beginning farmers, particularly in their early stages. Interestingly, net entry by BFRs and young farmers is unrelated to the average income from farming nor to non-farm income, possibly pointing out non-pecuniary benefits of being self-employed and having a long planning horizon. In fact, we find that in counties with more entrepreneurial people the net entry of younger farmers is lower, possibly due to substitutability between farming and other entrepreneurial activities. BFRs are more likely to do well in counties where agriculture is important for the economy, counties that grow more crops eligible for insurance and have more part-time farming opportunities.

Net entry increases with availability of non-real estate credit but decreases with real estate loans, which are used to finance capital investment and amplify revenue volatility increasing the risk of default. Thus, for BFRs' to acquire the assets needed to reach optimal scale, access to credit remains essential. Entry of BFRs increases with annual mean temperature at a decreasing rate and but net exit of retirement age farmers increases with temperature, whereas mean precipitation decreases net entry of young farmers and BFRs with less than 5 years of experience.

Overall, our results are largely consistent with the existing literature on farm entry and sector dynamics. They point out important entry barriers including economies of scale and fixed costs, local competition, and access to credit, which can be useful in policy design. In particular, the finding that entry dynamics is unaffected by government payments may be of use in deciding on reduction or withdrawal of the federal market facilitation payments (MFP) program as the trade war and the pandemic abate.

TABLES

Table 3.1:Summary Statistics

Dependent Variables	**Mean**	**s.d.**	**Independent Variables**	**Mean**	**s.d.**
BFR Operators (#)	197.58	177.45	**Access to Credit**		
BFR experience < 10 yrs	82.09	78.67	Bank per sq. mile	0.06	0.52
BFR experience < 5 yrs	32.37	32.77	FCS per sq. mile	0.06	0.07
BFR experience < 3 yrs	16.42	6.93	**Farm Sector Debt**		
Young operators, age <35	58.83	52.16	Real Estate Debt, $bil	166.23	41.35
Female operators (#)	326	307.56	Non-RE Debt, $bil	131.32	12.38
Operators, age > 65 (#)	227.4	200.99	**Economic Environment**		
All Operators (#)	1069	873.19	Share of Ag. GDP	0.02	0.02
Independent Variables			Non-Farm Propr. to Working Pop., %	5.73	2.56
Barriers to Entry			Ag. Price Index	0.84	0.21
Farm Operations, in '00s	6.97	5.53	Unemployment rate, %	0.84	0.19
Farm Productivity	0.21	0.21	Cropland, acres	135,695	150,387
Farm size, in '00s acres	6.44	15.3	Metro county	0.3	0.46
Net Cash Income per Operation, in $'00,000	0.41	0.61	Disaster declared county (share or # or %)	0.24	0.43
Non Farm Income per Operation, in $ '000s	56.6	1634.11	**Climate**		
Worked Off-Farm > 200 days, # Operators in '00s	2.94	2.5	Annual mean temperature	13.33	4.56
Indemnity/Acre, $ '000s	0.02	0.04	Annual temperature^2	198.4	124.42
Gov. Payment per Operation, in $'000s	7.81	13.59	Annual mean precipitation	82.37	34.28
Farmand Price, in log	7.84	0.68	Annual precipitation^2	7960.37	6593.61
			Year 2017	0.2	0.4

Table 3.2. Regression Results

VARIABLES	**BFR <10y** Net Entry Diff 10y	**BFR<5y** Net Entry Diff 5y	**BFR<3y** % of BFRs Diff 5y	**> age 65** Net Entry Diff 5y	**< age 35** Net Entry Diff 5y	**Women** Net Entry Diff 5y
Barriers to Entry						
Farm size	-0.026***	-0.038***	-0.152**	-0.014***	-0.025**	-0.023***
	(0.005)	(0.008)	(0.070)	(0.003)	(0.010)	(0.004)
Farm Productivity	-0.272***	0.012	1.220	-0.023	0.217*	-0.044
	(0.100)	(0.146)	(1.537)	(0.046)	(0.125)	(0.061)
Farmland Price	0.138***	-0.078	-1.572***	0.070***	-0.149***	0.039*
	(0.032)	(0.062)	(0.568)	(0.017)	(0.046)	(0.020)
Worked Off-Farm	0.029***	0.080***	0.327**	-0.021***	0.085***	0.009
	(0.009)	(0.014)	(0.153)	(0.005)	(0.012)	(0.006)
Farm Operations	0.094***	0.041***	-0.216	0.058***	0.010	0.064***
	(0.009)	(0.010)	(0.191)	(0.005)	(0.008)	(0.006)
Net Cash Income	-0.023	0.002	0.102	-0.045***	-0.031	-0.066***
	(0.014)	(0.030)	(0.311)	(0.010)	(0.028)	(0.012)
Non Farm Income	-0.001	-0.002	0.031*	-0.001	-0.001	-0.002***
	(0.001)	(0.001)	(0.018)	(0.001)	(0.006)	(0.001)
Indemnity/Acre	0.225**	0.704**	7.091**	-0.092	1.072***	-0.270***
	(0.098)	(0.340)	(2.989)	(0.074)	(0.243)	(0.083)
Gov. Payment	-0.001	-0.001	0.003	-0.000	-0.001	0.001
	(0.001)	(0.001)	(0.012)	(0.000)	(0.001)	(0.001)
Access to Credit						
Bank per sq mile	0.283	-2.623***	-16.27**	-0.168	-0.341	-0.173**
	(0.448)	(0.485)	(8.235)	(0.169)	(1.056)	(0.076)
FCS per sq mile	8.885	-4.140	20.254	3.679*	-15.713	6.317
	(37.393)	(9.486)	(98.269)	(2.208)	(39.396)	(17.520)
Farm Debt						
Real Estate Debt	-0.014***	-0.046***	-0.082**	-0.005***	-0.01***	-0.010***
	(0.001)	(0.004)	(0.034)	(0.001)	(0.003)	(0.001)
Non-RE Debt	0.056***	0.160***	0.424***	0.029***	0.060***	0.034***
	(0.003)	(0.011)	(0.091)	(0.003)	(0.007)	(0.002)
Economic Environment						
Share of Ag. GDP	3.779***	5.877***	21.853	-0.900**	4.852***	3.046***
	(0.908)	(1.554)	(13.356)	(0.418)	(0.985)	(0.607)
Unemployment	0.008*	-0.020**	-0.117	0.001	-0.006	-0.006*
	(0.004)	(0.010)	(0.096)	(0.003)	(0.008)	(0.003)
Non-Farm Proprietors	0.003	-0.009	-0.100	-0.003	-0.012**	-0.003
	(0.004)	(0.008)	(0.078)	(0.002)	(0.006)	(0.003)

Ag. Price Index		1.531***	3.982***	0.069*	0.805***	
		(0.157)	(1.374)	(0.039)	(0.110)	
Cropland	0.000	0.000	-0.000	0.000	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
All Operators			0.001			
			(0.001)			
Metro	-0.010	0.014	0.130	0.002	-0.012	-0.065***
	(0.036)	(0.041)	(0.392)	(0.012)	(0.028)	(0.023)
Disaster County	-0.002	0.005	-0.090	-0.011**	0.012	0.011
	(0.010)	(0.021)	(0.187)	(0.005)	(0.016)	(0.007)
Climate						
Annual mean temperature	0.037*	-0.022	-0.084	-0.045***	-0.022	-0.007
	(0.022)	(0.041)	(0.373)	(0.011)	(0.030)	(0.013)
Annual mean temperature ^2	-0.003***	0.001	0.007	-0.001**	-0.000	0.000
	(0.001)	(0.001)	(0.010)	(0.000)	(0.001)	(0.000)
Annual mean precipitation	-0.001	-0.005**	-0.006	0.002***	-0.007***	0.002***
	(0.001)	(0.002)	(0.020)	(0.001)	(0.002)	(0.001)
Annual mean precipitation^2	0.000***	0.000**	0.000	-0.000***	0.000***	-0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year 2017	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-7.509***	-13.77***	-16.031	-3.422***	-4.325*	-3.918***
	(2.280)	(1.175)	(10.424)	(0.290)	(2.216)	(1.109)
Observations	6,481	8,516	8,531	8,567	5,752	6,532
R-squared	0.497	0.350	0.179	0.459	0.488	0.483
Number of FIPS	2,466	2,491	2,497	2,502	2,019	2,480

Robust standard errors in parentheses: county level clustering *** p<0.01, ** p<0.05, * p<0.1.

Note: The dependent variable in the first column is the log difference of BFRs at time t and BFRs 10 years ago. The dependent variable in the second column is the log difference of BFRs with less than 5 years of experience at time t and the previous round of Agricultural Census (5 years). The dependent variable in the third column is the percentage of BFRs with less than 3 years of experience in all BFRs. The dependent variable in the fourth column is the log difference of the number of retirement age farmers (age >65 years) at time t and the previous Census of Agriculture (5 years prior). The dependent variable in the fifth column is the log difference of the number of young farmers (age <35 years) at time t and the previous Census of Agriculture (5 years prior). The dependent variable in the fourth column is the log difference of the number of women farmers at time t and those in the previous Census of Agriculture (5 years prior).

Table 3.3. Summary of the coefficient estimates by individual credit type, where each credit subgroup is included alone in stepwise fashion for the dependent variables corresponding to those in Table 3.2.

VARIABLES	**BFR <10y** Net Entry Diff 10y	**BFR<5y** Net Entry Diff 5y	**BFR<3y** % of BFRs Diff 5y	**> age 65** Net Entry Diff 5y	**< age 35** Net Entry Diff 5y	**Women** Net Entry Diff 5y
Access to Credit						
Bank per sq mile	0.283	-1.521***	-16.989**	-0.168	-0.341	-0.173**
	(0.448)	(0.194)	(7.680)	(0.169)	(1.056)	(0.076)
FCS per sq mile	8.885	-5.167	26.845	3.679*	-15.713	6.317
	(37.393)	(3.420)	(102.986)	(2.208)	(39.396)	(17.520)
Real Estate Debt						
Commercial Bank	0.001***	-0.004***	-0.022***	-0.001***	-0.003***	0.000***
	(0.000)	(0.000)	(0.005)	(0.000)	(0.000)	(0.000)
FCS	0.001***	0.022***	0.120***	0.008***	0.016***	0.000***
	(0.000)	(0.002)	(0.028)	(0.001)	(0.002)	(0.000)
FSA	0.013***	-0.020***	-0.107***	-0.007***	-0.015***	0.005***
	(0.001)	(0.002)	(0.024)	(0.001)	(0.002)	(0.001)
Farm Mac	0.014***	0.019***	0.100***	0.007***	0.014***	0.005***
	(0.001)	(0.002)	(0.023)	(0.001)	(0.002)	(0.001)
Individual	-0.010***	0.006***	0.031***	0.002***	0.004***	-0.004***
	(0.001)	(0.000)	(0.007)	(0.000)	(0.001)	(0.001)
Storage Facility and Others	0.145***	0.244***	1.882***	0.138***	0.180***	0.055***
	(0.013)	(0.022)	(0.338)	(0.009)	(0.030)	(0.009)
Life Insurance	0.015***	-0.018***	-0.098***	-0.006***	-0.013***	0.006***
	(0.001)	(0.002)	(0.022)	(0.001)	(0.002)	(0.001)
Non-Real Estate Debt						
Commercial Bank	0.004***	0.015***	0.082***	0.005***	0.011***	0.001***
	(0.000)	(0.001)	(0.019)	(0.001)	(0.002)	(0.000)
FCS	0.003***	0.021***	0.114***	0.007***	0.016***	0.001***
	(0.000)	(0.002)	(0.026)	(0.001)	(0.002)	(0.000)
FSA	0.121***	-0.026***	-0.140***	-0.009***	-0.019***	0.046***
	(0.011)	(0.002)	(0.032)	(0.001)	(0.003)	(0.007)
Individuals	0.013***	0.030***	0.158***	0.010***	0.022***	0.005***
	(0.001)	(0.003)	(0.036)	(0.001)	(0.003)	(0.001)

Robust standard errors in parentheses: county level clustering *** p<0.01, ** p<0.05, * p<0.1.

Note: This table summarizes the coefficient estimates of each disaggregate credit type. These estimates are from regressions where each credit subgroup is included in a stepwise fashion in regressions for the dependent variables denoted in the heading of the column with all other non-credit controls the same as those in Table 2.

End Notes

1. Authors' computations from the Census of Agriculture data.

2. Seminar on the status of BFRs, ERS and NASS, USDA, May 2019.

3. Specifically, Key and Lyons (2019) report that "47% of beginning farmer principal operators were classified as an off-farm occupation farm (GCFI less than $350,000 per year and principal operator reporting major occupation other than farming) over 2013-17. In 2017, 67% of beginning farm principal operators worked off-farm, *and* 22% worked off-farm part time (1-199 days). Some 45% of beginning farm operators worked off-farm full time (200+ days)."
4. Examples of entry barriers least applicable to farming but widely researched in the literature are government standards and permit requirements, intellectual property, market power in advertising, predatory pricing, and R&D costs (see McAfee *et al.,* 2004, for a detailed description).

5. The entry rates for young farmers during the 1997-2012 period varied from 12.5 to 14.1 % and the exit rates varied from 8.9 to 9.3.

6. Alternatively, the empirical model can be related to survival analysis where the estimated hazard function (of entering or exiting) is a product of the baseline hazard and a function of the covariates suggested by theory (as in Cox proportional hazard).

7. Prior to 2017, BFRs data is for only primary operators who have an experience of 10 years or less for operating a farm, rather than any operator. Thus, BFRs in 2017 include any operator with less than 10 years of experience. Clearly, this is a measurement error type of problem but since it is an issue for the left hand side variable, and we use all county data available the results remain unbiased and consistent.

8. "Non-farm proprietorships are full and part-time sole proprietorships, partnerships, and other private nonfarm businesses that are unincorporated and organized for profit. A sole proprietorship is an unincorporated business required to file Schedule C of IRS Form 1040 (Profit or Loss from Business)."

9. Available at https://cemhs.asu.edu/sheldus.

10. The share, rather than log difference, is the dependent variable. Private communication with NASS staff revealed that this particular class of BFRs is the hardest to identify and thus include in the Census data collection, rendering log difference variable less reliable and share to total BFR a preferred specification.

11. In 2017, NASS changed how it counted BFRs from counting only principal operators with less than 10 years of experience to counting any operator with less than 10 years as a BFR. This resulted in significant increase of BFRs between 2012 and 2017. Since this can be considered a left hand side measurement error, the estimated coefficients are still

are expected to be consistent and unbiased. We also add a dummy for the year 2017 to account for this change in definition.

12. For robustness checks, we also estimate models with controls for previous and current period BFRs and farmers over 65 without qualitative changes in the results (Table A.1 in the Appendix).

13. Due to a high level of collinearity, each type of credit variables is included one at a time.

14. Several robustness checks (not shown to preserve space) with additional controls such as lagged numbers of retirement age, BFRs, and young farmers, year dummy combinations and various scaling variables, show that the main results are retained for the regressions in Table 2 and those summarized in Table 3.

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APPENDIX

Table A3.1. Regression Results with Lagged Numbers of BFR, Young, and Established Operations

VARIABLES	**BFR <10y** Net Entry Diff 10y	**BFR<5y** Net Entry Diff 5y	**BFR<3y** % of BFRs Diff 5y	**> age 65** Net Entry Diff 5y	**< age 35** Net Entry Diff 5y	**Women** Net Entry Diff 5y
Barriers to Entry						
Farm size	-0.026***	-0.024***	-0.188**	-0.014***	-0.023**	-0.022***
	(0.009)	(0.009)	(0.080)	(0.003)	(0.010)	(0.007)
Farm Productivity	-0.436***	0.016	0.396	0.006	0.246**	-0.051
	(0.136)	(0.106)	(1.582)	(0.039)	(0.107)	(0.067)
Farmland Price	0.122***	-0.078**	-1.755***	0.040**	-0.161***	-0.010
	(0.036)	(0.037)	(0.635)	(0.016)	(0.039)	(0.021)
Worked Off-Farm	0.040***	0.000	0.189	0.025***	0.030**	0.013
	(0.010)	(0.020)	(0.173)	(0.010)	(0.014)	(0.010)
Farm Operations	0.072***	0.114***	0.260	0.057***	0.073***	0.058***
	(0.010)	(0.020)	(0.218)	(0.011)	(0.012)	(0.011)
Net Cash Income	-0.027	-0.009	-0.295	-0.040***	-0.051**	-0.060***
	(0.023)	(0.026)	(0.344)	(0.010)	(0.024)	(0.013)
Non Farm Income	-0.001	-0.003	-0.032	0.002*	0.002	-0.003**
	(0.003)	(0.005)	(0.045)	(0.001)	(0.005)	(0.001)
Indemnity/Acre	0.090	0.560***	8.315***	-0.099	0.787***	-0.312***
	(0.119)	(0.191)	(3.086)	(0.072)	(0.199)	(0.089)
Gov. Payment	-0.001	-0.001	0.006	-0.000	-0.002*	0.001
	(0.001)	(0.001)	(0.014)	(0.000)	(0.001)	(0.001)
BFRs, lag	0.000	-0.004***	-0.010***	-0.000**	-0.000**	-0.001***
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
Young, lag	-0.000	-0.002***	-0.011**	0.000	-0.012***	-0.001***
	(0.000)	(0.000)	(0.005)	(0.000)	(0.001)	(0.000)
Over 65, lag	-0.000*	-0.000	-0.000	-0.002***	-0.000*	-0.001***
	(0.000)	(0.000)	(0.002)	(0.000)	(0.000)	(0.000)
Access to Credit						
Bank per sq mile	-1.755*	-1.199	16.198	0.722**	-1.235	0.037
	(1.056)	(0.740)	(12.185)	(0.339)	(0.939)	(0.589)
FCS per sq mile	64.756	-3.048	17.253	2.370	-9.430	17.359
	(73.861)	(7.620)	(97.367)	(3.339)	(30.495)	(20.829)
Farm Debt						
Real Estate Debt	-0.013***	-0.016***	-0.054	-0.001	0.005*	-0.010***
	(0.001)	(0.003)	(0.037)	(0.001)	(0.002)	(0.001)

Non-RE Debt	0.053***	0.067***	0.359***	0.020***	0.011*	0.036***
	(0.004)	(0.007)	(0.098)	(0.003)	(0.007)	(0.002)
Economic Environment						
Share of Ag. GDP	4.087***	4.785***	35.788**	-1.818***	5.137***	2.788***
	(1.081)	(0.952)	(13.919)	(0.397)	(0.875)	(0.700)
Unemployment	0.010*	-0.019***	-0.102	-0.001	0.001	0.005
	(0.006)	(0.006)	(0.105)	(0.003)	(0.006)	(0.003)
Non-Farm Proprietors	-0.003	0.002	-0.114	-0.008***	-0.003	-0.005*
	(0.005)	(0.005)	(0.097)	(0.002)	(0.005)	(0.003)
Ag. Price Index		-0.112	2.154	0.106**	-0.471***	
		(0.106)	(1.570)	(0.041)	(0.110)	
Cropland	-0.000	-0.000	-0.000	-0.000	0.000***	0.000**
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
All Operators			0.001			
			(0.002)			
Metro	-0.029	-0.002	-0.126	0.008	-0.002	-0.037
	(0.036)	(0.025)	(0.397)	(0.010)	(0.026)	(0.026)
Disaster County	0.002	0.014	-0.007	-0.009*	0.009	-0.003
	(0.011)	(0.013)	(0.208)	(0.005)	(0.014)	(0.007)
Climate						
Annual mean temperature	0.022	0.039	-0.467	-0.029**	0.030	0.007
	(0.023)	(0.026)	(0.398)	(0.012)	(0.025)	(0.014)
Annual mean temperature ^2	-0.002***	0.000	0.019*	-0.000	-0.001	-0.000
	(0.001)	(0.001)	(0.011)	(0.000)	(0.001)	(0.000)
Annual mean precipitation	-0.002	-0.003**	-0.004	0.002***	-0.004**	0.002***
	(0.001)	(0.001)	(0.021)	(0.001)	(0.001)	(0.001)
Annual mean precipitation^2	0.000**	0.000**	-0.000	-0.000***	0.000**	-0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Year 2017	Yes	Yes	Yes	Yes	Yes	Yes
Constant	-9.829**	-5.451***	-5.184	-2.188***	-0.190	-4.024***
	(4.201)	(0.779)	(10.788)	(0.318)	(1.758)	(1.209)
Observations	4,853	6,759	6,759	6,770	5,747	4,867
R-squared	0.518	0.577	0.202	0.627	0.635	0.581
Number of FIPS	2,173	2,285	2,285	2,287	2,015	2,178

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