DOES PARTICIPATION IN TWO LIVELIHOOD PROGRAMS MAKE THE LOW-INCOME HOUSEHOLDS ANY BETTER?

A study on the effect of cash transfer on demand for work under the Employment Guarantee Scheme in Chandrapur district of India.

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ABSTRACT

Income support programs like Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS) and recently launched Prime Minister Kisan Samman Nidhi (PM-kisan) support over 90 million households together across rural India. Many researchers look at these programs as alternative policy options due to the negative effect of cash benefits on demand for conditional income support programs like MGNREGS. This paper investigates the alternative nature of these schemes by estimating the negative effect of PM-kisan on demand for work under the MGNREGS. To do so, we tracked 611 households from the Tata-Cornell Institute's survey on nutrition and income for benefits under both schemes for 2018 and 2019. The average treatment effect on treated was estimated using the difference-in-differences method. The result holds the hypothesis showing almost a decrease of 13 MGNREGS workdays in households receiving cash transfers under the PM-kisan program relative to the households not receiving cash benefits. This result bolsters the opinion about the alternative nature of both schemes as a policy option. Furthermore, PM-kisan beneficiary households in Maharashtra forgo more than 44 percent of PM-kisan benefit (INR 6000) by doing less work under MGNREGS in 2019. These losses are subjective to the prevailing wage rates in states.

BIOGRAPHICAL SKETCH

Kasim was born and raised in the Nagpur district of Maharashtra, India. He attended Nagpur University and completed his Bachelor of Science degree with a major in Physics, Chemistry, and Mathematics in 2006. He has completed three master programs: Master of Business Administration (2009) in Marketing and Finance from the Institute of Chartered Financial Analysts of India, Master of Professional Studies (2019) in Global Development, and Master of Science (2021) in Applied Economics and Management (AEM) from the Cornell University in the USA. He has completed both his master's programs at Cornell as a Tata-Cornell Institute (TCI) scholar. He will soon start his Ph.D. program in AEM as a TCI scholar in Fall 2021.

Kasim has more than eight years of professional experience as a development practitioner. He worked in an NGO for tribal health and nutrition in Maharashtra for three years. During his tenure, he contributed to bringing down the infant mortality rate from 84 to 32 per 1000 live births in the region. He joined TCI as a Project Coordinator in 2012. At TCI, Kasim administered various field-based programs ranging from agriculture, nutrition, education, women's empowerment, and water and sanitation.

He is interested in empirical research work on agriculture, health and nutrition, social welfare addressing the poverty and health issues in developing countries. His hobbies include painting, reading, working-out, listening to music. He is a recipient of the state-level '*Eklavya* Award' for painting.

Dedicated to all COVID-19 victims and fighters in my study area and around the world.

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CHAPTER I

INTRODUCTION

"Extreme poverty anywhere is a threat to human security everywhere." This quote by Kofi Annan, seventh Secretary-General of the United Nations, during the Millennium Development Goals (MDGs) launch reflects the global concern about the poor. The world has achieved MDGs five years before its schedule by removing 1 billion people from extreme poverty. We are moving towards achieving the Sustainable Development Goals; the goal is to end extreme poverty in all its forms everywhere by 2030. Using the World Bank definition of $1.90/day, as of 2016, roughly 1 in 10 people worldwide remained in extreme poverty. And nearly half of them live in India and China. Moreover, in 2018, four out of five people below the international poverty line lived in rural areas (World Bank, 2020). Despite the significant number of individuals still below the international poverty line, reduction in extreme poverty over the past twenty years has taken place in countries that have had governing institutions with a solid capacity to implement public welfare programs efficiently.

Various empirical studies show the impact of public welfare programs on poverty reduction (Bhattarai et al., 2018; Drèze & Khera, 2017; Hagen-Zanker et al., 2011; Handa & Davis, 2006; Hanlon et al., 2012; Narayanan et al., 2019; *Safety Net Programs and Poverty Reduction*, n.d.; Serraj & Pingali, 2018). These studies have consistently found that public welfare programs if implemented with better delivery mechanisms, conditionality, and supervision, can help in reducing poverty up to a large extent. Many income-support programs for poor households like Employment Guarantee Schemes (EGS) and cash transfers have shown positive results in countries implementing these programs. These effects have been evaluated for a standalone program as many countries either provide cash support or EGS as a means of income support for poor households. A few empirical analyses show an impact of one welfare program on the other, but these studies deal with different welfare objectives. For example, Sudhanshu Handa (2010) compares the impact of PROGRESA on the households also enrolled in PROCAMPO where the former is health- and education-based intervention and the latter is an income support program.

There are rare examples of counties having more than one income support program for the same agricultural households. One example is India: it provides income support to the same agrarian households through Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS) and Prime Minister Kisan Samman Nidhi (PM-kisan). MGNREGS provides wages for work, while PM-kisan provides universal cash transfers. Although the impact of MGNREGS has been studied in detail (Azam, 2011; Basu, 2013; Echeverri-Gent, 1988; Joshi et al., 2017), insufficient attention has been paid to cash transfer programs like PM-kisan so far. The impact of PM-kisan on the MGNREGS beneficiary households deserves further exploration as it will open a discussion regarding the net welfare effect on the households participating in more than one income support program. This paper is one of the first attempts to study the impact of both schemes together.

This study set out to answer the following question: Is there any effect of the cash transfers under PM-kisan on demand for work under MGNREGS? This question is important as many researchers look at these programs as alternative policy options (Hagen-Zanker et al., 2011). The work requirement under MGNREGS demands greater time contribution from the beneficiaries than that required under PM-kisan. The conditionality around time and effort plays a vital role in the decision regarding participation. Though a household may increase its income by taking up MGNREGS work, it will involve physical and time efforts for activities like applying for a job card, work request, work under supervision, wait for wages to be transferred, and grievance redressal, etc. If a household is in economic distress, there is the possibility that it will invest its time and energy to earn income by taking up MGNREGS work. If a household is also receiving cash transfers in the PM-kisan, then there is a possibility that a household can review its decision regarding participation in MGNREGS.

The above explanation about the alternative nature of these programs supports the hypothesis that there is a negative effect of PM-kisan on demand for work under MGNREGS. This hypothesis, if accepted, can bolster the general perception of researchers. Under this study, the negative impact of cash transfers on the MGNREGS was investigated using a sophisticated empirical approach. Simultaneously, the results from this study can help policymakers to review the conditionality of these programs to maximize their impact.

This paper, in chapter II, discusses the global history and current trends in public welfare programs with more focus on Indian schemes like MGNREGS and PM-kisan. Chapter III talks about the detailed methodology of the study, followed by the information regarding data characteristics discussed in chapter IV. Chapter V deals with empirical methods, analysis, results, and discussion. The final chapter sums up the findings with the conclusion.

CHAPTER II

LITERATURE REVIEW

The Encyclopedia Britannica defines social welfare as a type of government support intended to ensure that members of a society can meet basic human needs such as food, health, and shelter. More broadly, welfare covers the basic level of well-being through free or subsidized social services such as healthcare, education, housing, etc. It can take various forms, such as monetary payments, subsidies, vouchers, or housing assistance. Welfare systems differ from country to country, but welfare is commonly provided to unemployed individuals, those with illness or disability, the elderly, those with dependent children, and veterans. Programs may have a variety of conditions for a person to receive welfare.

History of welfare programs

Historically, welfare is an ancient concept and is the fundamental component of many religions. The emergence of Zakat (charity), one of the Five Pillars of Islam as contributions collected by the government, was the world's first instance of a codified universal social security tax (Jon P. Mitchell, 2009). Likewise, in Jewish tradition, charity (represented by tzedakah) is a matter of religious obligation (Ulmer, 2014). Christian missionaries are doing their charitable work for poor and needy people since their inception. In Hinduism, the concept of *dana* (donation) to Brahmins (upper castes) as an act towards God was there since the beginning (Nadkarni, 2007). This type of donation now also covering poor and needy people. In totality, almost all the religions focused on charity as a basic tenant of the religion.

Many countries introduced the organized system of state welfare in the late 19th and early 20th centuries. During the late 19s, Otto von Bismarck, Chancellor of Germany, introduced one of the first welfare systems for the working classes (Marian, 2015). The United Kingdom launched social security around 1913 and adopted the welfare state with the National Insurance Act 1946 (Robson, 1947). The governments in the countries of western Europe, Scandinavia, and Australasia provided social welfare out of the national tax revenues, and to a lesser extent, by non-government organizations (NGOs) and charities (social and religious). Despite having a long history of public welfare, the report published by the ILO in 2014 estimated that only 27% of the world's population has access to comprehensive social security (*World of Work Report, 2014*).

Welfare programs: Global experience

The experiences of several countries with welfare programs shaped the welfare approach globally. Several countries started their welfare programs because of public demand. For example, in Australia, the 1890s economic depression and the rise of the trade unions during this period led to a movement for welfare reform focusing on the laborers (Markey, 2004). Big countries like Canada found it efficient to de-centralize their social safety net programs and be run by the provinces. Welfare programs in countries like Denmark, Germany provide tax-funded universal support to its citizen in education, public childcare, medical care, etc.

In comparison, developing countries like India provide welfare services to poor households through the right-based life-cycle approach. Under this approach, low-income families receive assistance during different phases of life like mother care during pregnancy, nutritional and educational support during childhood (right to education), food assistance to food-insecure families (right to food), income support for the productive age group population (right to work), and retirement and insurance programs for older people. Similarly, the USA has need-based welfare programs. It covers health care through Medicaid, food insecurity through food and nutrition programs (SNAP), social safety net through Unemployment Insurance, Social Security, and Medicare. On the contrary, Italy follows a universalistic welfare model, offering several universal and free services such as a National Health Fund. Japan has priority population welfare schemes covering the ill or otherwise disabled, older people.

The positive impact of welfare programs in Latin America in recent decades helped shape the modern welfare programs around the globe (Barrientos & Santibáñez, 2009). This social protection comprises three major areas: social insurance, financed by workers and employers; social assistance to the population's poorest, funded by the state; and labor market regulations to protect worker rights. The economic crisis of the 1980s led to a shift in social policies as understandings of poverty and social programs evolved (Ghai & Alcántara, 1990). As a result, highly effective welfare programs like *Bonosol in Bolivia, Bolsa Familia in Brazil*, and *Prospera* in Mexico have emerged.

Based on prior experiences, welfare programs have integrated the multidimensional, social risk management, and capabilities approach into poverty alleviation. They focus on income transfers and service provisions while aiming to alleviate both long- and short-term poverty through, among other things, education, health, livelihood, and housing. The impacts of social assistance programs vary between countries, and many programs have yet to be thoroughly evaluated. According to Barrientos and Santibanez, the programs have successfully increased investment in human capital than in bringing households above the poverty line (Barrientos & Santibáñez, 2009).

Welfare programs: Indian experience

The constitution of India declares India as a welfare state. The National Food Security Act, 2013, guarantees food security to all Indians where the government provides food grains to economically vulnerable people at a very subsidized rate. Similarly, the Right to Work and the Right to Education are examples of the right-based acts under the Indian constitution. Indian government divides social security into seven branches: healthcare, old age/retirement; family and childcare; accident assurance;

and occupational disease, rural job guarantee, and food security. The Central Government of India's social security and welfare expenditures are a substantial portion of the official budget. State and local governments play roles in developing and implementing social security policies. Additional welfare measure systems are also uniquely operated by various state governments.

The government uses the unique identity number (Aadhaar) that every Indian possesses to distribute welfare measures in India. Aadhaar is the world's largest biometric ID system (Rawat & Morris, 2019). The government of India uses this unique identification number to distribute social security and welfare measures to its citizens.

In developing countries like India, formal social security arrangements are often absent for most of the working population due to reliance on the informal economy (Sakthivel & Joddar, 2006). Additionally, limited infrastructure and resources limit the outreach capacity of the state. In this context, community-based programs help alleviate poverty and provide security against unemployment (Gau et al., 2014). As of 2020, the Indian government's public welfare expenditure was approximately 7.3% of its gross domestic product (GDP) (*India Economic Survey, 2020*). Table 1 shows different social security programs of India and their budgetary provision.

Table 1: Social security programs in India with budgetary provisions

Region	**Social security program**	**Crore Rupee**	**Billion US$**
Pan India	Food Security (subsidy)	11,000	20.83
Pan India	Petroleum (subsidy)	2500	16.17
Pan India	Health	200,000	30
Pan India	Pensions	600,000	60
Pan India	Accidents	130,000	20

Rural	Fertilizer (subsidy)	70,000	11
Rural	MGNREGS (non-subsidy)	151,500	25
Rural	Child development (ICDS) (non-subsidy)	26,000	4.5
Rural	Indira Awaas Yojana (Affordable Housing) (non-subsidy)	20,000	10
Rural	Maternal and childcare benefits(non-subsidy)	30,000	10
States	Various programs of state govts (subsidy/non-subsidy)	50,000	7
Rural	Prime Minister Kisan Samman Nidhi	5,214,125	700

Source: Niti Ayog (niti.gov.in)

This paper will mainly focus on the workfare and cash transfer scheme providing income support to rural households.

Mahatma Gandhi National Rural Employment Guarantee Scheme (MGNREGS)

MGNREGS is the largest anti-poverty public employment program in the world. MGNREGS was created under The National Rural Employment Guarantee Act (NREGA) to implement the scheme so that the employment guarantee comes into effect. The Act (NREGA) came into force in February 2006. In October 2009, the NREGA was amended to change its name to Mahatma Gandhi National Rural Employment Guarantee Act (MGNREGA). It was implemented in 200 districts in the first phase in 2006 and extended to 130 districts in 2007. The remaining districts were included under the Act in 2008. Currently, the Act is under implementation in 714 districts of the country, serving 80 million individuals.

The central objective of the scheme is to provide at least one hundred days of guaranteed employment to rural households whose adult members volunteer to do unskilled manual work. The scheme also mentions providing daily unemployment allowance in case of failing to deliver work within fifteen days of work demand. It requires beneficiaries to work for seven hours daily to receive fixed wages. Any rural household willing to do unskilled labor work can apply for work throughout the year. Chart 1 illustrates the mechanism of demand and supply of work under the program.

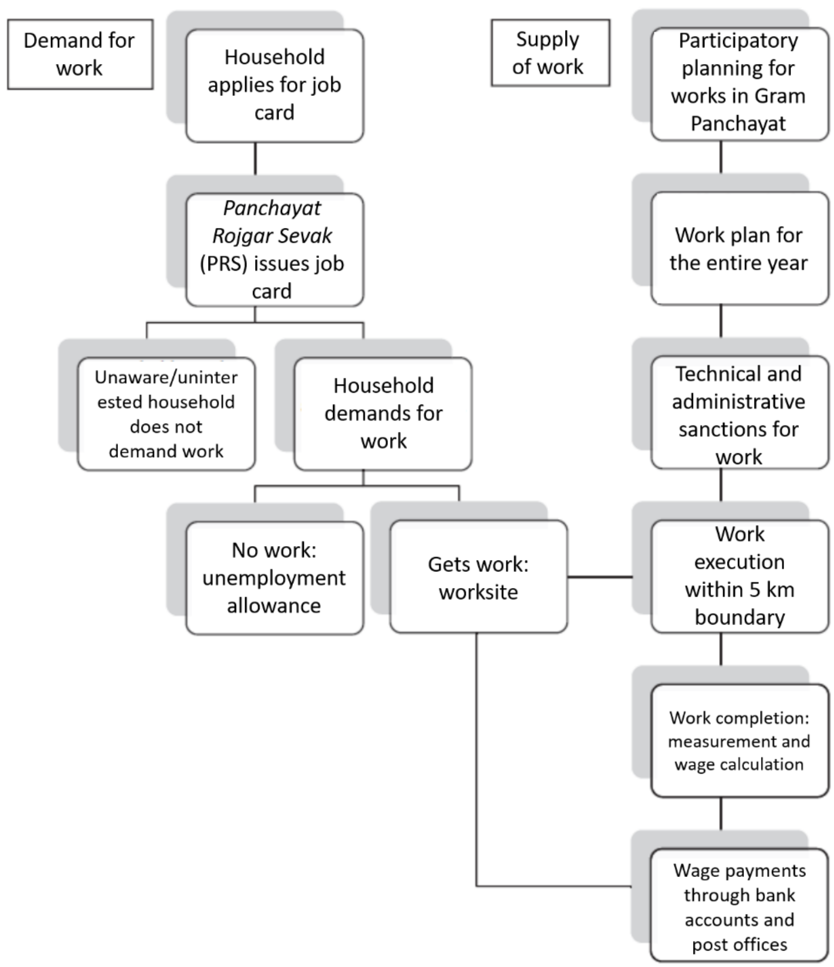
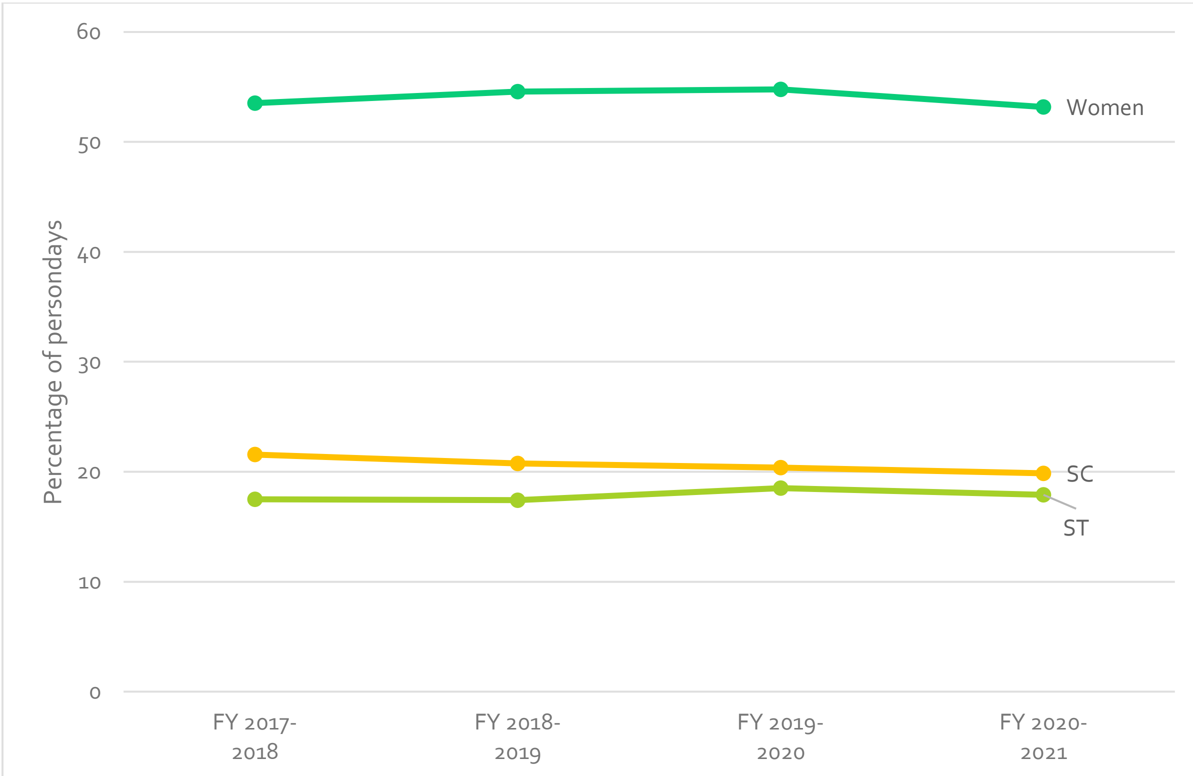


Chart 1: MGNREGS work flowchart

MGNREGS also advocates a better working environment with provisions like employment within five kilometers of the applicant's village, weekly/bi-weekly payment, continuous employment for at least fourteen days with a maximum of six days in a week. The program focuses on labor-intensive rural development works and has provisions for safe drinking water, shade for children, and periods of rest, first-aid box, creche, etc. Additionally, to promote wage equity and women empowerment, the scheme requires at least one-third of the labor force as women with equal wage rates. Despite these promising provisions, many functional problems like unmet demand, delay in payment, low women participation, occupational hazards, inadequate on-the-sight facilities keep emerging from many states from time to time (Goswami & Dutta, 2014; Kumar et al., 2018; P K, 2011).

Despite these challenges at the implementation level, MGNREGS, with its self-targeting mechanism, could largely eliminate poverty in rural India (Dutta et al., 2012). This mechanism helped in significantly reducing extreme levels of poverty and decreasing the poverty gap by one-fifth (Klonner & Oldiges, 2012). This self-targeting approach of the program, to a large extent, could filter out both the non-poor who will not want to do such work and poor people who will readily turn away from the program when better opportunities arise. It worked well in focusing on impoverished households. Economists like Jean Dreze and Ritika Khera investigated that the MGNREGS addressed some of the underlying causes of poverty in rural India. It can act as an effective tool for poverty alleviation (Drèze & Khera, 2017). On a similar note, Azam Mehtabul found a positive impact of the MGNREGS on the labor force market, mainly driven by female labor force participation (Azam, 2011). Graph 1 shows the percentage of Scheduled Caste (SC), Scheduled Tribe (ST), and women person-days. Even with its self-targeting resulting in better labor force market participation of poor households, net transfers under the program, in general, are pretty modest, which limits its poverty alleviating potential (Jha et al., 2012).

Graph 1: SC, ST, and women person-days under MGNREGS



Source: Based on the author's calculation on the data collected from nrega.nic.in

MGNREGS has shown some indirect positive effects on the wage rates in the rural labor market. To a large extent, it enforced the minimum wage rate on all casual work, including work outside the program, by declaring a statutory minimum wage rate and guaranteeing work at that wage rate. This enforcement could alter the bargaining power of poor people in the labor market. It indirectly benefited the laborers who did not even participate in the program (The World Bank, 2013). Two different rounds of the National Sample Survey show the same effect: in the 2004/05 round, three-quarters of India's casual laborers were paid less than the country's statutory minimum wage rates (before the launch of the MGNREGS), whereas, in 2009/10, the proportion of casual labors getting paid less than the minimum wage rates decreased to two-thirds (ibid).

Furthermore, MGNREGS has improved the health and nutrition status of the participant households. It significantly helped improve the quality of diet (protein and calories) for the rural families from scheduled castes and tribes (Deininger & Liu, 2013). A cross-sectional study on the infants in Rajasthan found an association between MGNREGS work and reduced infant malnutrition (Nair et al., 2013). It has also shown some complementary effects on health when associated with food security programs like Public Distribution System (PDS). A study by IFPRI using a nationally represented sample with the non-parametric DID method estimated a positive impact on the BMI of participating women and their children. It also demonstrated a negative effect on women's morbidity (Narayanan et al., 2019). Improved health and nutrition reduce the chances of disease occurrences and helps in maximizing participation in income-generating activities resulting in better household income.

To sum up, MGNREGS is a leading example of direct interventions against poverty that imposes work requirements on participants. It is a bottom-up, demand-driven, self-selecting, and rights-based program. It provides a legal guarantee for wage employment by providing allowances and compensation both in failure to provide work on demand and delays in payment of wages for work undertaken. MGNREGS is gradually transforming from the relief program of the past to a sustainable asset creator. It has the potential to reduce future poverty by creating valuable assets. For example, it can help regenerate the natural resource base and expand rural connectivity through road rehabilitation and reforestation.

India recently launched a welfare program for farmers' income support in the form of cash transfers. The following section discusses this type of welfare scheme in detail.

Pradhan Mantri Kisan SAmman Nidhi (PM-kisan)

PM-kisan was launched as a central sector scheme to provide income support to all landholding farmer's families (LFFs) in the country in December 2018. The scheme aims to supplement the financial needs of all LFFs in procuring various agricultural inputs and domestic needs. It provides INR 6000 ($80) per year to an LFF in three equal installments of INR 2000 ($26) each through online Direct Benefit Transfer (DBT) mode. A landholding farmer's family is defined as "a family comprising of husband, wife and minor children who own cultivable land as per land records of the concerned State/UT." The scheme excludes its benefits to all government servants, pensioners with a monthly pension of more than INR 10000, income-tax payers, professionals, tenant farmers, and landless farmers.

Though being the first pan-India cash transfer scheme for landholding farmers, PM-kisan is not a novel intervention. The scheme is inspired by the Telangana government's *Rythu Bandhu* (Brother farmer) scheme. Launched in May 2018, the scheme is called Farmer's Investment Support Scheme (FISS). It offers INR 10,000 ($133) per acre per year (for two crops in two seasons) without any cap on the landholding, benefiting around 60 lakh farmers in the state. Besides this, two more Indian states are running their version of cash transfer programs for farmers. First is Andhra Pradesh, the neighboring state of Telangana. It has started *Annadatha Sukhibhav* (stay blessed, farmer!) scheme in February 2019 for all farming families, including tenant farmers. This scheme offers INR 15000 ($200) per annum to all agricultural households covering nearly 70 lakh farmers in the state. This amount includes INR 6000 ($80) from the PM-KISAN. Second is Odisha, the eastern state of India. A cash transfer is one of the components of the Kalia scheme in which the state government offers a cash support of INR 5000 ($66) per season per farm family for five consecutive seasons (from Feb 2019). The scheme's objective is to assist farmers in purchasing farm inputs like seeds, fertilizers, and pesticides. Table 2 below compares several components of different cash transfer schemes.

Table 2: Cash transfer schemes for farmers

Components	PM-KISAN	*Rythu Bandhu*	Annadatha Sukhibhava	KALIA scheme
Unit	Per Family	Per Acre	Per Family	Per Family
Tenant Farmers	Not Covered	Not Covered	Covered	Covered
Started by	Union Government of India	Telangana Government	Andhra Pradesh Government	Odisha Government
No of Beneficiaries	Approx. 120 million	Approx. 6 million	Approx. 7 million	Approx. 6 million
Exclusion	Last year Income Taxpayers, Civil Servants with High Income	No Exclusion	No Exclusion	No Exclusion
Eligible	Landowners only	Landowners Only	Landowners and Tenant farmers	Landowners and Tenant farmers
Cap	No Cap	Landholding of 51 acres agriculture land and 21 acres dry land	No Cap	Small & Marginal farmer (up to 5 acres)
Assistance	₹ 6,000 per year in 3 installments	₹ 10,000 per year per acre in two installments	₹ 9,000 Extra in addition to PM Kisan Benefit, ₹ 15,000 for Non-beneficiaries of PM Kisan	Rs.5,000 per farm family over five seasons
Annual Budget	₹ 700 Bn	₹ 120 Bn	₹ 50 Bn	₹ 40 Bn

Source: Ministry of Statistics and Program Implementation (mospi.nic.in)

Income support through cash transfers is a relatively new approach to welfare in India. All the above schemes are launched recently, and there is not enough evidence to quantify their impact on the farming families. However, these schemes effectively collected more votes for the political parties in the recent state and federal elections (Davala, 2019).

Globally, cash transfers are considered a well-tested tool for public welfare programs. Many Latin American and the African continent governments are implementing cash transfer programs for the last few decades. For example, Malawi's Social Cash Transfer Scheme provides cash support to labor constraints, ultra-poor households.[1] Under the scheme, an average household receives $14 monthly as a cash benefit from the government. An impact assessment of this scheme on agricultural production shows a substantial increase in ownership of the productive agricultural asset, coupled with a sharp decrease in distress labor, which is often used as a coping mechanism in the event of food insecurity. This research indicates that cash transfer programs can better equip extremely poor farm households to expand agriculture production and reducing reliance on distressed labor activities (Boone et al., 2013). Based on these findings, one can expect a reduction in participation in the MGNREGS as an effect of cash transfers under PM-kisan, especially in the case of poor non-separable agricultural households[2].

If linked to the required conditions appropriately, literature shows that cash transfers can help achieve desired outcomes (Davis et al., 2002; Fiszbein & Schady, 2009; Gertler, 2004; Handa & Davis, 2006). For example, Mexican cash transfer programs like PROGRESA, a national anti-poverty scheme, and PROCAMPO, a scheme designed to compensate farmers for the adverse price effects of the North American Free Trade Agreement (NAFTA), target different groups of beneficiaries with different objectives. PROGRESA is targeted at women and conditioned on schooling and health outcomes, and PROCAMPO is generally targeted at men and conditioned on land use. Analysis of the program data shows that PROGRESA leads to more significant schooling expenditure and school attendance, and increased health outcomes. In contrast, PROCAMPO led to increased investment in agriculture. These results suggest that conditionality may influence longer-term (human capital) and medium-term

[1] A household lacking able-bodied adults between the ages of 19 and 64 or having a dependency ratio worse than three, and being ultra-poor, defined as consuming one meal or fewer per day and a lack of valuable or productive assets.

[2] Agricultural households with consumption and production decisions cannot be separated.

(productive) investments. This finding advises policymakers to review the conditionality of a program, depending on the desirables outcomes of the transfer scheme (Davis et al., 2002).

In another study, Sudhanshu Handa (2010) found the significantly smaller impact of PROGRESA on the households also enrolled in PROCAMPO. His finding shows that the conditional cash transfer programs must consider multiple program participation and non-separable agricultural households when designing the program and assessing impacts (Handa et al., 2010).

Both PROGRESA and PROCAMPO are crudely comparable with MGNREGS and PM-kisan. In the Indian context, MGNREGS is an employment guarantee scheme where the cash transfer (wage) is conditioned on the work. PM-kisan being a universal cash transfer scheme for farmers with landholding, can be considered conditioned on the land usage. Both schemes serve almost the same non-separable agricultural households. Suppose we relate the above finding of the PROGRESA and PROCAMPO to both of the Indian schemes. In that case, we may find a smaller impact of MGNREGS on the PM-kisan beneficiary households, maybe in terms of participation (less number of MGNREGS workdays).

An Indian experience with cash transfer schemes is scattered across states and plagued with the sociopolitical scenario of that state during implementation. For example, the conditional cash transfer program of the Bihar government provided cash transfers to subsidize diesel for paddy irrigation in drought-affected areas in 2008. A study done by Avinash Kishore shows that this scheme has not been effective in increasing paddy irrigation. The probable reasons mainly include operational challenges like low awareness and penetration among smallholders, alongside uncertainties and delays in the disbursal of the subsidy (Kishore et al., 2015). However, more than a decade of a learning curve and a better disbursal mechanism (DBT) can help the Indian government meet the objectives of PM-kisan.

The selection of a correct type of cash transfer plays a crucial role in meeting the program's objectives. The transfer can be in the form of cash or kind or both. Extensive research by the World Bank and IFPRI on a two-year pilot safety net program - Transfer Modality Research Initiative tries to answer the suitable cash transfer type for social safety net programs focusing on health and nutrition. With two randomized control trials in Bangladesh, this study shows that cash transfers can be more effective over in-kind benefits like distribution of food grains in improving the nutritional status of children in poor households of Bangladesh (Ahmed et al., 2013). In contrast, livelihood support programs focusing on promoting better technologies for increasing agricultural productivity and income may need a different approach. Narayanan (2011), in his research, discusses different types of cash transfer approaches for public welfare schemes. For schemes focusing on the agricultural inputs, such as fertilizers, "cash-assisted kind" transfers can be the better option (NARAYANAN, 2011). Vouchers meant for purchasing inputs can be provided to the farmers to ensure expenditure on the desired input. However, the dual objective of the PM-kisan (support for procuring various agricultural inputs as well as domestic needs) makes cash transfers a more practical option (Ahmed et al., 2013).

Furthermore, households receiving cash transfers under PM-kisan may experience some degree of "repulsion" on their involvement in MGNREGS, which is having a conditionality of work (Handa & Davis, 2006). In simple words, we may see a decrease in the number of MGNREGS workdays for households receiving cash transfers under PM-kisan. This paper tries to investigate the negative effect of cash transfers on MGNREGS.

The substitutional nature of MGNREGS and PM-kisan

A work requirement under MGNREGS demands greater time contribution from the beneficiaries than that required under PM-kisan. The conditionality around time and effort plays a vital role in the decision regarding participation. Though a household may increase its income by taking up

MGNREGS work, it will involve physical and time efforts for activities like applying for a job card, work request, work under supervision, wait for wages to be transferred, and grievance redressal, etc. If a household is in economic distress, there is the possibility that it will invest its time and energy to earn income by taking up MGNREGS work. If a household is also receiving cash transfers in the PM-kisan, then there is a possibility that a household can review its decision regarding participation in MGNREGS. In that case, participation is based on many factors like the need for money, time and energy constraint, the perceived value of the benefit under PM-kisan compared to that of MGNREGS, etc. For this reason, the two interventions are considered as alternative policy options (Hagen-Zanker et al., 2011).

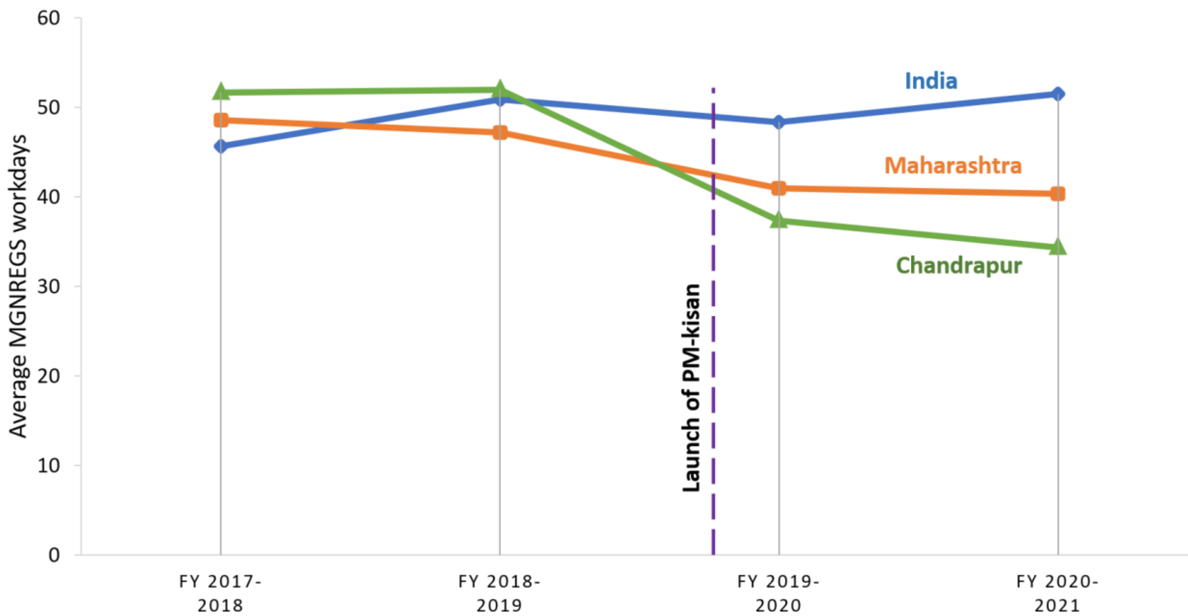
In the case of India, both MGNREGS and PM-kisan are mutually inclusive, allowing the same rural households to participate in both programs simultaneously.[3] This allowance may impact the involvement under MGNREGS negatively for the households participating in both schemes. This substitutional behavior of households can lead to a decrease in average MGNREGS workdays.

First, we can look at the available government data to draw some inferences to bolster our assumption about the effect of PM-kisan on the number of MGNREGS workdays. Graph 2 shows trendlines for average MGNREGS workdays for India, Maharashtra, and Chandrapur (study area) for corresponding years. We can see a decrease in average workdays after the launch of the PM-kisan scheme in Dec 2018. This drop is for all geographical points and supports the finding of Handa and Davis (2006). The trendline later recovers for India for the financial year 2020-21. This recovery can be the result of the nationwide lockdown after March 2020 due to COVID-19, when migrant workers

[3] Though any rural household (with or without agricultural land) willing to do un-skilled work, can apply for MGNRGS, PM-kisan requires households to possess agricultural land in order to receive cash benefits.

from all locations came back to their villages and joined the MGNREGS program in large numbers (*MGNREGA was a "Lifesaver" for Laborers During Lockdown*, 2021).

Graph 2: Average MGNREGS workdays for India, Maharashtra, and Chandrapur

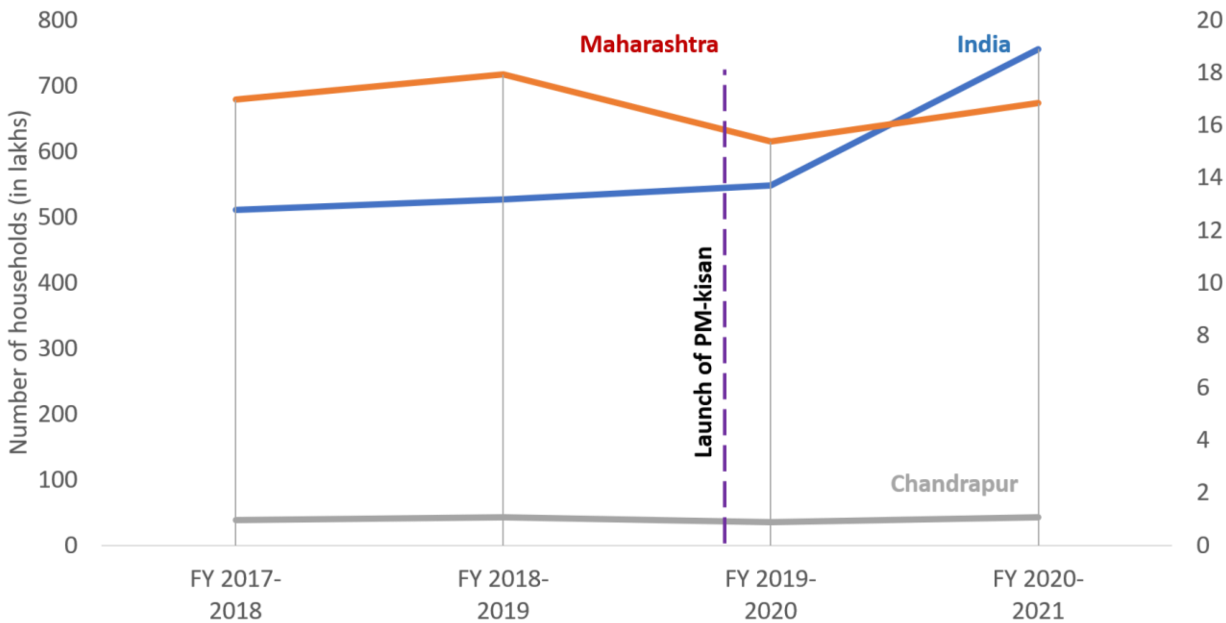


Source: Based on the author's calculation on the data collected from nrega.nic.in

Graph 3 shows the same trend for the number of households participating in MGNREGS work. The initially increasing trend reverses after the launch of the PM-kisan scheme. This 'reversal in trend' is significant for Maharashtra and Chandrapur. We can see the increase in participation under the MGNREGS for all the regions for the financial year 2020-21. This increase can be attributed to the "reverse migration" during the lockdown period due to Covid-19, as discussed in the previous paragraph.

Interestingly, in India's case, we can see a decrease (6%) in average MGNREGS workdays and a slight increase (4%) in the number of households. It reflects that some intra-household factors affect the average workdays of an individual negatively but while aggregating at the household level, showing a slight increase. These factors can be anything from age, gender, occupation, income, etc., and can play an essential role in affecting the individual's participation in MGNREGS. This paper will try to identify these factors and quantify their impact on the average MGNREGS workday.

Graph 3: Number of households participating in MGNREGS work



Source: Based on the author's calculation on the data collected from nrega.nic.in

In the next chapter, we will discuss the research methodology involved in data collection and analysis. It will help identify different individual and household level factors and quantify their impact on the participation of households in MGNREGS if the same household is receiving cash transfers under PM-kisan.

CHAPTER III

METHODOLOGY

Methodological approach

This paper investigates the impact of participation in two income support programs on the earnings of low-income households: does participation in one program undermine the intended welfare from another program? To evaluate this question, we identified two public welfare programs for low-income rural households in India: MGNREGS and PM-kisan. Both programs have a pan-India presence. MGNREGS is being implemented since 2006, whereas PM-kisan was launched in 2019. Both programs are different in their welfare approach: MGNREGS is an Employment Guarantee Scheme requiring beneficiaries to do unskilled work to get compensated in wages, whereas PM-KISAN is a universal cash transfer program for landholding farmers. This difference in approach and timeline makes it possible to investigate a cause-and-effect relationship between these programs. This paper tries to answer an exploratory research question: is there any effect of cash transfers under the PM-kisan on demand for the MGNREGS workdays?

Methods of data collection and analysis

Primary data was collected to quantify the effect of cash transfers on the MGNREGS workdays. This study used a database of the second round (2017) of TCI survey on nutrition and income in the Chandrapur district of India. This database made use of a two-stage sample design. At the first stage, 24 villages were selected based on probability proportionate to population size (8 villages from each farming cluster). At the second stage, 40 households within each village were selected based on simple random sampling using a random number generator. For this paper, the same survey households were traced for their involvement in MGNREGS. Out of 960 TCI survey households, 611 were identified based on their involvement in the MGNREGS.

A two-stage matching exercise was carried out for tracking the TCI survey households. In the first stage, households were traced for their registration under the MGNREGS. This tracing was done by searching the household-level database available on the government portal for public access using the unique identifier from the TCI survey. Each household registered under the MGNREGS receives a unique job card ID. This ID was used to access the MGNREGS related information for the household. This exercise collected intra-household information like the number of registered family members, total MGNREGS workdays, gender, and age for 611 households for 2018 and 2019.

In the second stage, these 611 households were traced for their status under the PM-kisan using the publicly available database on the program's portal. A total of 97 households was identified as PM-kisan beneficiary for the launch year 2019. The remaining households were not part of the program at the time of the data collection.

The tracking exercise for 611 households for 2018 and 2019 was carried out during July – Dec 2020. All the observations were aggregated at the household level based on unique job card ID. "Household" means the adult (age 18 and above) members of a family related to each other by blood, marriage, or adoption and normally residing together and sharing meals or holding a common job card under MGNREGS.

Socioeconomic record for the selected households was collected from the TCI survey data. It includes the village, block, caste, agricultural land size, livestock, allied livelihood activities, and PDS access. Before analysis, the gathered data was prepared. The dataset was checked for missing data and inconsistencies. The data was then analyzed using statistical software STATA.

Statistical approach

A difference-in-differences method was applied to estimate the average effect on those who received the treatment. It is one of the most venerable causal inference methods used by researchers. Instead of comparing outcomes between the treatment and comparison groups after the intervention, the difference-in-differences method compares trends between the treatment and comparison groups (*Impact Evaluation in Practice*, 2016). A research question and study design allow us to estimate the average effect of the PM-kisan on the beneficiary households' MGNREGS workdays. This estimation approach relies on two differences. The first is the difference across periods. The second is a difference between the treatment group and the control group. Both these differences eliminate time-invariant and time-variant unobserved group characteristics that confound the effect of the treatment on the treated group (Villa, 2016). This feature of DID makes it the most suitable econometric model for estimating ATET in this type of quasi-experimental study design. The result was tested with several robustness checks on the findings. In all cases, the conclusions drawn from DID are confirmed.

CHAPTER IV

DATA

The data used in this paper are from the TCI's survey on nutrition and income. The TCI conducted this survey in the Chandrapur district of Maharashtra state of India in two rounds. Soumya Gupta, a TCI Ph.D. scholar, administered the first round in 2014, while Vidya Vemireddy, another TCI Ph.D. scholar, administered the second round in 2017. This paper has considered the socioeconomic data of the second round for the analysis purpose.

The TCI survey data with a follow-up design provides updated information on the socioeconomic variables. Some TCI data summary statistics for the period 2017 are provided in appendix A.

The estimates in this paper are based on matched data with the TCI survey. The matching was done in two levels. First, households were matched for their MGNREGS status using the personal identifier in the dataset. The matching was restricted for the households having job cards under the scheme. Total MGNREGS workdays were calculated by using the household-level job card information for 2018 and 2019.

Additionally, the intrahousehold variables like gender and age of registered family members under the scheme were collected. Second, the matched households were tracked for their status under the PM-kisan for 2019. The final study sample contained panel data of 611 households, including workdays for the year 2018 and 2019 and PM-KISAN beneficiary status for the year 2019.

The 'Workdays' variable is used for the analysis in this paper, defined as the number of total workdays per year of a household under the MGNREGS. It is the appropriate variable to assess the household-level demand for work under the MGNREGS. It is assumed that the beneficiaries were received the same work demanded by them, and there was no demand and supply gap. This assumption holds from the job card information: no 'no-work allowance' (provision under the MGNREGA in the event of excess demand for work) was given to any beneficiary as per the compensation record for the study period. The data used here are restricted to those aged 18 or over, which is the age cut-off for the MGNREGS work.

The 'PMK beneficiary' variable is the treatment variable in the data, coded '1' if the household is registered under the PM-KISAN, '0' if not. It is assumed that a household is getting all the benefits of the scheme if registered under it. These benefits include three equal installments of INR 2000 in a year.

The collected data was divided into two groups for analysis: PM-kisan beneficiary households in a treatment group and non-PM-kisan beneficiary households in a control group. There are 97 households in the treatment group and 514 households in the control group.

Table 3 compares different variables for PM-kisan beneficiary and non-beneficiary households. We can see a significant decrease in the number of workdays in 2019 for PM-kisan beneficiary households as compared to 2018. There is a 47 percent increase in the PM-kisan households with 'no workdays' during 2019 as compared to 2018. This increase can also be seen in non-beneficiary households, but the percent increment is less (15%) than the other group. MGNREGS workdays trend for 2018 clearly shows more workdays for the treatment group before the launch of the PM-kisan. This trend gets reverse for the launch year, especially for the period of more than 60 workdays. However, other variables like caste, livelihood, and PDS card type show a similar distribution in both groups indicating a balanced division.

Table 3: Summary statistics of PM-kisan beneficiary and non-beneficiary households

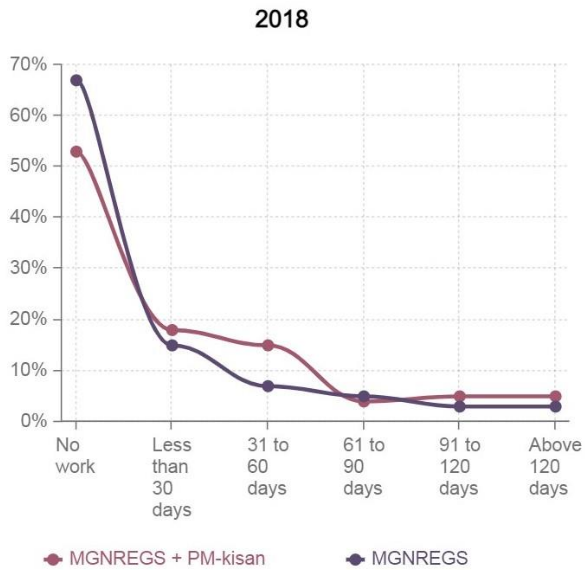
Variables		PM-KISAN beneficiary households (Treatment group)	No PM-KISAN beneficiary households (Control group)
MGNREGS workdays 2018	No work	53%	67%
	Less than 30 days	18%	15%
	31 to 60 days	15%	7%
	61 to 90 days	4%	5%
	91 to 120 days	5%	3%
	Above 120 days	5%	3%
MGN	No work	77%	76%

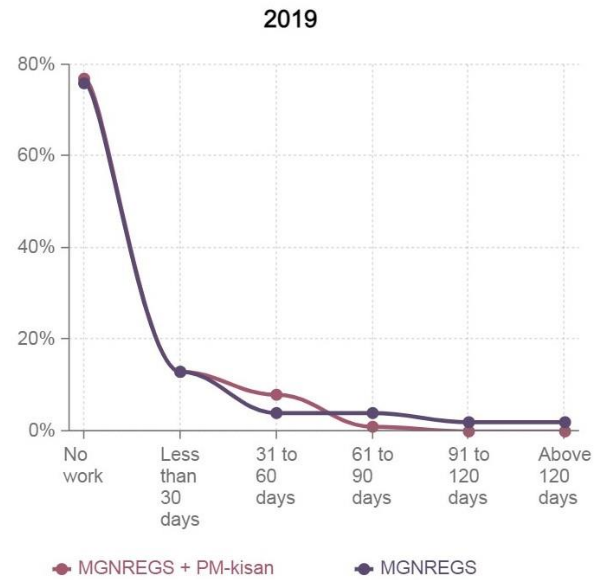
	Less than 30 days	13%	13%
	31 to 60 days	8%	4%
	61 to 90 days	1%	4%
	91 to 120 days	0%	2%
	Above 120 days	0%	2%
MGNREGS job seekers	Average job seekers	3.79	3.02
	Average female job seekers	1.86	1.37
	Average male job seekers	1.92	1.65
	Average age group 18 to 30	1.94	1.58
	Average age group 31 to 45	1.41	1.12
	Average age group 46 to 60	0.37	0.29
	Average age group above 60	0.06	0.02
Social caste	Upper caste	3%	5%
	Scheduled Caste	11%	13%
	Scheduled Tribe	18%	27%
	Other Backward Castes	61%	44%
	Nomadic Tribe	7%	11%
Livelihood activities	Average land size	3.22	2.8
	Own livestock	73%	72%
	Livestock grazer	3%	4%
	Forest resource collection	25%	27%
	Off-farm employment, other than MGNREGS	13%	13%
PDS card type	Above Poverty Line (APL)	42%	33%
	Below Poverty Line (BPL)	42%	43%
	Antodaya	5%	9%
	Annapurna	1%	1%
	No PDS card	9%	13%

Source: Based on the author's calculation of primary data

Graph 4 demonstrates a decreasing trend in workdays for both groups. The left side graph plots the workdays for treatment and control groups for the year 2018 (pre-launch period), while the right-side graph shows the trend for the year 2019 (post-launch period). In 2018, though the trend is decreasing for both groups, it shows more decrease in workdays for the control group. This trend is reversed for the year 2019, especially for more than 60 days. This trend indicates a causal effect on the MGNREGS workdays. In the next chapter, we will examine this causality deeper with the help of a statistical approach.

Graph 4: Percentage of total workdays for PM-kisan beneficiary and non-beneficiary households for 2018 (left) and 2019 (right)





Source: Based on the author's calculation of primary data

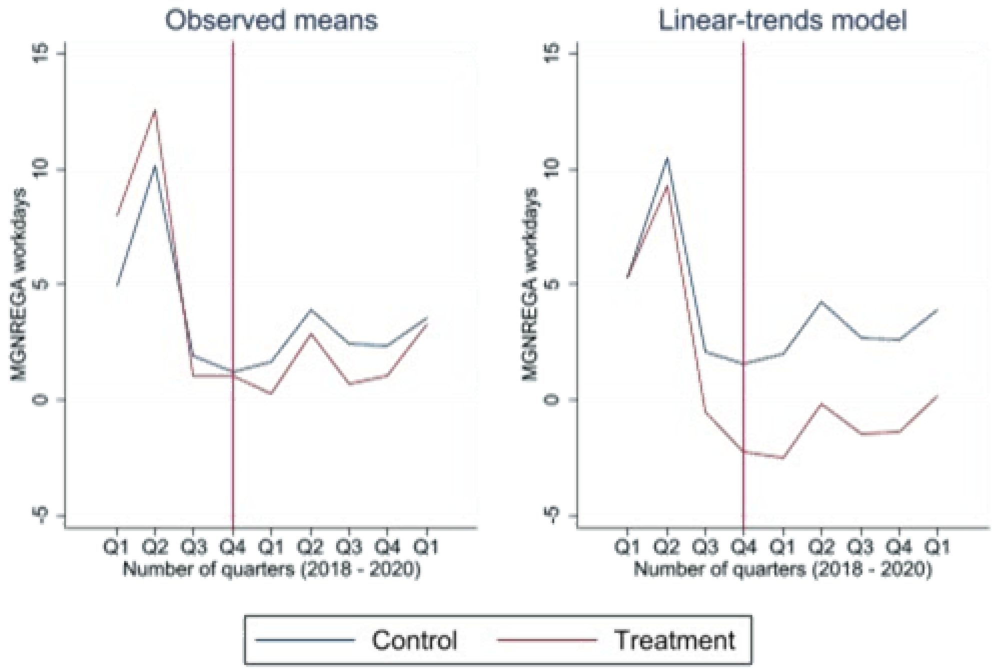
CHAPTER V

RESULTS AND DISCUSSION

To investigate the effect of cash transfers under the PM-kisan on the MGNREGS workdays, the average effect of a treatment (PM-kisan benefit) on the households who received the cash transfers was calculated using Difference-in-differences (DID) estimators. In technical terms, the Average Treatment Effect on the Treated (ATET) of a binary treatment (PM-kisan benefit) on the continuous outcome (workdays) was estimated by fitting a linear model with time fixed effect (year) and group (household) fixed effects. For the estimation purpose, the households without PM-kisan benefit served as the control group, whereas the other households with PM-kisan benefit served as a treatment group. Comparing the treatment group with the control group before and after the treatment can give us a better understanding of whether the PM-kisan benefits made any difference in the MGNREGS workdays.

Graph 5 shows the observed mean MGNREGS workdays and linear trends between the two groups. For both the treatment and control group, we see, there was a decrease in mean workdays in 2019. If the treated group had not received the PM-kisan benefit in a DID setup, we would expect the treatment and control group to experience the same trends. A treatment effect would imply a systematic deviation from a common trend observed in the graph.

Graph 5: Graphical diagnostic of parallel trends



Source: Based on the author's calculation of primary data using STATA

Here both groups experienced a decrease in 2019, but the treatment group decrease is more substantial. The difference in the decreases across groups may indicate the effect of the treatment. This graphical illustration signals the negative impact of the PM-kisan benefit on the MGNREGS workdays.

The DID estimate considers two differences. The first is a difference across time. This across-time difference eliminates time-invariant unobserved group characteristics that confound the effect of the treatment on the PM-KISAN beneficiary households. The time-varying unobserved confounders with an effect on the mean MGNREGS workdays such as seasonal effect, market fluctuations, etc., can be controlled by incorporating the second difference between the PM-KISAN beneficiary households and non-beneficiary households. DID eliminates time-varying confounders by comparing the treatment group with a control group subject to the same time-varying confounders as the treatment group. The ATET is then consistently estimated by differencing the mean outcome for the treatment and control groups over time to eliminate time-invariant unobserved characteristics and differencing the mean outcome of these groups to eliminate time-varying unobserved effects common to both groups.

We consider household-level panel data for which we sample the same households at a different time – 2018 and 2019. The PM-kisan benefit is delivered at the household level. All members in the household either are PM-kisan beneficiaries or not at a given year. Our panel identifier and group variable are households. We index household by h and time by t. We are interested in the effect of PM-kisan, $D_{ht} \varepsilon \{0,1\}$, on workdays, W_{ht}. Suppose the potential mean workdays of a household at time t that does not receive PM-KISAN benefit is given by:

$$E\{W_{ht}\ (0) \mid h, t\} = \gamma_h + \gamma_t$$

γ_h and γ_t denote group and time effects, respectively. Also, suppose the potential mean value of workdays for a household that receives PM-KISAN benefit is given by:

$$\{W_{ht}\ (1) \mid h, t\} = \gamma_h + \gamma_t + \delta$$

Then, the potential outcome framework described above allows us to think of the regression model:

$$W_{ht} = 1\{D = PMKSY\ ben\} + 1\{t = 2019\} + \delta D_{ht} + \varepsilon_{ht}$$

Where $1\{D = PMKSY\ ben\}$ is an indicator function that is 1 if the household receives the treatment and 0 otherwise. Similarly, $1\{t = 2019\}$ indicates that we are in the period for which the treatment is active.

A regression estimate of δ, the coefficient on the indicator of treatment, consistently estimates the ATET in this simplified framework subjected to the parallel trend assumption. It implies that if the households had not received the cash transfers, the groups defined by D_{ht} = 1 and D_{ht} = 0 would have the same trends. We demonstrated this parallel trend in graph 5. Another way of testing the parallel trend assumption is the parallel trends test for the pre-treatment period. We do not have evidence to reject the null hypothesis of parallel trends in this case. Both the test and the graphical analysis support the parallel-trends assumption and, therefore, our ATET estimate.

While a standard linear regression model can estimate the ATET, the best estimate of the standard error requires some consideration. Bertrand, Duflo, and Mullainathan show that the standard errors for DID estimates are inconsistent if they do not account for the serial correlation of the outcome of interest (Bertrand et al., 2004). Because the outcomes studied usually vary at the group and time levels, it makes sense to correct for serial correlation. The authors show that using cluster–robust standard errors at the group level where treatment occurs provides correct coverage in the presence of serial correlation. Based on this discussion, DID estimate used the cluster-robust standard errors at the household level.

Table 4: Difference in differences estimate for ATET

```
Number of groups and treatment time

Time variable: Year
Control:       PMK_beneficiary = 0
Treatment:     PMK_beneficiary = 1
```

	Control	Treatment
Group		
Sl	514	97
Time		
Minimum	2018	2019
Maximum	2018	2019

```
Difference-in-differences regression                    Number of obs = 1,222
Data type: Longitudinal

                                   (Std. err. adjusted for 611 clusters in Sl)
```

Workdays	Coefficient	Robust std. err.	t	P>|t|	[95% conf.	interval]
ATET						
PMK_beneficiary						
(1 vs 0)	-12.91211	4.830483	-2.67	0.008	-22.39851	-3.425715

Note: ATET estimate adjusted for panel effects and time effects.

Source: Based on the author's calculation of primary data

Table 4 shows the DID estimate for ATET. The 2018 period of the data was one with no cash transfer in place under the PM-kisan at either the start or finish date. It, therefore, represents a 'pre-treatment period and is a potential comparison year for the DID estimates. The first table gives information about the treated and control groups and treatment timing. The first segment with the title Group tells us the number of treated and control households: 514 households were not taking the benefit of PM-kisan, and 97 households were the PM-kisan beneficiaries. The second segment of the table gives information about the first time we observe households in the control group. The first time we observe the treatment (the PM-kisan benefit) for households in the treatment group. In our data, all households that registered under the PM-kisan did so in 2019.

The ATET is -12.91, almost a decrease of 13 MGNREGS workdays relative to the households in a control group. In other words, if the households that registered under the PM-kisan had not done so, their MGNREGS workdays would be more by almost 13 days on average. Both the test and the graphical analysis support the parallel-trends assumption and, therefore, our ATET estimate.

An average reduction of 13 workdays due to the PM-kisan benefit costs the household INR 2678 (as per the wage rate INR 206 for the year 2019). The same household is getting INR 6000 as PM-kisan benefit. The household's net income from the PM-kisan after deducting its effect on the MGNREGS workdays amounts to INR 3392. Suppose we assume a constant ATET and can control other extraneous factors. In that case, the loss due to a reduction in workdays will increase in years to come due to increased wages, whereas the PM-kisan benefit will remain constant. For example, the MGNREGS wage rate for Maharashtra for 2020 was INR 238, which increased the loss due to reducing workdays to INR 3094. This amount is more than 50 percent of the total annual benefit under the PM-kisan.

The MGNREGS wage rates are different for each state. Hence, the loss due to the reduction in workdays will be different. As per the prevailing wage rates for 2020, the wage loss will be the lowest (INR 2470) for the MGNREGS workers in Madhya Pradesh and Chhattisgarh due to the lowest wage rate (INR 190), whereas the same will be the highest (INR 4017) for Haryana due to the highest wage rate (INR 309). Table 5 shows the state-wise variation in losses due to missed MGNREGS workdays for 2019 and 2020.

Table 5: State-wise variation in losses due to missed MGNREGS workdays for 2019 and 2020

Sl #	State	Loss due to missed workdays (2019)	Loss due to missed workdays (2020)
1	Andhra Pradesh	₹ -2,743	₹ -3,081
2	Arunachal Pradesh	₹ -2,496	₹ -2,665
3	Assam	₹ -2,509	₹ -2,769
4	Bihar	₹ -2,223	₹ -2,522
5	Chhattisgarh	₹ -2,288	₹ -2,470
6	Goa	₹ -3,302	₹ -3,640
7	Gujarat	₹ -2,587	₹ -2,912
8	Haryana	₹ -3,692	₹ -4,017
9	Himachal Pradesh	₹ -2,405	₹ -3,224
10	Jammu and Kashmir	₹ -2,457	₹ -2,652
11	Jharkhand	₹ -2,223	₹ -2,522
12	Karnataka	₹ -3,237	₹ -3,575
13	Kerala	₹ -3,523	₹ -3,783
14	Madhya Pradesh	₹ -2,288	₹ -2,470
15	Maharashtra	₹ -2,678	₹ -3,094
16	Manipur	₹ -2,847	₹ -3,094
17	Meghalaya	₹ -2,431	₹ -2,639
18	Mizoram	₹ -2,743	₹ -2,925
19	Nagaland	₹ -2,496	₹ -2,665
20	Odisha	₹ -2,444	₹ -2,691
21	Punjab	₹ -3,133	₹ -3,419
22	Rajasthan	₹ -2,587	₹ -2,860
23	Sikkim	₹ -2,496	₹ -2,665
24	Tamil Nadu	₹ -2,977	₹ -3,328
25	Telangana	₹ -2,743	₹ -3,081
26	Tripura	₹ -2,496	₹ -2,665
27	Uttar Pradesh	₹ -2,366	₹ -2,613
28	Uttarakhand	₹ -2,366	₹ -2,613
29	West Bengal	₹ -2,483	₹ -2,652
30	Andaman and Nicobar	₹ -3,250	₹ -3,575
31	Dadra and Nagar Haveli	₹ -2,912	₹ -3,354
32	Daman and Diu	₹ -2,626	₹ -2,951
33	Lakshadweep	₹ -3,224	₹ -3,458
34	Puducherry	₹ -2,977	₹ -3,328

Source: Based on the author's calculation of wage data from ngrega.nic.in

Several robustness checks on these findings were conducted. In all cases, the conclusions drawn from table 4 are confirmed. The equivalent estimates when controls are included for location, caste, land size, livestock, PDS food access, active MGNREGS workers in the family are very similar to those in table 4, and the conclusions are unaltered. Table 6 shows the estimates using a random-effect model.

Table 6: Estimates using a random-effect model

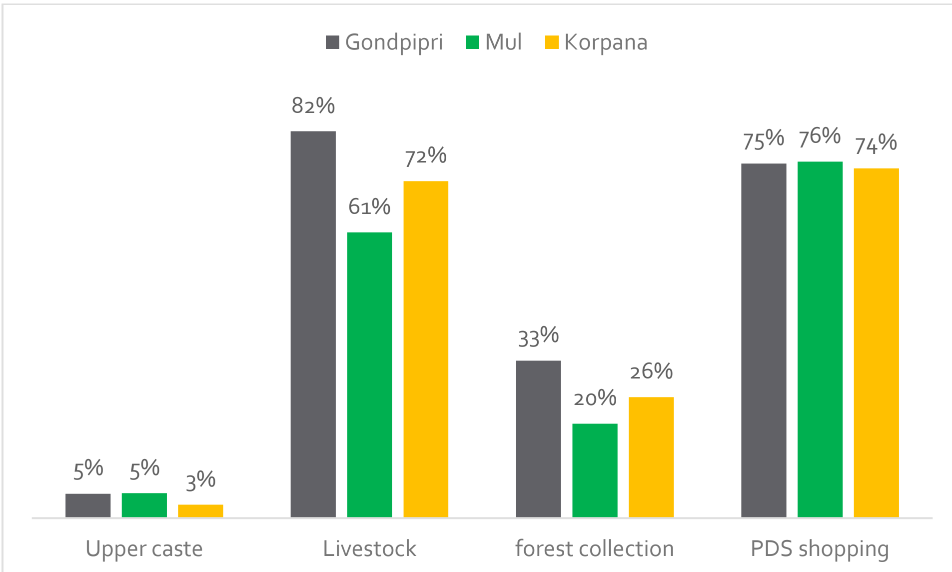
	(1)	(2)	(3)
	Workdays	**Workdays**	**Workdays**
Econometric model	*Random effect (without control)*	*Random effect (with control)*	*Difference in differences (Fixed Effect)*
PM-KISAN beneficiary	**-10.91***	**-12.90***	**-12.91**
	(-5.47)	(-5.19)	(-2.67)
2.Block: Mul		**7.318**	
		(3.22)	
3.Block: Korpana		**2.523***	
		(2.37)	
2.Caste: Scheduled Caste		0.813	
		(0.18)	
3.Caste: Scheduled Tribe		1.235	
		(0.30)	
4.Caste: Other Backward Classes		1.778	
		(0.44)	
5.Caste: Nomadic Tribe		7.127	
		(1.39)	
6.Caste: Minority		3.271	
		(0.74)	
Land size (acres)		-0.0322	
		(-0.27)	
No livestock grazer		**6.293***	
		(2.04)	
Number of working household members		**12.90***	
		(7.82)	

Number of working household members: female		-3.435	
		(-1.17)	
Constant	**15.05*****	-10.62	**18.63*****
	(13.23)	(-1.20)	(22.40)
Controls			
The 2019 Year			**-6.840*****
			(-3.83)
N	1222	1210	1222

Source: Based on the author's calculation of primary data using STATA

As shown above, the Random Effect (RE) estimates of the effect of PM-KISAN benefit on the MGNREGS workdays is significant and almost as same as the DID estimate. A household shows a significant effect of location (blocks) on the MGNREGS workdays. For Mul, workdays decrease to 6 days whereas, for Korpana and Gondpipri, the decrease is 10 and 13 days. There can be four major reasons behind this block-level variation in the MGNREGS workdays. First, the predominant cropping patterns in these blocks: *Mul* is a paddy growing block whereas *Korpana* is a cash crop producing block which includes cotton, soybean, and chilis; *Gondpipri* block has the most diversified cropping pattern among three. It produces both cash and food crops like paddy, cotton, and vegetables. More variation in cropping patterns provides better income and coping mechanisms, reducing the chances of distress employment (Pellegrini & Tasciotti, 2014). Second, better irrigation facilities in *Gondpipri* compared to the other two blocks allow the farming households to have production in two seasons (Gupta et al., 2020), giving them less time to participate in MGNREGS activities compared to other blocks under the study. Third, Gondpipri block households have the highest livestock (82%), giving them an allied livelihood activity with farming which provides additional income but leaves less time for participation in MGNREGS work. Finally, *Gondpipri* has the highest number of upper caste households in the sample. Many studies indicate that the participation of upper caste households in MGNREGS is less than the other socially backward communities (Joshi et al., 2017) (*Journal of Economic Policy & Research*, 2018). Graph 6 shows Block-wise percentages of caste, livestock, forest and PDS access.

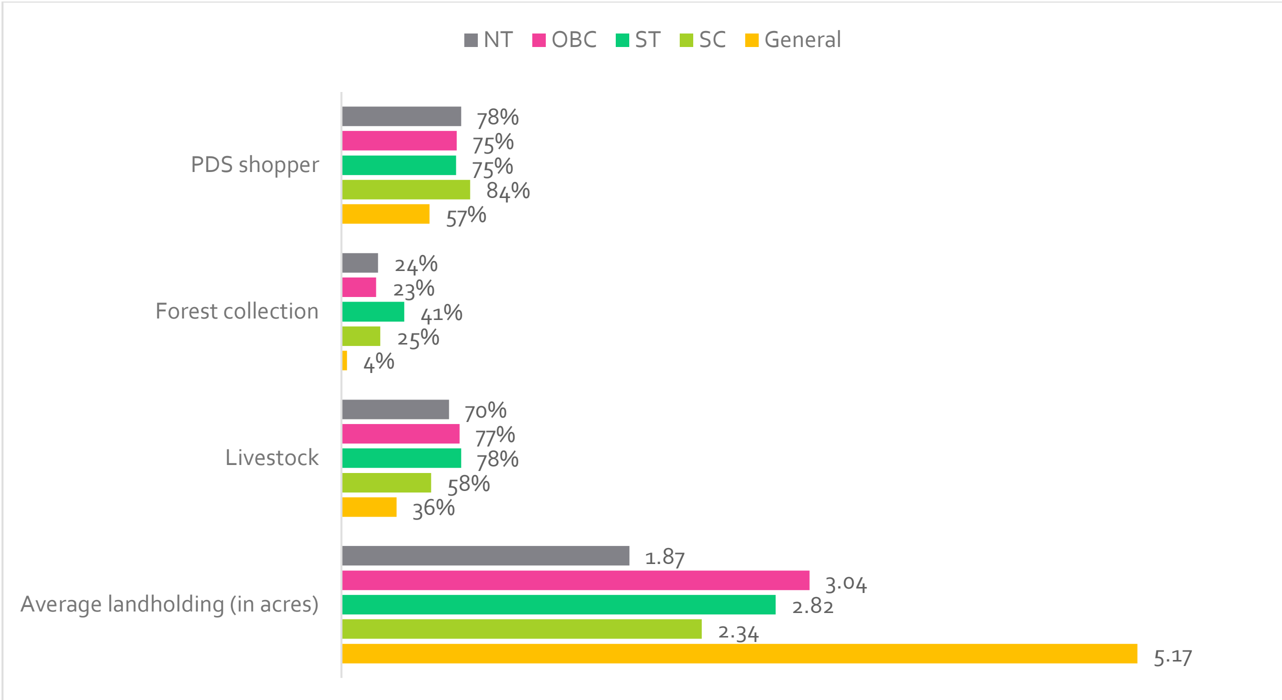
Graph 6: Block-wise percentages of caste, livestock, forest and PDS access



Source: Based on the author's calculation of primary data

In continuation with the above discussion, caste seems to play an important role in participation in the MGNREGS. Rural households with lower caste backgrounds (SC, ST, OBC) are more likely to be exposed to resource constraints like agricultural land, livestock, etc., which significantly hamper household income (Borooah, 2005). In a household with less income-generating resources, the dependence on the distress employment activities like MGNREGS increases substantially (Joshi et al., 2017). Though not significant, the result shows the same trend where the MGNREGS workdays of lower caste households are more than the upper caste households. The highest participation of Nomadic Tribes among the other lower caste households can be attributed to the less landholding (<2 acres) and other livelihood activities. Graph 7 shows the caste-wise information about the landholding, livestock, dependence on the forest resources, and PDS shopping behavior which strengthens the above inference that the lower caste households show more participation in MGNREGS than the upper caste households.

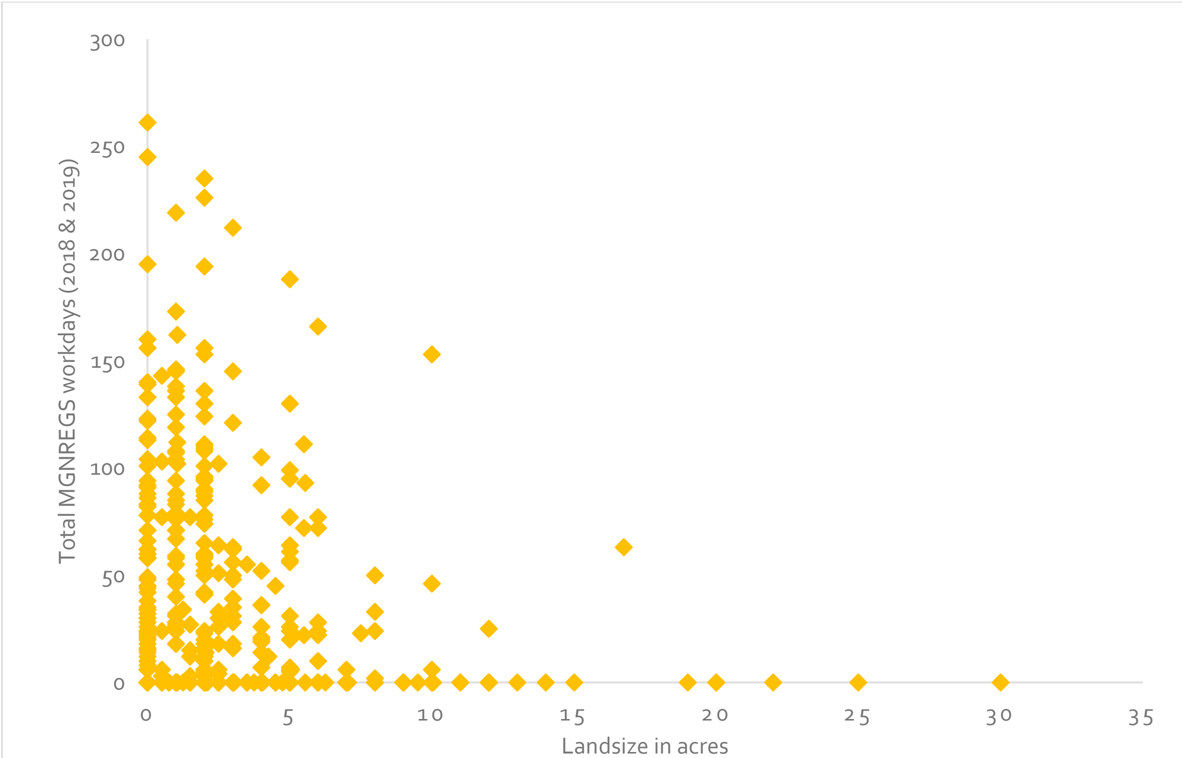
Graph 7: Caste wise landholding, livestock, dependence on the forest resources, and PDS shopping behavior



Source: Based on the author's calculation of primary data

Agricultural land is the most important livelihood resource in the rural economy. More landholding correlates to better income (Das & Srivastava, 2021). Marginal and smallholder farmers tend to explore other employment opportunities in and outside the farming setup to increase their income. Hence, the participation of smallholder farmers in MGNREGS work is more than the medium and large landholders. Jha Raghubendra et al., in their study in Rajasthan, found that the size of landholdings is a negative predictor of participation in the MGNREGS (Jha et al., 2009a). Our result supports this statement where additional acres of landholding impact the MGNREGA workdays negatively. This inference is also more evident from graph 8, showing the relationship between the total MGNREGS workdays and landholding.

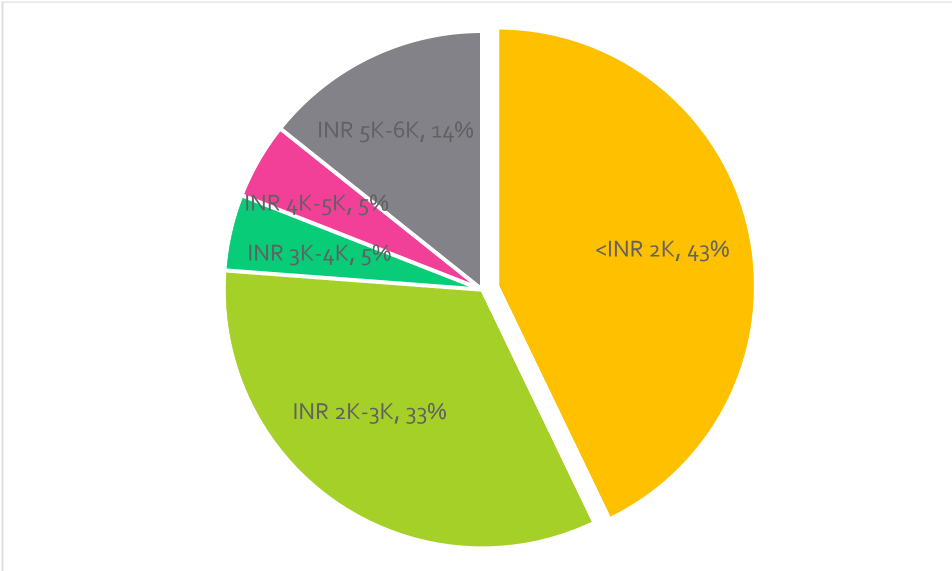
Graph 8: Total MGNREGS workdays and landholding



Source: Based on the author's calculation of primary data using STATA

Livestock grazing is one of the allied occupations among the Small and Marginal Farmers (SMFs) in the study area. Graph 9 shows a break-up of the reported monthly household income from the livestock grazing activity (TCI survey, 2017). As per graph 9, about one-fourth of the households involved in livestock grazing activity earn INR 3000 to 6000 per month. This income is 3 to 6.5 times more than the average monthly income of SMF households involved in MGNREGS work in 2018. Though it gives better income, it involves 6 to 8 hours of workload daily for almost all days of the month. Better income and time constraints can be the reasons behind less participation in the MGNREGS work than the households not involved in livestock grazing activities.

Graph 9: Monthly income from livestock grazing activity



Source: Based on the author's calculation of primary data

The result shows that additional adult members involving in the MGNREGS work can increase the annual MGNREGS workdays by 13 days. This result is highly statistically significant. Interestingly when we consider women's participation under MGNREGS, we see a decrease in workdays compared to men. Though this result is not significant, it makes sense due to two reasons. First, household and farm-level responsibility: women are responsible for household chores, livestock care, and many agricultural activities like plantation, crop management, pre-and post-harvest activities. This workload creates fatigue and provides a tiny window of time to participate in MGNREGS work. Second, unfavorable work environment under MGNREGS: the work profile under the program sparsely addresses the life cycle issues and physical ability (Sudarshan et al., 2010). Inadequate sanitary facilities, pregnancy period, not having enough creche arrangement, etc., are some reasons behind poor participation under the program.

Though the household-level data aggregates the MGNREGS workdays for all family members, 58 percent of households did not do any work under MGNREGS during the study period. Table 7 shows the key characteristics of households probably responsible for their no participation under the

MGNREGS work. First, the average landholding of these households is 3.38 acres which is more than the average (2.87 acres) of the study sample. As discussed in the previous paragraph, the size of landholdings is a negative predictor of participation in the MGNREGS (Jha et al., 2009b). Second, these households have less workforce for MGNREGS work: more than three-fourths of households have three or fewer members who want to work under MGNREGS. Eighty-nine percent of families have at least one female job-seeking member. The data indicate that a decrease in human resources (less number of adult family members seeking employment under MGNREGS) and more female job-seeking members in the family reduces the total number of workdays under MGNREGS. Third, besides having more landholding, about 73 percent of households own livestock, and 23 percent of households depend on forest collection activities. Also, about 13 percent of households mentioned that they have at least one family member involved in off-farm employment other than MGNREGS. Participation in these allied livelihood activities reduces dependence on distressed employment like MGNREGS. Time and energy constraints due to involvement in these activities are also responsible for no participation under the MGNREGS program.

Furthermore, 23 percent of these households received cash benefits under the PM-kisan. These cash transfers provided additional income to families in 2019. The cash support of $80 is about 66 percent of the average annual wage ($120) of the household under MGNREGS. The conditionality of work under MGNREGS makes PM-kisan a good alternative to MGNREGS for families not in immediate economic distress, and they can forgo their wages by not participating in the program. Still, a longer work-trend of these households would help assess their participatory behavior under MGNREGS and the impact of PM-kisan on their participation in the program. Provided the fewer time-period observations of the MGNREGS workdays (only for 2018 and 2019), removing these households from the data can provide an absolute effect of PM-kisan on the households working under MGNREGS. We can do it by assigning a sophisticated statistical method addressing zero inflation in the data.

Table 7: Characteristics of zero workday households

Characteristics of non-working MGNREGS households	Percentage
Households with no work under MGNREGS	58%
3 or fewer MGNREGS job-seeking members in the house	77%
At least one female jobseeker in the house	89%
At least one 45 above member in the house	23%
Livestock owning house	73%
PM-KISAN beneficiary house	23%
Forest resource collecting house	23%
Off-farm employment other than MGNREGS	14%
Average land size (in acres)	3.38

Source: Based on the author's calculation of primary data

This zero-inflation issue has been addressed with Poisson Fixed Effect (PFE) model for panel data. The PFE estimate, though different in magnitude, shows the statistically significant negative effect of PM-kisan benefits on the MGNREGS workdays. If we remove the non-working households under MGNREGS, we can see the effect on working households increases from -12.90 to -1.38. A table shows the comparative estimates of the effect of PM-kisan benefit on the MGNREGS workdays using different statistical models:

Table 8: Comparative estimates of the effect of PM-KISAN benefit on the MGNREGS workdays

	(1)	(2)	(3)	(4)	(5)
	Workdays	Workdays	Workdays	Workdays	Workdays
Statistical model	*Poisson fixed effect*	*Fixed effect*	*Random effect (without control)*	*Random effect (with control)*	*Difference in differences (Fixed Effect)*
PMK beneficiary	**-1.388*****	**-19.75*****	**-10.91*****	**-12.90*****	**-12.91****
	(-5.34)	(-4.40)	(-5.47)	(-5.19)	(-2.67)
N	514	1222	1222	1210	1222

Source: Based on the author's calculation of primary data using STATA

Overall, the evidence from the DID estimate suggests a statistically significant decrease in workdays for PM-kisan beneficiary households. This result is robust to the various statistical approaches. Additionally, the reduction in MGNREGS workdays can reduce the net benefit from the PM-kisan up to more than 61percent for some states like Haryana.

CHAPTER VI

CONCLUSION

This paper investigates the possible effect of PM-kisan benefit on the MGNREGS workdays. It uses a very natural approach to estimating the causal effect of PM-kisan benefit on MGNREGS workdays. It asks whether the observed households' MGNREGS workdays changed of those initially (i.e., before the launch of PM-kisan in 2019) in a specified interval below or above the prevailing trends that one would expect to observe if the PM-kisan had not been launched.

A difference-in-differences estimator is taken in this paper to address this question. The analysis finds the highly significant effect of PM-kisan benefit on the MGNREGS work days for the year 2019. It demonstrated that if the household received PM-kisan benefit, then there is a decrease of an average of 13 MGNREGS workdays as compared to the households not receiving PM-kisan benefit for the year 2019. The robustness checks using various statistical approaches show a similar trend of about the same magnitude.

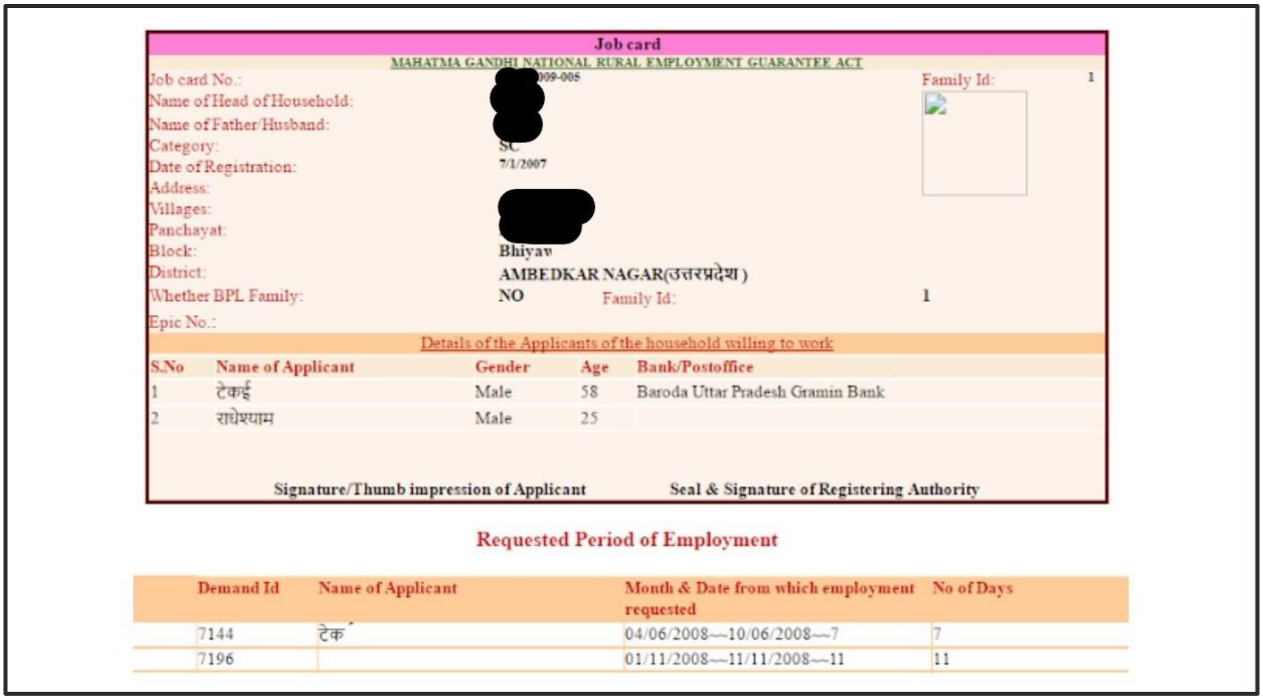
It has been suggested that the decrease in MGNREGS workdays can reduce the net benefit to the household. If we assume a constant ATET and control other extraneous factors, we can observe the reduction in net benefit up to 61 percent for states like Haryana for the year 2019. For Maharashtra, this reduction can be more than 44 percent. This effect shows a strong trend of "drainage" of labor supply for MGNREGS work. Although PM-kisan is recently launched and in its early stage of implementation, its long-term effects on the broad objective of MGNREGS, such as natural resource management through unskilled works, would be worth investigating in the coming years.

APPENDIX A

	Variable	Obs	Mean	Std. dev.	Min	Max
Index	Serial number	1,222	315.275	183.4149	1	631
	ID	1,222	1798.787	1096.124	27	3741
Social	Village	1,222	4.819967	2.167512	1	8
	Block	1,222	1.747954	0.738754	1	3
	Caste	1,222	3.453355	0.999116	1	6
Livelihood	Land size (acres)	1,222	2.87144	4.131872	0	60
	Owns livestock	1,222	1.281506	0.449918	1	2
	Livestock grazer	1,222	1.96563	0.182252	1	2
	Forest collection	1,222	1.731588	0.443315	1	2
	Off-farm employment	1,222	1.522095	0.499716	1	2
PDS acces	PDS shopper	1,210	1.239669	0.427058	1	2
	PDS card holder	1,222	1.126023	0.332011	1	2
	PDS card type	1,068	1.726592	0.692824	1	4
Registration under MGNREGS	Registered members under job card	1,222	3.145663	1.628994	1	11
	Registered members: Female	1,222	1.450082	0.923998	0	6
	Registered members: Male	1,222	1.695581	1.015343	0	8
	Registered members of age: 18 to 30	1,222	1.639935	1.296872	0	7
	Registered members of age: 31 to 45	1,222	1.168576	0.911872	0	4
	Registered members of age: 46 to 60	1,222	0.304419	0.582826	0	3
	Registered members of age: above 60	1,222	0.032733	0.19555	0	2
Involvement under MGNREGA	Working HH members under NREGA	1,222	1.294599	1.460914	0	8
	Working HH members: Female	1,222	0.589198	0.772043	0	5
	Working HH members: Male	1,222	0.705401	0.855653	0	4
	Working HH members of age: 18 to 30	1,222	0.736498	1.019528	0	5
	Working HH members of age: 31 to 45	1,222	0.487725	0.760036	0	4
	Working HH members of age: 46 to 60	1,222	0.065466	0.266568	0	2
	Working HH members of age: above 60	1,222	0.00491	0.069928	0	1
Workdays	Total HH workdays	1,222	14.18494	33.38805	0	361
Time	Year	1,222	2018.5	0.500205	2018	2019
PM-kisan	Cash transfer benefit under PM-kisan	1,222	0.079378	0.270439	0	1

APPENDIX B

Job card sample screenshot



Job card

MAHATMA GANDHI NATIONAL RURAL EMPLOYMENT GUARANTEE ACT

Job card No.: [redacted]009-005

Family Id: 1

Name of Head of Household: [redacted]

Name of Father/Husband: [redacted]

Category: SC

Date of Registration: 7/1/2007

Address: [redacted]

Villages:

Panchayat:

Block: Bhiyaw

District: AMBEDKAR NAGAR(उत्तरप्रदेश)

Whether BPL Family: NO

Family Id: 1

Epic No.:

Details of the Applicants of the household willing to work

S.No	Name of Applicant	Gender	Age	Bank/Postoffice
1	टेकई	Male	58	Baroda Uttar Pradesh Gramin Bank
2	राधेश्याम	Male	25	

Signature/Thumb impression of Applicant

Seal & Signature of Registering Authority

Requested Period of Employment

Demand Id	Name of Applicant	Month & Date from which employment requested	No of Days
7144	टेक	04/06/2008~~10/06/2008~~7	7
7196		01/11/2008~~11/11/2008~~11	11

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