Essays on Household Welfare and Anti-Poverty Programs in India

Inaugural-Dissertation
zur Erlangung des Doktorgrades
des Fachbereichs Wirtschaftswissenschaften
der Ruprecht Karls Universität Heidelberg

vorgelegt von Christian Oldiges

Heidelberg
Juli 2016

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Dedicated to my Father

And to my Brother(s) and Sisters around the Globe

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Acknowledgement

I wish to thank Jean Drèze for being an inspiration throughout my studies. I am very grateful for his constant support, advice, humor, and encouragement. Likewise, I am thankful for Stefan Klonner's close supervision throughout my PhD from which I and my work have benefited immensely. The field work would not have been possible without Sudha Narayanan's patience, guidance, and willingness to share her ideas with me. Many thanks are due to Sabina Alkire for her guidance while I was still deciding to pursue a PhD, as well as for being an inspiration, and providing encouragement to keep going. I am very grateful to my family for all the opportunities provided, which eventually allowed me to follow my interests. In particular, I want to thank my father for teaching me to embrace the world with open arms. I thank Vanita Leah Falcao for feedback on innumerous drafts. Finally, I want to thank Suchi Pande and Faizan Jawed Siddiqi for invaluable support during the last stretches of this marathon.

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Chapter 1

Introduction to the Essays

Amartya Sen famously postulates that income is only a means to an end (Sen, 2001). Thus, if one seeks to measure welfare in a society, one ought to focus on the quality of life instead of income alone. Sen's capability approach provides a framework to capture the quality of life. He states that humans have a variety of "functionings" that they value (Sen, 1980; Nussbaum and Sen, 1993). Functionings include "beings" and "doings" such as being well-nourished, well-educated or living in a safe environment. These functionings span a person's capability set, which ideally captures the maximum quality of life. While capabilities are difficult to measure, realizations within each functioning, achievements, are often quite tangible and measurable given today's data availability. For instance, an achievement in being well-nourished is a certain number of calories consumed.

Some argue that with economic growth everyone's capabilties set expands, and higher achievements are a logical consequence of income growth. Thus, growth alone might solve all matters (Bhagwati and Panagariya, 2013). Since the 1980s India's gross domestic product (GDP) has grown at an annual rate of over five per cent and some years have even touched double-digits. For various reasons and reforms, the "Hindu Rate of Growth" of the 1960s and 1970s transformed into high-rate growth (Rodrik and Subramanian, 2004; Nayyar, 2006; Panagariya, 2008; Drèze and Sen, 2013). India's growth story is widely celebrated. This celebration is reflected in the change in narrative adopted by economists such as Bhagwati and Panagariya (2013) who no longer speak of a growth's "trickle-down" effect but of "pull-up" growth, which would lead to employment for the masses of the poor. One would expect the high growth rates and its corresponding 'pull-up' effect to reflect in lower poverty rates.

During the 1980s, more than 40 per cent of India's population was living on less than one US dollar a day (Chen and Ravallion, 2010). By 2005, this figure had decreased to around 25 per cent (Chen and Ravallion, 2010). Using its national poverty line, the Government of India (2014b) estimates a similar stark decline in the poverty headcount ratio, with consumption poverty reducing by more than half between 1993-94 (45 per cent) and 2011-12 (22 per cent).

Given this success story in achieving high economic growth and reducing consumption poverty, the enthusiasts of the growth story would also expect such high growth rates to transform the quality of life, even without redistribution of resources (Bhagwati and Panagariya, 2013). However, a closer look at achievements in various functionings of health and education reveals that India has been under-performing in many social indicators (Drèze and Sen, 2012; Drèze and Sen, 2013). For example, the authors find that the mean years of schooling has only increased to 4.4 years in 2010, from a meager three years in 1990. They also establish that amongst India's South Asian neighbors, who are mostly worse off in terms of GDP per capita, only Nepal accounts for a lower rate in mean years of schooling in 2010. Likewise, in terms of child mortality (under five years of age), India is second last among South Asian countries. While Sri Lanka, for instance, has a child mortality rate of 17 per cent in 2010, India's rate is 63 per cent. India also accounts for the largest number of underweight children world-wide. Almost every second child under three years was underweight in 1998-99 and 2005-06 (Deaton and Drèze, 2009). A measure that captures India's poor performance using household level data is the multidimensional poverty index (MPI). Counting joint deprivations in ten indicators within the dimensions of health, education, and living standards, almost 50 per cent of India's rural population was deprived in at least one third of the indicators, in 2005-06. Thus, while income growth certainly matters, for higher tax collection for example (Drèze and Sen, 2013), evidence shows that it does not immediately and necessarily translate into improved welfare or quality of life.

In this dissertation, I highlight the state of India's welfare during the last decade. I focus on the most fundamental end, consumption, and consider income a means to this end. Consumption as an indicator of welfare is measured in two ways - increase in consumption as a response to welfare programs, and smoothing of consumption patterns in the context of fluctuating household income. Given the high undernourishment as a result of food consumption deprivation, I also examine the composition of food consumption of rural Indian households to determine the incidence, intensity and type of nutritional inadequacies. In the following paragraphs, I briefly discuss the themes and chapters of this dissertation.

Recognizing the abject poverty and severe living conditions of it's population (especially in rural areas), since independence, the Government of India (GoI) has been implementing social welfare programs, such as food rationing, support prices for farmers, drought relief, and employment schemes amongst other public initiatives (see Drèze and Sen, 1989, for a discussion on the history and usefulness of public action). During the period of high growth rates, too, the GoI implemented several social security reforms, most of them following a rights-based approach (see Drèze and Khera, 2015, for an extensive overview). One such major program is the National Rural Employment Guarantee Act (NREGA), enacted in 2005. Its primary aim was to "improve the livelihood of the poor" (Government of India, 2013b), by providing 100 days of work to any rural household that demanded it. The coverage of the NREGA is extensive, with more than 40 million households receiving employment in some years (e.g. 2009-10). The program costs the Indian exchequer on average four per cent of its annual expenditure. In the early years, much employment was generated in some of the poorest districts of the states of Rajasthan, Chhattisgarh, and Madhya Pradesh, employing many tribal communities and female workers (Drèze and Oldiges, 2011).

Despite such achievements, several questioned the purpose of the Act (e.g. Economist, 2008), while others discussed its effectiveness to reduce poverty (Murgai and Ravallion, 2005). Though the NREGA has received resistance and criticism (consult Drèze, 2011, for a discussion), research on the NREGA has largely found positive effects for the rural population. Labor market studies, for instance, find that the NREGA has increased rural wage rates by up to five per cent (Azam, 2012; Berg et al., 2012; Imbert and Papp, 2015), while female wage rates registered some increase (Zimmermann, 2014). Given the large female workforce employed under the NREGA, studies on the impact of female employment on child education find that the NREGA has an indirect but beneficial effect on school enrollment and learning outcomes of children (Afridi et al., 2012; Das and Singh, 2013). While it is generally found that the NREGA empowers women (Narayanan, 2008), research also finds that manifold and useful assets are built under the NREGA, even in the state of Maharashtra, where the NREGA was known to be less active (Ranaware et al., 2015). Deininger and Liu (2013) and Ravi and Engler (2009) find welfare enhancing effects and declining poverty rates due to NREGA works in South India. In general, however, research on welfare effects of the NREGA has been limited to certain regions.

Architects of the NREGA envisioned it as a social safety net for the poor, to rely on during times of great distress, and it has proven to be one. For instance, during the drought-year 2009-10, NREGA employment peaked. Rural households are generally considered to be highly vulnerable to diverse shocks such as droughts and the subsequent destruction of crop, livestock, and land. Further, poor households are often not well insured against health shocks, death in the family, unemployment and other risks. Due to the reliance on agriculture and casual labor, income of rural households is considered to be highly volatile. However, research on rural Indian households with data on the 1970s and 1980s from the Indian Crop Research Institute of the Semi-arid Tropics (ICRISAT) shows that household consumption does not follow as volatile a path as income. Instead, it is shown to co-move with average village consumption and is much less affected by idiosyncratic shocks as one might expect (Townsend, 1994; Jacoby and Skoufias, 1998). Further research on the ICRISAT villages for the same time period shows that households are able to smooth consumption by smoothing labor income (Kochar, 1995, 1999; Morduch, 1995). In India, microfinance institutions have grown immensely, and access to microfinance is considered a promising tool for the poor to smooth consumption (Morduch, 1998, 1999a). Some of the latest research, however, questions whether the poor are indeed able to smooth consumption as hypothesized by so many, reiterating concerns by Jalan and Ravallion (1999). A recent study on rural households of Central India, using consumption and income data for 2009, 2010, and 2011, shows that the poorest households are much less insured against rainfall shocks than wealthier households (Gaurav, 2015). Therefore, there is reason to believe that the poorest are not immune to idiosyncratic shocks, despite economic growth and its "pull-up" factors. In addition, given the emergence of microfinance institutions and a general increase in the access to banking, the question arises whether and how the rural poor are able to utilize the latest development to mitigate income risks.

In terms of the composition of food consumption realized by rural households, and given the huge rates in child undernourishment, it is natural to ask what diets rural Indian households follow. Being well-nourished is certainly the most basic functioning in the capability space of health. However, unlike other countries which experienced economic growth and a subsequent transition to more diverse diets (Drewnowski and Popkin, 1997; Tilman and Clark, 2015; Smith et al., 2016), evidence for India does reveal some, albeit weak evidence, for a transition away from cereals-based diets (Kumar et al., 2007). Deaton and Drèze (2009) show for the last decades, that there has been a decline both in per capita calorie consumption as well as in proteins and other nutrients. While nutritional diversity is an end in itself for many and carries an intrinsic value, there is an established link between diverse diets and nutritional outcomes (Arimond and Ruel, 2004a). Several determinants of the quality of life depend to a large extent on adequate and diverse nutrition. Diverse childhood nutrition is shown to impact cognitive development, physical stature, strength, earlier school enrollment, and ultimately adult productivity (Alderman et al., 2005). For India in 2005-06, Menon et al. (2015) demonstrate that dietary diversity of young children is strongly correlated with height-for-weight z-scores (HAZ), weight-for-age (WAZ) z-scores and underweight. Even though their findings do not allow causal interpretations, inadequate nutrition is very likely one of several reasons for the extremely high rates of child undernourishment. Thus, it is warranted to provide for a clear picture of dietary diversity in India using appropriate measures.

In this dissertation, I discuss the three topics related to consumption as a measure of welfare in three separate chapters.

Safety Net for India's Poor or Waste of Public Funds? Poverty and Welfare in the Wake of the World's Largest Job Guarantee Program

In the first essay, titled "Safety Net for India's Poor or Waste of Public Funds? Poverty and Welfare in the Wake of the World's Largest Job Guarantee Program," co-authored with Stefan Klonner, I study the effect of the NREGA on rural households' welfare. In line with the Act's official objective of "ensuring social protection for the most vulnerable people living in rural India," one particular focus of our analysis is the NREGA's potential for improving the situation of the most disadvantaged and marginalized groups of the rural population. We study households belonging to scheduled castes and scheduled tribes (SC/ST), which account for about 30% of India's rural population according to the 2011 Census.

We make use of the phase-wise roll-out of the Act. The NREGA was implemented first in 200 districts in the fiscal year 2006-07 (Phase 1), in another 130 districts in 2007-08 (Phase 2), and the remaining 295 districts in 2008-09. We construct a district-level panel with NSS consumption and program coverage data for the years 2005-06 and 2007-08 to estimate effects of the presence of NREGA on rural households' consumption expenditures and consumption-based poverty measures. To deal with potential endogeneity in the assignment of program placement, we conduct an instrumental variable estimation similar to Zimmermann (2012). Toward this, we use an official district poverty ranking by India's National Planning Commission from 2003, which has served as the basis for program allocation to districts in Phase 2 in 2007-08. Following Zimmermann (2012), we predict actual program status of a district in 2007-08 by whether it is among the 130 poorest eligible districts according to the 2003 Planning Commission ranking, and regress the outcomes of interest on program status thus instrumented.

Our results are as follows. For the sample of all rural households residing in NREGA Phase II and Phase III districts, we find a statistically significant effect on neither the average level of consumption nor consumption-based poverty measures. For the subsample of SC/ST households, in contrast, we find large effects on both average consumption and poverty for the agricultural slack season in spring while there are no statistically significant effects for the fall season. According to our point estimates, which are imprecisely measured, the Act has increased SC/ST consumption during the spring season by as much as 20 percent and reduced poverty by 40 percent. Our findings are compatible with a scenario where the Act has reduced seasonal consumption fluctuations for SC/ST households in India's poorer districts in a sustained fashion by increasing spring consumption to levels close to those during the fall season. Based on rough cost-benefit analysis of the NREGA, we conclude that households have used the bulk of the wages earned from the program for immediate consumption and that the program's wage expenditures have been highly cost-effective in increasing consumption of SC/ST households. According to our findings, the Act appears to have successfully delivered on the two goals, reaching out to the most vulnerable and improving livelihood security.

Income Shocks, Consumption Smoothing and Financial Market Transactions: Evidence from Indian Villages

While the first chapter addresses the employment program's welfare effects at a national level, in the second chapter's essay, titled "Income Shocks, Consumption Smoothing and Financial Market Transactions: Evidence from Indian Villages", I investigate how NREGA wage payments are used by households in four South Indian villages for smoothing consumption and risk sharing in the presence of volatile income. large body of literature that includes the seminal work by Townsend (1994) on three villages visited by the International Crop Research Institute (ICRISAT). Research in the ICRISAT villages has produced diverging results on the extent of mutual insurance in village economies. Townsend (1994) largely cannot reject the hypothesis of full insurance, and finds that consumption co-moves with average village income. Jalan and Ravallion (1999) and most recently Gaurav (2015) are prominent studies, rejecting the hypothesis of full insurance for the poorest households. While there are many studies since the 1990s on Low Income Countries (LICs), examining the effect of changes in income on changes in consumption, the data quality of self reported income has been a constant concern (Deaton, 1990; Townsend, 1994). Involving potentially a huge measurement error in income and given its endogeneity with respect to income, many have found ways to instrument changes in income, and most convincingly so via rainfall shocks (Paxson, 1992; Jacoby and Skoufias, 1998; Fafchamps and Lund, 2003; Gaurav, 2015).

In this work, I adopt a unique never before used approach to explore a much explored research question - how does consumption react to changes in income. Further, I explore what mechanisms are used by poor households to smooth consumption especially in light of the recent expansion of microfinance and banking sector. For this purpose, I have visited the ICRISAT villages in Andhra Pradesh that Townsend visited three decades before me, for example Aurepalle in the district of Mahbubnagar. I conducted this field study in collaboration with Sudha Narayanan. I set out to study the functioning of the NREGA, and the usefulness of NREGA wages for consumption and financial transactions. From the interviews with NREGA beneficiaries, it was learned that NREGA wages were often used for immediate consumption, as well as for the repayment of loans. With this information as a starting, I combine data collected during the two months of field work with local administrative data on NREGA activities and ICRISAT's household-level data. I show that households face considerable uncertainty regarding the timing of NREGA wage payments. Based on this, I conceptualize the wage payments as positive income shocks. In high-frequency panel data analyses, I find that these income shocks do not affect monthly consumption in three of the four villages. In the poorest of the four villages, however, consumption responds statistically significantly to changes in wage income. I calculate propensities to consume of .6, implying that 60 per cent of additional wage income is immediately consumed for consumption purposes. Also, for the same village, I find that NREGA wage payments induce repayments to microfinance loans. I conclude that consumption among the households in three of the four villages is well-insured against moderate income shocks. For the poorest, however, I reject the hypothesis of full risk sharing. I argue that access to innovative formal financial institutions plays an important role in how households deal with income fluctuations. In addition, I identify female wage payments, allowing me to shed light on intra-household allocations of income. The latter have been studied much (e.g. Bourguignon et al., 1993; Browning et al., 1994), but especially in LICs it has been been methodologically difficult to identify gender-wise payments empirically (Hopkins et al., 1994). According to my findings, female wage incomes are the key driver for the high propensities to consume and to pay back microfinance loans. I conclude that the poor utilize a broad ranging portfolio of insurance options to smooth consumption and that women empowerment can go a long way in achieving that goal.

Measuring Malnutrition and Dietary Diversity: Theory and Evidence from India

In the third and final essay, titled "Measuring Malnutrition and Dietary Diversity: Theory and Evidence from India," I develop a framework, the *Nutritional Deprivation Index (NDI)*, to measure the most basic functioning in the capability space of health: being well-nourished.

I design the *NDI* to accurately identify both the incidence and intensity of nutritional deprivation. Using 2011-12 Indian National Sample Survey (NSS) data on food consumption, I exemplify various properties of the framework empirically.

Arguing that traditional counting measures, such as the Dietary Diversity Index *DDI*, inhibit great limitations, the *NDI* serves as a powerful and insightful alternative. It overcomes three weaknesses of the widely used *DDI*. These are: one, a neglect of measuring the intensity of food inadequacy; two, a lack of indicator-specific cut-offs, and three, the absence of person-specific thresholds. Conceptualizing the *NDI* framework, I adapt and extend the Alkire-Foster counting methodology, a framework widely used in multidimensional poverty measurement (Alkire and Foster, 2011; Alkire et al., 2015). I develop two versions of the *NDI* framework, one applicable for individual-level data, the other for ordinary household-level data. Overcoming the inherent weaknesses of the *DDI*, the *NDI* framework yields both the incidence and intensity of food inadequacy. In contrast to the *DDI*, the *NDI* allows for idiosyncratic and food group-specific thresholds and is thus more effective in identifying the nutritionally deprived (incidence). At the same time, the *NDI* reveals the extent (intensity) of food inadequacy as well as the kind of food deprivation the inadequately nourished face.

Applied to the Indian NSS data, the *NDI* predicts that more than 30 per cent of India's rural population is nutritionally deprived in at least five of eight food groups with an average intensity of six. Utilizing several advantageous properties of the adjusted AF methodology, such as dimensional breakdown and subgroup decomposability (Foster et al., 1984; Alkire et al., 2015), the *NDI* highlights that the inadequately nourished mostly under-consume leafy vegetables, fruits, and pulses. The average intensity of nutritional deprivation of the inadequately nourished is close to 70 per cent. Decomposing the *NDI* by states and socioeconomic subgroups reveals that historically disadvantaged regions and subgroups inhibit the greatest nutritional deprivations. These include many poor Northern states, stretching from Rajasthan to Orissa, as well as Scheduled Tribes and Scheduled Castes. I conclude that the *NDI* may prove as a useful tool for public policies to target the most inadequately nourished.

Chapter 2

Safety Net for India's Poor or Waste of Public Funds? Poverty and Welfare in the Wake of the World's Largest Job Guarantee Program

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Abstract We examine the effects of India's National Rural Employment Guarantee Act on consumption and poverty in rural India. Exploiting the district-wise rollout of the program, we employ a regression discontinuity design to estimate program effects. We find large, season-specific effects among a traditionally deprived sub-group of the rural population. A cost-benefit analysis elicits that consumption increases are of the same order of magnitude as the wage outlays of the program. Given that consumption among the households that benefited most had previously exhibited severe systematic seasonal fluctuations we conclude that the employment program has primarily improved consumption smoothing across agricultural seasons.

Published under the same title as AWI Discussion Paper Series No. 564, Heidelberg University

2.1 Introduction

Poverty around the globe is concentrated in rural areas. For 2002, Chen and Ravallion (2007) have estimated that more than two thirds of the 1.14 billion living on less than a dollar per day resided in rural areas while, at the same time, the rural population share figured at less than one third. Rural development and poverty alleviation programs have been and continue to be popular, in particular in low and middle-income countries. Well-known programs have involved cash-transfers, pensions, free or subsidized food provision including school feeding programs, subsidized credit and directed lending, asset creation, and various kinds of agricultural subsidies and extension work (Basu, 1991). In addition to bringing down poverty figures, the declared purpose of most of these programs is to help poor rural households to cope with various forms of risk (Lal et al., 2010).

A fundamental problem of all such programs is targeting, that is reaching out to the most needy (Besley and Coate, 1992). When benefits come at no cost for the recipients and administrative capacities for ensuring proper targeting are limited, the benefits from welfare programs have often been found to be captured by wealthy and politically well-connected households (Basu, 1991; Gaiha, 2000). An additional key challenge of programs which aim at the mitigation of risks faced by poor households is that they have to be flexible and able to deliver immediate benefits when a household experiences an income shock (World Bank, 2013).

It is primarily on these grounds that public works programs have been popular with governments around the globe (Subbarao, 2003). According to the World Development Report 2014, in sub-Saharan Africa alone, around 150 public works programs are currently active, and Subbarao (2003) enumerates several large-scale public works programs in Asia and Latin America from the 1980s and 1990s. The effort involved in the physical labor has the potential to ensure proper targeting (Besley and Coate, 1992; Basu, 1991) and households can decide on a day-to-day basis whether to supply their labor and receive benefits. In addition, public works programs have the potential to build growth-enhancing local public goods (World Bank, 2013).

Ethiopia's Productive Safety Net Program appears to have been the relatively most costly recent public employment program in low and middle income countries, consuming two percent of the country's GDP in 2007 (Lal et al., 2010). India's Mahatma Gandhi National Rural Employment Guarantee Act (NREGA) has been the largest public works program ever in terms of absolute outreach and cost, providing employment to fifteen percent of India's workforce. In 2012, it accrued a cost of close to \$10 billion, about one percent of the country's GDP. Introduced in 2006, the NREGA guarantees one hundred person days of employment to every rural household whose adult members are willing to perform unskilled manual labor at a statutory minimum wage.

Several recent papers have evaluated the Act's labor market effects on a national scale econometrically. Studies using National Sample Survey data on employment (Azam, 2012; Imbert and Papp, 2013; Zimmermann, 2012), as well as Berg et al. (2012), who use agricultural wage data from the Indian Ministry of Agriculture, find that the Act has resulted in increases in agricultural wages. Moreover, female workers and marginalized groups belonging to scheduled castes and scheduled tribes, formerly untouchables within the Hindu caste system, appear to be among the main beneficiaries of the Act.

While rural wages and rural consumption are likely positively correlated, particularly among India's rural poor (Lanjouw and Murgai, 2009; Berg et al., 2012), increases in agricultural wages are merely a second order, general equilibrium effect of a public employment program. In our view, the net welfare effects of this large employment program have received too little attention in comparison. In this paper, we set out to assess whether the NREGA has increased rural households' consumption, to what extent the Act has helped rural households to smooth consumption, and whether the program has been well-targeted as far as the distribution of welfare effects over the rural population is concerned.

We combine data from two waves of India's nationally representative National Sample Survey on household consumption with information on the district-wise roll-out of the NREGA. We make use of the phase-wise roll-out of the Act. The NREGA was implemented first in 200 districts in the fiscal year 2006-07 (Phase I), in another 130 districts in 2007-08 (Phase II), and in India's remaining 263 districts in 2008-09 (Phase III).[1] We construct a district pseudo panel with consumption and program coverage data for the agricultural years 2006-07 and 2007-08 to estimate program effects on rural households' consumption expenditures and consumption-based poverty measures. To deal with potential endogeneity in program placement, we employ a modification of Zimmermann's (2012) regression discontinuity approach. We use an official district backwardness index published by India's National Planning Commission in 2003, which has served as the basis for allocating districts to different phases of the program's roll-out. In this process, the declared intention of policy makers has been to give more backward districts earlier access to the program. Following Zimmermann (2012), we predict a district's actual program status in 2007-08 by whether it is among the 130 most backward districts according to the Planning Commission's index, and regress the outcomes of interest on program status thus predicted. To be precise, we estimate local average treatment effects of the Act, where "local" pertains to the fact that our estimated effects are for districts that are the least backward among the 130 districts predicted to obtain the program in Phase II, or equivalently the most backward among the 263 districts predicted to obtain the program in Phase III.

To assess whether the Act has been well targeted, we study households belonging to scheduled castes and scheduled tribes (SC/STs), which account for 29.8 percent of India's rural population according to the Census 2011 (Government of India, 2011), in detail. In our sample, among scheduled castes and scheduled tribes, poverty is close to three times the figure for the non-SC/ST population. Further, we assess to what extent NREGA employment has helped households to smooth consumption across agricultural seasons. Given that, at least in backward districts, consumption used to plummet during the agricultural slack season in spring, a particular focus of our analysis is on the Act's effect on seasonal consumption fluctuations.

Our results are as follows. For the sample of all rural households residing in NREGA Phase II and Phase III districts, we find a statistically significant effect on neither the average level of consumption nor consumption-based poverty measures. For the sub-sample of SC/ST households, in contrast, we find large effects on both average consumption and poverty for the agricultural slack season in spring while there are no statistically significant effects for the

[1]These numbers are based on the 2001 Census definition of districts(Government of India, 2001). By now, the Act is active in all 640 Census 2011 districts (Government of India, 2011).

fall season. According to our point estimates, which are imprecisely measured, the Act has increased SC/ST consumption during the spring season by as much as 30 percent and halved poverty.

In addition to the econometric estimations, we also carry out a detailed descriptive analysis of seasonal consumption patterns with National Sample Survey data from 2003 to 2012. We document that, prior to 2007-08, SC/ST households in NREGA Phase II districts experienced far greater systematic consumption fluctuations between fall and spring seasons than in the generally better-off NREGA Phase III districts. From 2007-08 onward, in contrast, we find substantially smaller differences in seasonal consumption and poverty patterns across these two groups of districts. Combining these descriptive with the econometric results, our findings are suggestive of a scenario where the Act has reduced seasonal consumption fluctuations for SC/ST households in India's more backward districts in a sustained fashion by increasing spring consumption to levels close to those during the fall season.

We also conduct a rough cost-benefit analysis of the NREGA by combining our estimates with program expenditure data. According to NREGA expenditure figures, more than 80 percent of the program's wage expenditures in Phase II districts during the agricultural year 2007-08 occurred during the agricultural slack season, that is the spring of 2008, when NREGA wages paid to SC/ST employees amounted to about Rs. 60 per rural SC/ST individual. Per rural SC/ST individual, our most conservative point estimates predict an increase in monthly average individual consumption due to the NREGA of around Rs. 70. We conclude that the program's wage expenditures have been cost-effective in increasing slack-season consumption of SC/ST households, even if our point estimates of the program's effect on consumption are overstated.

This paper contributes to a rapidly growing literature on welfare effects of rural anti-poverty and development programs. To name only a few examples, Djebbari and Smith (2008), among many others, study welfare effects of the Mexican PROGRESA conditional cash transfer program. Duflo (2003) studies the effect of old-age pensions on child nutrition in South Africa. Kochar (2005) and Tarozzi (2005) estimate nutritional effects of India's public food distribution system. Rural credit expansion and poverty in India and Bangladesh is the subject of Burgess et al. (2005) and Pitt and Khandker (1998). Moyo et al. (2007) analyze the effect of agricultural extension on poverty in Uganda. Regarding public works programs prior to the NREGA, most existing econometric studies focus on targeting rather than welfare and poverty (Jayne et al., 2002). An exception is Datt and Ravallion (1994), who find a moderate poverty-reducing effect of the Maharashtra Employment Guarantee Scheme, a predecessor to the NREGA active in only one of India's states. Regarding the NREGA, most existing empirical research by economists is on labor market rather than welfare effects (see the citations above). Exceptions are Afridi et al. (2012), who find a positive effect on child schooling in data from six districts in the state of Andhra Pradesh. Scandizzo et al. (2009) find that the NREGA smooths household income in two villages in the state of Maharashtra. Under the assumption that the manual labor required to receive NREGA benefits is a burden for program participants, Lagrange and Ravallion (2012) propose to correct welfare and poverty effects by the disutility from working on NREGA sites and illustrate this conceptual approach with cross-sectional National Sample Survey data from the state of Bihar.

In terms of the study object, welfare effects of the NREGA, the following three papers are closest to ours. Ravi and Engler (2009) use a small panel data set of 320 households residing in the state of Andhra Pradesh and find that consumption expenditures increase by about ten percent in response to the Act. Their program effect estimates are based on propensity score matching and, in our view, rely on rather strong identifying assumptions. Deininger and Liu (2013) use a panel of 4,000 households residing in the same state. With three waves of data from 2004, 2006 and 2008, they perform double and triple differences estimations and propensity score matching. Similar to our empirical results, they find that the program was well targeted and had large effects on food consumption and asset accumulation, particularly among SC/STs and casual laborers, whose magnitudes exceed the value of direct transfers. Our analysis differs from these studies in four regards. First, in terms of scope, we consider all major Indian states. Second, our empirical identification strategy does not rely on parallel trend assumptions, which we find not to hold in various placebo estimations. Third, we consider effects not only on consumption averages, but also on consumption-based poverty. Fourth, and most importantly, we unfold the seasonal pattern of program effects and show how the NREGA has not only reduced poverty levels but contributed to consumption smoothing. Bose (2013) uses two waves of Indian National Sample Survey data to estimate the effect of the first phase of the NREGA on consumption and poverty. Employing a differences-in-differences estimation technique with Phase I as treatment and Phase III as control group, which requires strong identifying assumptions, her estimated program effects are similar to ours.

The structure of this paper is as follows. In Section 2.2, we discuss the NREGA in some detail and present the data used in our analyses. We introduce our empirical approach and identification strategy in Section 2.3. Section 2.4 contains the empirical results, Section 5 various robustness checks and extensions. A cost-benefit analysis is the subject of Section 6. The final section concludes.

2.2 Background and Data

2.2.1 The National Rural Employment Guarantee Act

The NREGA, enacted in 2005 by the United Progressive Alliance government, was envisioned as a safety net for rural households. Under the Act every rural household is entitled to 100 days of work at the statutory minimum wage, which is set by the respective state government. The NREGA guarantees employment within 14 days to any rural resident who is willing to work, irrespective of income level, gender, caste, or religion. The Act includes a provision for an unemployment allowance in case of failure to provide work within this time frame. The NREGA as a policy instrument is remarkable in two ways; first because of its rights-based approach and, second, its provisions for transparency and accountability (Khera, 2011). As to the first, the NREGA marks a move away from doling out benefits to recognizing certain basic entitlements, including the notion of a right to work and to a minimum income. The NREGA also draws strongly on the spirit of the Right to Information Act, enacted in 2006, by defining provisions for enabling transparent and easily accessible administrative records, as well as processes for public scrutiny and accountability of officials toward beneficiaries. As a result, since its implementation in 2006, it has been closely monitored by civil society, which in turn has helped to expose several instances of corruption (Vanaik and Siddhartha, 2008a,b).

The NREGA is not the first public works program in post-independence India. The National Food for Work Programme (NFFWP) implemented between 2004 and 2006, is viewed as the predecessor of the NREGA. The Maharashtra Employment Guarantee Scheme, enacted in 1977 and active until the inception of the NREGA, has received some interest by researchers in the past (Basu, 1981; Drèze, 1990; Ravallion et al., 1993).

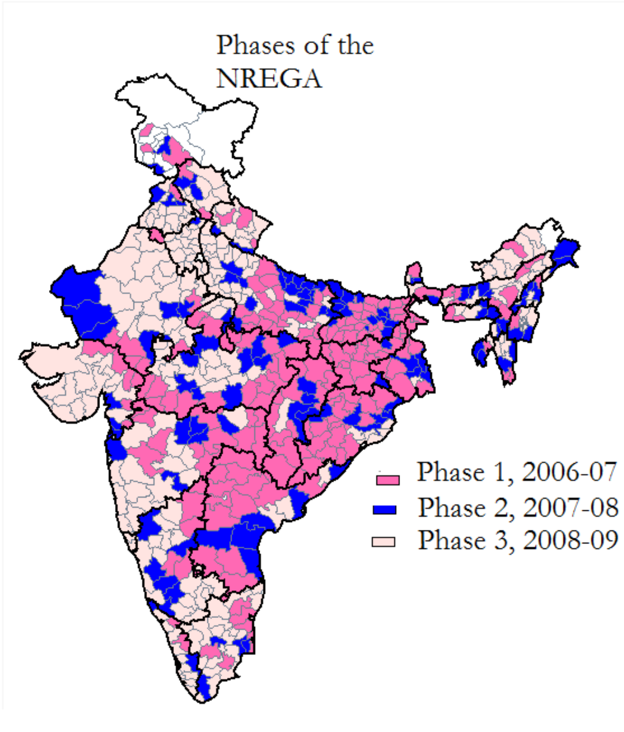

Figure 2.1: Phase-wise Roll-out of the NREGA Across Districts

The NREGA started in 200 districts, which we will refer to as Phase I districts, in the fiscal year spanning from April 2006 to March 2007. In April 2007, another 130 districts started implementing the Act (Phase II), and in April 2008 all remaining 263 districts were covered (Phase III). The spatial pattern of districts' allocation to the three phases is mapped in Figure 2.1. We identify Phase II and Phase III districts as published on the official website of the Ministry of Rural Development (Government of India, 2013c). From the same source we collected year, district, and month-wise program intensity data. In our subsequent analysis, where we approach the NREGA roll-out as a natural experiment, we focus on the fiscal year 2007-08 and regard Phase II districts as treatment group and Phase III districts as control group. We disregard Phase I of the NREGA for two reasons. First, in the 200 Phase I districts, the NFFWP had been operating up to the initiation of the NREGA making it difficult to separate effects of the NREGA from those of the NFFWP. Second, unlike for Phase II and III districts, we are not aware of a convincing empirical strategy addressing the problem of selection of districts into this Phase.[2]

Planning Commission Backwardness Index

In the subsequent analyses we employ a district-wise backwardness index published by India's National Planning Commission (Government of India, 2003). For 447 districts in India's major states, this index is calculated from three sub-indices, percentage of SC/ST population, agricultural output per worker, and the agricultural wage rate. The final composite index figures between 0.078 (most backward) to 2.159 (least backward). This index has served as the basis for allocating districts to each of the three phases of the NREGA (Zimmermann, 2012). In our empirical analysis we use this index for dealing with selection problems in district-wise program status assignment. Unfortunately, the index is available for only 92 and 163 of the NREGA's 130 Phase II and 263 Phase III districts, respectively. All districts listed by the Planning Commission belong to the seventeen major Indian states of Andhra Pradesh, Assam, Bihar, Chhattisgarh, Gujarat, Haryana, Jharkhand, Karnataka, Kerala, Madhya Pradesh, Maharasthra, Orissa, Punjab, Rajasthan, Tamil Nadu, Uttar Pradesh, and West Bengal. As our identification strategy can only accommodate districts for which the Planning Commission's backwardness index is available, our subsequent analysis is restricted to those 255 Phase II and III districts for which the backwardness index is available.

Descriptive Statistics

Table 2.1 presents key program statistics for our sample of 92 Phase II districts during the fiscal year 2007-08.[3] According to Table 2.1, seventy percent of the program's expenditures of about Rs. 30 billion were spent on wages. Given a population of 25.5 million households, this amounts to Rs. 840 per rural household residing in these districts. Employment in NREGA works and thus NREGA expenditures follow a marked seasonal pattern. They peak during the dry spring season when labor demand in rural areas plummets. To illustrate, Figure 2.2 depicts NREGA wage expenditures per rural inhabitant (not per NREGA worker) in our sample districts by month. Accordingly, wage expenditures per rural inhabitant stood at less than Rs. 10 per month during the first six months of Phase II for which program expenditure data is available (May to October 2007). This figure more than tripled to about Rs. 30 per month

[2]See, however, Bose (2013) for a comparative analysis of Phase I and III districts in the fiscal year 2006-07.

[3]For a discussion of the quality of official NREGA program data see Drèze and Oldiges (2011).

Table 2.1: NREGA Facts for Phase II Sample Districts

NREGA Expenditure in Phase II Sample Districts	
Total Expenditure (in million INR)	29,926.17
Expenditure on Wages (in million INR)	21,437.76
Share of Exp. on Wages in Total Exp. (in %)	71.64
Population in Phase II Sample Districts	
Rural Population (in million)	149.41
Rural Households (in million)	25.50
Rural SC/ST Population (in million)	38.74
Rural SC/ST Households (in million)	7.11
NREGA Employment in Phase II Sample Districts	
Households Employed under the NREGA (in million)	8.99
Per Cent of Rural Households Employed under the NREGA	35.27
SC/ST Households Employed under the NREGA (in million)	4.26
Per Cent of Rural SC/ST Households Employed under the NREGA	59.94
NREGA Person-Days in Phase II Sample Districts	
Total Person-Days (in million)	287.14
Person-Days per Rural Population	1.92
Person-Days per Rural Household	11.26
SC/ST Person-Days (in million)	136.05
SC/ST Person-Days per SC/ST Population	3.51
SC/ST Person-Days per SC/ST Household	19.14
Number of Districts	92

NREGA figures pertain to the fiscal year 2007-08. They are in current prices, and are calculated from district-wise statistics as published online by the Ministry of Rural Development.
Population totals are calculated from district-wise Census 2001 figures.
We use household size figures from our respective NSS samples as given in Table 2.2 and 2.3 to calculate household population totals.
We use SC/ST shares in Person-Days as a multiplier to calculate SC/ST-wise employment figures.

during the agricultural off-season, the first half-year of 2008. During the same period, monthly wage expenditures amounted to Rs. 55 per capita among SC/ST households. The same figure also demonstrates that this cyclical expenditure pattern continues into the fiscal year 2008-09.

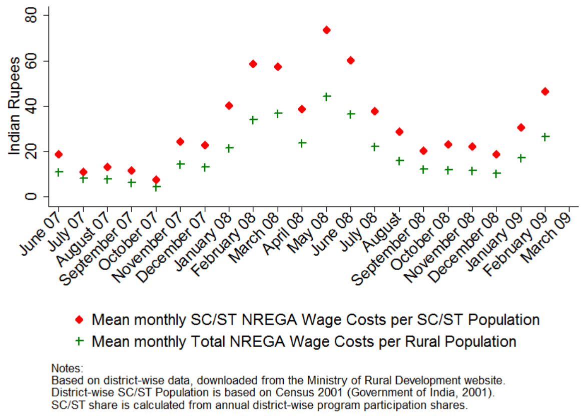

Figure 2.2: NREGA Wage Costs

2.2.2 Household Welfare

In our main empirical analysis, we use the 63rd and 64th round of the Indian National Sample Survey's (NSS) consumption expenditure module. These two rounds cover the agricultural years July 2006 to June 2007 and July 2007 to June 2008. Our reason for this choice of rounds is as follows. For a differences-in-differences estimation of the program effect of NREGA's Phase II with one baseline and one endline wave of data, we are bound to use the 64th round as endline since this is the only agricultural year in which the Act was active in all Phase II districts but in none of the Phase III districts.[4] The natural choice for the baseline is the 63rd round canvassed in 2006-07. In comparison to prior rounds, such as the large 61st or the slightly smaller 62nd round, using a baseline as close to the endline as possible minimizes the effect of confounding factors, which we expect to be numerous given India's rapid rate of transformation during the 2000s. There is an additional reason in favor of the 63rd, and against the 61st round, which serves as baseline in Azam (2012) and Zimmermann (2012). The summer monsoon rainfall (June to September) of 2004 was more than fifteen percent below the long-term average for India as a whole resulting in a kharif (fall) crop failure (Government of India, 2012), while the monsoon rainfalls during the three following years were exceptionally similar with deviations from the long-term average of -1.3, -0.4 and +5.7 percent in 2005, 2006 and 2007, respectively (Government of India, 2014a). Hence, as far as weather conditions are concerned, the three agricultural years covered by the 62nd, 63rd and 64th round are similar in terms

[4]This statement is not exactly true as the program commenced in the Phase III districts with the beginning of the fiscal year 2008-09, that is in April 2008. However, this occurred at a low intensity with average monthly wage expenditures per capita of less than Rs. 10 in April and May of 2008, which compares to an average of Rs. 34 in our Phase II sample districts. While the former figure increased to Rs. 23 during the month of June, the resulting total wage expenditures per capita during the first half-year of 2008 in our Phase III sample districts amount to no more than Rs. 42, which compares to Rs. 204 in our Phase II sample districts. Moreover, since we expect some lag between wage disbursement and households' consumption, and since the interviews conducted by the NSS rely on a thirty day recall period, we regard the start of NREGA in the Phase III districts in April 2008 as a minor threat to our empirical approach, which treats Phase II districts as treatment and Phase III districts as control group. Nonetheless, we will revisit this issue in the robustness checks section.

of weather conditions, which is mirrored by growth rates of the agricultural gross domestic product of 5.1, 4.2 and 5.8 percent, while there was zero growth in 2004-05 (Government of India, 2012). We will revisit the issue of alternative baselines when we address the robustness of our empirical results.

In all our analyses, a household is the unit of observation; we do not aggregate welfare outcomes at the district-level. Throughout, we use the sampling weights provided with the NSS data, which are meant to ensure that consumption aggregates calculated from the household-level data are representative for the rural population at the individual (not the household) level. While India's National Sample Survey Organization (NSSO) points out that consumption estimates are representative at the district level for neither the 63rd nor the 64th round because of a sample size which is small by NSS standards (Chaudhuri and Gupta, 2009), we shall point out here that random sampling within each district is sufficient for consistent estimation of program effects within our empirical approach. The smaller numbers of observations in these two "thin" rounds (on average 14,000 households rather than 32,500 in the "thick" 61st round) will merely reduce the estimation precision.

Our key outcome variable of interest, Monthly per Capita Consumption Expenditure (MPCE), takes into account a mixed recall period applied by the NSSO, thirty days for high-frequency items and 365 days for certain lumpy expenditure items. In line with common practice (Deaton, 2008), all prices are deflated to constant 2004-05 prices using the monthly Consumer Price Index for Agricultural Laborers (CPI-AL).[5] At 0.5 percent per month, rural inflation was similar to the overall rate of inflation in India during the time period we consider, July 2006 to June 2008. We calculate two poverty measures based on MPCE figures and state-wise poverty lines suggested by the Tendulkar Commission (Government of India, 2009), the headcount ratio (HCR), P_0, and the poverty gap ratio (PGR), P_1 (Foster et al., 1984). The 2004-05 Tendulkar poverty line for rural India, which equals Rs. 446.68 (about 30 US Dollars, purchasing power parity concept) is higher than the previously common Indian national poverty line, equal to Rs. 356.30 (or \$23) (Government of India, 2007). Hence the Tendulkar poverty measure captures roughly "one dollar a day" poverty. We also experimented with poverty measures based on the traditional national poverty line but faced a problem of too little estimation precision because less than fifteen percent of the rural population in our sample districts is poor by that definition. For the Tendulkar poverty line, this figure stands at 32 percent in our sample.

Summary statistics for the sample of all rural households and the sub-sample of SC/ST households for the 63rd and 64th NSS round are set out in Tables 2.2 and 2.3, respectively. Each table gives sample means by year, phase, and season. For considerations of space, we have opted not to report standard deviations or standard errors. In accordance with the general trend since the 1990s, there is a decline in poverty in both samples. Both in Phase II and Phase III districts and across both groups of households, poverty according to the headcount ratio

[5]India's Labour Bureau provides these figures online (Government of India, 2013a).

and the poverty gap ratio has declined between 2006-07 and 2007-08. At the same time, as expected, poverty in Phase II districts is higher than in Phase III districts in each of these two NSS rounds.

There are marked seasonal variations in the distribution of consumption, in particular its lower part, by NREGA phase. For the sample of all rural households, there is an increase in poverty as measured by the headcount ratio from fall to spring in Phase II districts in both rounds while the opposite is true in the less backward Phase III districts. Such a pattern is in line with smoother consumption across seasons in more forward districts. Given the general secular decline in rural poverty in India, a smooth consumption path across seasons implies a slight decrease in poverty from fall to spring in each agricultural year and hence NSS round. It is only the less backward Phase III districts that achieve such a pattern, however, while consumption in Phase II districts mirrors the annual agricultural cycle, where the bulk of agricultural activity, employment and yield occurs during the monsoon-fed kharif (fall) season.

2.3 Empirical Approach: Regression Discontinuity Design

In this section, we lay out our estimation strategy. While the papers by Azam (2012), Berg et al. (2012), Imbert and Papp (2013) as well as Bose (2013) all rely on the phase-wise roll-out of the program and use differences-in-differences estimation techniques to identify labor market effects of the NREGA, Zimmermann (2012) casts doubts on the identifying assumptions behind such an approach. The intention of the phase-wise roll-out of the program has been to bring the program to India's poorest districts first. The critical identifying assumption of a differences-in-differences analysis which uses Phase II districts as the treatment and Phase III districts as control group is that time trends are parallel between the baseline and endline, 2004-05 and 2007-08 in Azam (2012), for example, across Phase II and Phase III districts, that is between two groups of districts with markedly different baseline characteristics. While Azam (2012) finds no evidence against such a parallel time trend assumption in employment data spanning the time period 1999 to 2005, we find strong evidence against this assumption in NSS consumption data from the 2005-06 and 2006-07 NSS rounds (see below). In our view, this is not surprising. Given that monthly per capita consumption expenditures were more than twenty percent higher in Phase III relative to Phase II districts in 2006-07, our baseline year, Phase II and Phase III districts likely also exhibit markedly different structural features, such as access to financial and other markets and non-farm employment opportunities for rural households. That such structural features are predictors of subsequent growth and poverty reduction rates has been shown for Indian states by Datt and Ravallion (2002) and is, in our view, likely for districts, too.

To provide intuition for our empirical identification strategy, consider the union set of Phase II and III districts and suppose that, within this set, Phase II status was assigned to only the 130 most backward districts according to the Planning Commission's 2003 district back-

Table 2.2: Summary Statistics for All Rural Households

	2006-07			2007-08		
	All Year	Fall	Spring	All Year	Fall	Spring
	Phase II and Phase III Sample Districts					
MPCE	643.71	651.36	636.46	670.09	672.96	667.20
Log. MPCE	631.80	632.94	630.71	637.47	636.76	638.18
HCR	35.60	35.89	35.33	29.31	30.29	28.32
PGR	7.66	7.45	7.86	5.38	5.87	4.89
HH-size	6.10	6.07	6.13	5.93	6.03	5.82
Crank	3.04	3.73	2.38	3.33	3.32	3.34
SC/ST[a] (in %)	29.34	27.89	30.71	26.37	25.60	27.15
Laborers (in %)	38.62	39.62	37.68	36.10	35.31	36.89
Number of HHs	14860	7446	7414	12901	6456	6445
Districts	255	255	255	255	255	255
	Phase II Sample Districts					
MPCE	558.44	585.65	535.42	587.13	590.04	584.27
Log. MPCE	619.50	622.88	616.64	627.09	627.38	626.80
HCR	42.85	41.69	43.84	34.98	34.22	35.72
PGR	9.90	9.20	10.49	6.54	6.59	6.49
HH-size	6.20	6.06	6.32	5.86	5.89	5.83
Crank	−2.27	−1.43	−2.98	−1.91	−2.00	−1.82
SC/ST[a] (in %)	34.99	31.50	37.94	29.80	27.90	31.65
Laborers (in %)	40.69	42.81	38.90	37.17	37.26	37.09
Number of HHs	5703	2856	2847	5450	2728	2722
Districts	92	92	92	92	92	92
	Phase III Sample Districts					
MPCE	711.14	698.20	724.54	728.64	730.19	727.06
Log. MPCE	641.52	640.11	642.98	644.80	643.24	646.40
HCR	29.87	31.75	27.92	25.31	27.58	22.97
PGR	5.89	6.20	5.56	4.56	5.36	3.74
HH-size	6.02	6.07	5.96	5.98	6.13	5.82
Crank	7.23	7.41	7.04	7.03	6.99	7.07
SC/ST[a] (in %)	24.87	25.32	24.41	23.95	24.01	23.89
Laborers (in %)	36.99	37.36	36.61	35.34	33.97	36.74
Number of HHs	9157	4590	4567	7451	3728	3723
Districts	163	163	163	163	163	163

[a] Scheduled Castes and Scheduled Tribes.

Notes: Calculated from NSS rounds 63 and 64.

"Log. MPCE" is the natural logarithm of monthly per capita consumption expenditures, multiplied by 100.

Individual weights provided by the NSSO are used so that all figures are representative for the rural population of individuals.

"Fall" and "Spring" include observations from July to December and from January to June, respectively.

The sample is restricted to Phase II and Phase III districts for which the Planning Commission Backwardness Index is available.

All measures in 2004-05 constant prices using monthly CPI-ALs, and state-wise Tendulkar poverty lines for 2004-05.

Table 2.3: Summary Statistics for Rural Households Belonging to Scheduled Castes and Scheduled Tribes

	2006-07			2007-08		
	All Year	Fall	Spring	All Year	Fall	Spring
	Phase II and Phase III Sample Districts					
MPCE	496.93	511.59	484.32	547.39	542.60	551.94
Log. MPCE	610.19	614.25	606.69	621.52	619.85	623.10
HCR	52.72	49.03	55.90	42.56	43.80	41.39
PGR	13.50	12.06	14.74	8.61	9.73	7.55
HH-size	6.20	5.84	6.51	5.60	5.70	5.51
Crank	1.97	2.85	1.22	2.53	2.70	2.37
Laborers (in %)	57.13	61.17	53.65	58.64	56.36	60.81
Number of HHs	3579	1785	1794	2724	1352	1372
Districts	253	239	245	252	240	238
	Phase II Sample Districts					
MPCE	446.23	494.02	412.67	517.34	511.50	522.40
Log. MPCE	599.00	609.55	591.58	615.88	614.50	617.07
HCR	61.44	50.25	69.31	46.35	46.50	46.21
PGR	17.25	13.60	19.80	9.57	10.32	8.92
HH-size	6.59	5.86	7.10	5.45	5.53	5.38
Crank	−3.34	−3.35	−3.33	−2.44	−2.48	−2.40
Laborers (in %)	53.15	55.03	51.83	56.31	52.78	59.36
Number of HHs	1661	829	832	1341	643	698
Districts	92	86	90	92	91	89
	Phase III Sample Districts					
MPCE	553.33	527.17	581.40	573.77	567.54	580.19
Log. MPCE	622.64	618.42	627.17	626.47	624.14	628.87
HCR	43.02	47.94	37.74	39.24	41.63	36.78
PGR	9.33	10.69	7.87	7.77	9.25	6.25
HH-size	5.77	5.82	5.71	5.73	5.83	5.63
Crank	7.87	8.34	7.37	6.89	6.86	6.92
Laborers (in %)	61.56	66.62	56.12	60.69	59.23	62.21
Number of HHs	1918	956	962	1383	709	674
Districts	161	153	155	160	149	149

Notes: See Table 2.2.

wardness index. Under the identifying assumption that expected consumption growth in a district is continuous in the Planning Commission's (PC) backwardness index, a local average treatment effect of the NREGA could be estimated using a sharp regression discontinuity design (RDD) by regressing consumption growth of a district between 2006-07 and 2007-08 on a flexible polynomial in the PC backwardness index and a dummy for belonging to the 130 most backward districts. Notice that, in this case, such a dummy equivalently captures Phase II status. That dummy's regression coefficient would yield a consistent estimate of the program's expected effect for a district whose PC backwardness index is at the Phase II - Phase III cutoff value.

The way the NREGA's Phase II was implemented deviates from such a clean scenario in two ways. First, the assignment of Phase II status to districts was implemented at the state rather than at the national level. This means that, in a first step, each state s was prompted to nominate a given number of districts, m_s say, for Phase II with the guideline that the state's poorest districts as measured by the PC backwardness index are to be given priority. Second, because of constraints in administrative capacity or other reasons such as political favoritism (Gupta, 2006), no state government nominated precisely the m_s poorest districts - as measured by the PC index - within its boundaries. Instead, some districts that should have been nominated following the PC index rule did not obtain Phase II status while some less backward districts in the same state did.

The first complication can be addressed by implementing a regression discontinuity design for each state. The required identifying assumption is that, within each state, a district's expected consumption growth rate conditional on the district's PC index is continuous in the latter. The second complication can be resolved by employing a fuzzy RDD at the state level. Toward this, a district's consumption growth rate is regressed on predicted Phase II status, where the prediction is based on the district's PC backwardness index and the state-wise PC index rule, rather than actual Phase II status. The additional two identifying assumptions needed for this procedure are, first, that a district's probability to be in Phase II is continuous in its PC index and, second, that there is a discontinuous jump in this probability at the state-specific threshold value of the PC backwardness index.

We implement this latter procedure in two steps. Consider a district as the unit of observation. In the first step, for each district of state s, we predict the probability of being notified in Phase II based on whether the district is among the m_s most backward districts of that state according to the PC index. In the second, consumption growth in each district is regressed on the predicted Phase II probability from the first step and a flexible polynomial in the backwardness index.

For practical purposes, Zimmermann (2012) suggests to use each district's within-state PC backwardness rank rather than the index itself and to force the polynomial of all states to be identical. More precisely, for each state, we rank the union set of all Phase II and III districts in descending order of the Planning Commission's index. Denoting the PC backwardness index for district d in state s by x_{sd}, we consider a district's rank among the Phase II and III districts of the same state, $rank_{sd}$. To be precise, we define

$$rank_{sd} = \sum_{i=1}^{n_s} 1\{x_{si} \geq x_{sd}\},$$

where n_s is the number of Phase II and III districts in state s and $1\{\cdot\}$ denotes the indicator function. Recall that x_{sd} is smaller, the more backward the district. Then, the way $rank_{sd}$ is defined, the least (most) backward district of state s is assigned the first (n_s'th) rank. Taking m_s as given for each state, we define the *centered rank* of a district within its state by $crank_{sd}$, where

$$crank_{sd} = rank_{sd} - m_s.$$

Notice that, within each state, the centered rank of the least backward district that would obtain Phase II status if, within that state, selection of Phase II districts was based solely on the PC index, equals zero. Accordingly, the dummy variable $1\{crank_{sd} \leq 0\}$ tells whether district d of state s should be a Phase II district if, in each state, districts were allocated to phases following the PC backwardness index strictly.

Using local linear regression as recommended by Lee and Lemieux (2010), our first stage estimating equation is

$$\begin{aligned} Phase2_{sd} = {} & c_s + \alpha\, 1\{crank_{sd} \leq 0\} + \eta_1\, crank_{sd} \\ & + \eta_2\, crank_{sd} * 1\{crank_{sd} \leq 0\} + u_{sd}, \end{aligned} \tag{2.1}$$

where $Phase2_{sd}$ equals one if district d in state s has Phase II status and u_{sd} is a stochastic error term. Notice that we allow for state-specific intercept terms and a different slope of the regression function to the left and the right of the cutoff value. Figure 2.3 plots the relative frequency of Phase II status averaged over all seventeen states in our sample over the variable $crank$ together with a piece-wise linear regression function in the forcing variable, which includes a jump at zero. We have trimmed the sample to include only districts whose $crank$ is no greater than ten in absolute value. There clearly is a downward jump in the data where the centered rank equals zero. This is mirrored by our first stage estimation results, which are set out in the first column of Table 2.4. Accordingly, conditional on a district's within-state centered rank, its probability to be in Phase II increases by 67.3 percent if it is among the state's m_s poorest districts.

Table 2.4: Predictors of NREGA Phase II Status

Unit of observation:	District		Household					
Sample:			All Rural Households			Rural SC/ST[a] Households		
	All Year (1)	No State FE (2)	All Year (3)	Fall (4)	Spring (5)	All Year (6)	Fall (7)	Spring (8)
Phase II-Status	0.673***	0.745***	0.670***	0.659***	0.681***	0.705***	0.788***	0.621***
by PC Score rule (Dummy)	(0.089)	(0.089)	(0.104)	(0.104)	(0.105)	(0.127)	(0.112)	(0.143)
Crank	0.020*	0.018	0.023	0.020	0.025*	0.027	0.032*	0.021
	(0.011)	(0.011)	(0.014)	(0.013)	(0.014)	(0.018)	(0.016)	(0.020)
Crank*Positive-Crank-Dummy	−0.027	−0.030*	−0.020	−0.018	−0.021	−0.030	−0.028	−0.032
	(0.019)	(0.018)	(0.023)	(0.023)	(0.024)	(0.028)	(0.026)	(0.030)
Observations	201	201	10394	5196	5198	2268	1116	1152
Clusters			201	201	201	199	189	188
State Fixed Effects	Yes	No	Yes	Yes	Yes	Yes	Yes	Yes

[a] Scheduled Castes and Scheduled Tribes.

Notes: Columns 3-8: Robust Standard Errors in parentheses, clustered at the district level. * p<0.1, ** p<0.05, *** p<0.01.
Based on the 64th NSS round, 2007-08, individual weights provided by the NSSO.
The sample is trimmed to Phase II and Phase III districts whose crank is not smaller than -10 and not greater than 10.
Phase II status by PC score rule (Dummy) equals one if the district's centered rank is equal to or smaller than zero and zero otherwise.
Postive-Crank-Dummy equals one if the district's centered rank is greater than zero and zero otherwise.

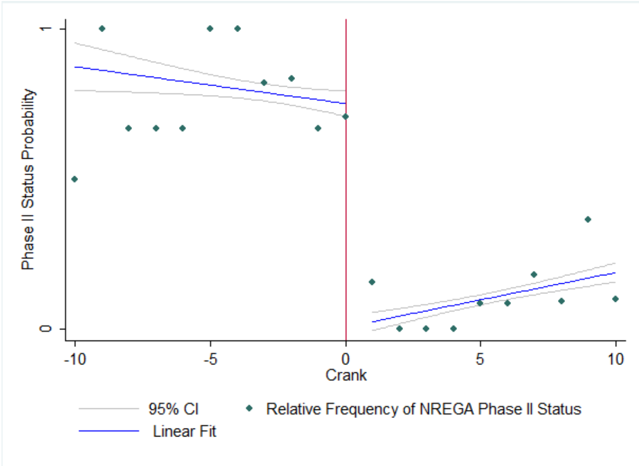

Figure 2.3: Probability of NREGA Phase II Status by Centered Rank

While the first estimation stage is for a cross-section of districts, our second stage is for a repeated cross-section of households forming a district pseudo panel,

$$\begin{aligned} y_{sdit} = \mu_{sd} + \gamma_{st} + \beta\, \widehat{Phase2_{sd}} * D0708_t + \delta_1\, crank_{sd} * D0708_t \\ + \delta_2\, crank_{sd} * {}^1\{crank_{sd} \leq 0\} * D0708_t + \epsilon_{sdit}, \end{aligned} \tag{2.2}$$

where y denotes an outcome of interest, i and t are subscripts for households and time periods, respectively, and ϵ_{sdit} is a stochastic error term. There are two time periods, one for each of the NSS rounds canvassed in 2006-07 and 2007-08. The dummy variable $D0708_t$ equals one if an observation is from the latter NSS round. For estimating (2.2), we use the survey weights provided by the NSSO. This second stage can be viewed as a modified differences-in-differences estimating equation for a district pseudo panel. The first modification is the addition of a control variable, the centered within-state rank, which is assumed to be related to the outcome variable in a piece-wise linear fashion, the second one the use of a predicted value for a district's Phase II status rather than the district's actual program status.

Our estimation strategy as laid out in (2.1) and (2.2) gives each district an equal weight in the first stage while each district's implicit weight in the second stage estimation equals its population share. An alternative, more standard, approach to the estimation of the program effect would be to estimate (2.2) with $Phase2_{sd}$ substituted for $\widehat{Phase2_{sd}}$ by instrumental variables, where $Phase2_{sd}$ is treated as endogenous regressor and ${}^1\{crank_{sd} \leq 0\} * D0708_t$ is used as identifying instrument (see Lee and Lemieux, 2010). In such a specification, each district is given the same weight, its population share, in both estimation stages. The resulting point estimate of β is a Wald estimator, the extent of the discontinuity in the outcome variable of interest divided by the extent of the discontinuity in the probability of being notified in Phase II. An essential feature of our subsequent empirical analysis is that we will consider alternative subsets of households. In the instrumental variables approach, the first stage estimation results and hence the denominator of the Wald estimator of the program effect depend on the district weights implied by the respective subset of households that is being considered. As the vector of implied district weights varies greatly across the sub-samples which we will consider, the instrumental variables approach yields substantially different program effect estimates in two alternative sub-samples, even if the discontinuity in the outcome variable of interest is exactly the same in both sub-samples. System (2.1) and (2.2), on the other hand, avoids this artefact because the program effect estimates for different sub-samples are essentially Wald estimators with an identical denominator.[6] We will revisit this issue in Section 2.5.4.

We close this section with a discussion of the computation of standard errors for our two-stage approach. As shown by Murphy and Topel (1985), ordinary least squares standard errors are biased when a "generated regressor" is used, as in our second stage. Another complication regarding the calculation of standard errors is that, for each of the two NSS rounds, we want to allow for a non-zero correlation among the error terms of households residing in the same district. Since we were not able to find explicit formulas for standard errors when there is a generated regressor as well as the need for clustering, we calculate clustered standard errors as if there was no generated regressor in (2.2) and correct those standard errors as suggested by Murphy and Topel (1985; equation 17) for non-clustered standard errors by the factor $\sqrt{1+\widehat{\beta}^2 MSE_1/MSE_2}$, where $\widehat{\beta}$ is the estimate of β from an ordinary least squared estimation of (2.2) and MSE_k denotes the mean squared error from estimation of the k'th stage estimating equation. We realize that such an approach is somewhat ad hoc. On the other hand, it is beyond the scope of this paper to assess whether the resulting standard errors are consistent. Therefore, in Section 2.5.4, we also estimate a standard two stage least squares version of system (2.1) and (2.2), where consistent clustered standard errors are available, without obtaining any qualitatively different results - that is with respect to sign and statistical significance - from the ones reported in the next section.

2.4 Results

2.4.1 Main Results

Our outcomes of interest are individual consumption and consumption-based poverty measures. Table 2.5 contains the coefficient estimates of β in (2.2) for alternative dependent variables and different (sub-)samples of households. We also report the number of districts for which there are observations in both the 63rd and the 64th NSS round as our estimates of the program's effect are based on only such districts. For all regressions whose results are reproduced in this table, the predicted values of Phase II status for each district are obtained from the estimation of (2.1) whose results are set out in the first column of Table 2.4. In all regressions,

[6] While the point estimate of β in our approach does not exactly equal the ratio between the second-stage and the first-stage discontinuity, none of the point estimates in Table 2.5 differs from that ratio by more than 1.5 percent of the respective standard error.

the sample is trimmed such that only districts with a $crank$ of no more than ten in absolute value are included.

Standard errors are calculated as described above, that is we conduct an ordinary least squares estimation of (2.2), calculate clustered standard errors, where a cluster is the set of households residing in the same district in a given NSS round, and adjust the standard error for $\widehat{\beta}$ thus obtained according to equation 17 in Murphy and Topel (1985). The correction factor that obtains for the estimations whose results are set out in Table 2.5 never exceeds 1.1. All results in Table 2.5 are estimated from the 2006-07 and 2007-08 NSS rounds. From the upper left panel, it is evident that the trimming results in a loss of 54 districts, 201 instead of 255. Since the 63rd NSS round fails to contain one of these 201 districts, there are 401 clusters. Comparing the upper and center left panels, we see that 23 percent of the households that are sampled in the two relevant NSS rounds and reside in either a Phase II or a Phase III district, belong to scheduled castes or scheduled tribes. That this fraction is substantially smaller than the share of SC/ST households in all rural households, 26.5 percent, is due to the sampling stratification employed by the NSSO, by which relatively wealthy households are systematically oversampled in thin survey rounds (see Table 2.6). While the sampling methodology in both NSS rounds ensures that almost all districts are represented in each round, SC/ST households are not sampled deliberately. Hence, even if there are SC/ST households in each district, random sampling within each district results in no SC/ST households being interviewed in some districts. Comparing the upper and center left panels of Table 2.5, we see that this has happened in three instances, that is district-year pairs. A loss of clusters also occurs when we consider observations from only one of the two agricultural seasons, that is July to December or January to June. Comparing the center left with the two panels to its right, we see that such random drawing of the interview date results in a loss of twenty and sixteen clusters in fall and spring, respectively.

In each panel, the column "MPCE" has logarithmic monthly per capita consumption expenditures at constant prices as dependent variable, while in columns HCR and PGR, the headcount ratio and poverty gap ratio are the dependent variables, respectively. As pointed out previously, the estimated effects are not average treatment effects for the set of all Phase II districts, but local treatment effects capturing the expected program effect for a household residing in a district that is on the edge of being allocated to Phase II or Phase III as predicted by the district's backwardness index.

Turning to the estimation results, there are only small and statistically insignificant results for our full sample. For SC/ST households, we estimate an increase in logarithmic consumption and economically significant decreases in poverty when pooling the observations from both agricultural seasons (center left panel). The disaggregated seasonal analyses for SC/ST households reveal that the effects for the full year are entirely driven by the spring season, where we find large increases in consumption expenditures and decreases in poverty. Albeit imprecisely estimated, the center right panel's entry in the MPCE column implies that SC/ST

Table 2.5: Regression Discontinuity Analysis of Consumption and Poverty

	MPCE	HCR	PGR	MPCE	HCR	PGR	MPCE	HCR	PGR
	Sample: All Rural Households								
	All Year			**Fall**			**Spring**		
Year0708 * $\widehat{Phase2}$	0.586	−6.964	−0.935	−2.305	−6.328	0.711	2.584	−8.130	−1.887
	(5.547)	(6.414)	(1.668)	(6.521)	(7.640)	(1.974)	(7.658)	(7.993)	(2.028)
Households	22929	22929	22929	11435	11435	11435	11494	11494	11494
Clusters	401	401	401	401	401	401	401	401	401
Dist. in both years	200	200	200	200	200	200	200	200	200
	Sample: Rural Households Belonging to Scheduled Castes and Scheduled Tribes								
	All Year			**Fall**			**Spring**		
Year0708 * $\widehat{Phase2}$	23.380***	−29.102***	−6.798**	−4.963	−3.774	1.581	37.283***	−45.196***	−11.678***
	(6.888)	(10.814)	(2.918)	(9.803)	(13.342)	(4.504)	(10.156)	(16.153)	(3.838)
Households	5285	5285	5285	2607	2607	2607	2678	2678	2678
Clusters	398	398	398	378	378	378	382	382	382
Dist. in both years	197	197	197	178	178	178	181	181	181
	Sample: Rural Laborers								
	All Year			**Fall**			**Spring**		
Year0708 * $\widehat{Phase2}$	6.518	−1.532	0.591	6.805	−8.087	2.317	9.740	−0.319	−2.187
	(6.399)	(8.720)	(2.691)	(6.900)	(9.536)	(2.820)	(8.694)	(12.843)	(3.414)
Households	6881	6881	6881	3379	3379	3379	3502	3502	3502
Clusters	400	400	400	393	393	393	389	389	389
Dist. in both years	199	199	199	192	192	192	189	189	189

Notes: Robust standard errors (Murphy Topel) in parentheses, clustered at the district-year level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$
Additional regressors whose coefficients are not displayed in the table: District fixed effects, state-year interactions, a crank-year 2007-08 interaction, and crank-year 2007-08 above the crank cutoff (Dummy) interaction. Weights: Individual weights as provided by the NSSO.
Data: NSS rounds 63 and 64 for the years 2006-07 and 2007-08, sample trimmed to Phase II and Phase III districts with a crank no smaller than -10 and no greater than 10.
"Fall" and "Spring" include observations from July to December and from January to June, respectively.

Table 2.6: Second Stage Stratification by NSS Round

Year	NSS Round	SSS[a]	Type	Relative Frequency of Second Stage Sub-Stratum (SSS): As per NSS (%)	All-India Rural NSS Sample	All-India Rural Population (%)[b]	Rural NSS Sample Used in Estimations (%)	Population in Districts Used in Estimations (%)[b]	Oversampling: All-India Rural NSS Sample	Rural NSS Sample Used in Estimations
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
2005-06	62	1	Land-poor	50	54	84	53	84	0.6	0.6
2005-06	62	2	Land-rich	50	46	16	47	16	2.9	2.9
2006-07	63	1	Public works employment	33.3	19	12	13	8	1.6	1.6
2006-07	63	2	Of the rest, land-poor	33.3	51	75	56	79	0.7	0.7
2006-07	63	3	Of the rest, land-rich	33.3	30	13	31	14	2.3	2.2
2007-08	64	1	Affluent	50	48	8	49	8	6.0	6.1
2007-08	64	2	Non-affluent	50	52	92	51	92	0.6	0.6

[a] Second Stage Stratum, [b] Calculated from sampling weights provided by the NSSO.
"As per NSS": Sampling proportions for each surveyed village according to NSS instructions.
Columns 8 and 9 refer to the sample used in the estimations (Phase II and III districts for which $-10 \leq crank \leq 10$).
Column 10 is the ratio of column 6 and 7, and column 11 is the ratio of column 8 and 9.
Sources: National Sample Survey Organisation (2008a,b, 2010) and own calculations.

consumption expenditures have increased by 37.3 percent on average due to the presence of NREGA sights during the agricultural lean season, the spring of 2008. Turning to the poverty measures, our estimates imply a reduction in the incidence of poverty as measured by the headcount ratio of 45 percentage points and a decrease in the poverty gap measure of 11.7 percentage points. These effects are very large taking into account the 2006-07 reference values of 69.3 and 19.8 for these two measures. The limited number of observations in the seasonal SC/ST analyses, each of which comprises only a little more than a tenth of the observations in our full data set, and the loss of clusters due to random sampling results in a considerable loss in estimation precision and a lamentable increase in standard errors.

For reference, Table 2.16 contains estimates of β for a variation of (2.2) in which actual Phase II program status, $Phase2_{sd}$, is substituted for predicted program status $\widehat{Phase2_{sd}}$. Such a specification amounts to a standard differences-in-differences estimation of the NREGA's program effect. While it allows for different time trends in the outcome variable across districts by centered rank, it fails to purge any bias in the estimation of β arising from selection issues. Such a bias will occur in particular if, absent the NREGA, a district that is assigned Phase II (III) status with a centered rank greater (weakly smaller) than zero exhibits a systematically different growth rate in the outcome of interest than predicted by that same district's $crank$. To make a case, suppose that districts that should have been in Phase II according to the state-wise PC index rule, that is $Phase2_{sd} = 1$ if and only if $crank_{sd} \leq 0$, but end up in Phase III, have an especially poor administrative capacity. If administrative capacity of a district is positively correlated with its rate of consumption growth absent the NREGA, then such selection will bias an estimate of β upward because on average the growth rate of a district actually in Phase II is greater than predicted by its $crank$ and the converse is true for Phase III districts. Regarding the seasonal pattern of program effects, the point estimates obtained from this approach exhibit marked qualitative differences relative to the ones obtained from our two stage procedure for the sample of SC/ST households. As expected, the coefficients are estimated much more precisely when actual rather than predicted Phase II status is used. We will turn to the credibility of these differences-in-differences estimates in the context of a placebo experiment in the next section.

2.5 Extensions and Robustness Checks

2.5.1 Alternative Sub-sample of Vulnerable Households

In this subsection we consider an alternative subgroup of especially poor and vulnerable households, rural laborers. This is facilitated by the fact that the NSS consumption questionnaires report the household's principal occupation. While we would have preferred to look at only agricultural laborers, we found the resulting sub-sample too small. The union set of agricultural and other laborers, in contrast, is of a similar size (twelve percent larger, to be precise) as the one comprising all SC/ST households. According to the descriptive statistics for our base year 2006-07 in Table 2.14, this group's and SC/ST's welfare characteristics, as captured by consumption and poverty, are very similar. Rural laborers' average monthly per capita consumption expenditure, headcount ratio and poverty gap ratio figure at Rs. 513, 51.4 percent and 12.3 percent in 2006-07, which compares to Rs. 497, 52.7 percent and 13.5 percent among SC/STs, respectively. Still, the two subgroups overlap only partially. In the data set that we use for our core analysis, 26.5 percent of the population belong to scheduled castes and scheduled tribes and 36.2 percent are laborers. A little more than half of the SC/ST population report themselves as laborers. As a consequence, fifteen percent of the population in our full sample are both SC/ST and laborers, which implies that the majority of laborers, 58 percent to be precise, does not belong to scheduled castes and tribes. Analogous to our core analysis, we estimate system (2.1) and (2.2) with the sub-sample of rural laborers only. According to the bottom panel of Table 2.5, there is no statistically significant effect of the NREGA for this part of the rural population.

We end this subsection by pointing out that the sub-sample of SC/ST households is our preferred group of especially vulnerable households. Classification as rural laborer is in response to a question regarding the household's principal occupation, where the three relevant categories for our purposes are laborer, self-employed, and other. In this connection, we fear two potential problems in conjunction with the NREGA. The first one is a selection issue. The presence of NREGA sights creates additional non-farm employment opportunities, which may affect a household's choice of principal occupation. For example, the extra availability of non-farm employment may prompt a household head that would have formerly reported himself as working primarily as agricultural laborer to report the household as doing primarily non-agricultural labor. Such an effect of the NREGA should not jeopardize the consistency of our analysis of rural laborers' welfare because we consider the union set of agricultural and non-agricultural laborers. Among marginal farmers, however, it is conceivable that NREGA employment opportunities prompt some households to move from the category self-employed in agriculture to laborers. As a consequence, the laborer sub-samples in our baseline and endline rounds would, in general, not be comparable. The second issue may be labelled reporting bias. The answer to the occupational question is based on a perception of the household head. Even if the household's own occupational activities do not change with the NREGA, the change in behavior among peer households, in this case working more in non-farm wage employment, may affect a household's perception of its principal occupation. Any of these two effects is likely to result in biased program effect estimates, even within our identification framework.

2.5.2 Migration

A concern that arises in the context of our analysis is that the program potentially alters migration incentives and hence the composition of the rural population in the Phase II and III districts differently between the baseline and endline surveys. For the Mexican PROGRESA, for example, Stecklov et al. (2005) find that exposure to PROGRESA reduced out-migration to the United States by about one fifth while it did not affect domestic migration in a measurable way. Given a rate of out-migration to the US of less than a one percent per year, however, such a program effect on migration would not severely jeopardize an analysis like ours, where baseline and endline together span no more than two years.

In rural India, migration is substantial. According to the 2001 Census of India, the annual rate of rural-urban migration stood at around seven percent per year. Our results of substantial welfare improvements among SC/ST households would be jeopardized if the availability of NREGA sights increased the rate of out-migration among especially poor households or decreased the rate of out-migration of especially wealthy, non-poor households. In such a scenario, improvements in poverty due to the NREGA would merely be due to a relocation of poverty away from the rural areas of the Phase II districts. Using a differences-in-differences estimation approach and NSS migration modules from two years, Ravi et al. (2012) find that the NREGA drives down migration in Phase II districts by as much as a quarter. Similarly, in a study of two north-western states of India, Imbert and Papp (2014) find that the NREGA reduces short-term migration of rural laborers. Such a pattern would lead to a systematic increase in the population of Phase II districts relative to our control (Phase III) districts. While these authors do not explicitly disaggregate migration flows by initial wealth, both papers find that the entire effect of NREGA on migration is driven by laborers, which are far more likely to belong to the poorer half of the rural consumption distribution (see Table 2.14). This implies that the migration effect of NREGA will result in lower average consumption in Phase II districts - as one would expect intuitively. Hence, our estimates regarding household welfare should be conservative ones.

2.5.3 Placebo Experiment (or Falsification Test)

In this subsection, we assess the validity of one of the identifying assumptions underlying our two-stage analysis. In particular, we test whether a district's expected growth rate conditional on its $crank$ does not exhibit a discontinuity at $crank$ equal to zero absent the NREGA. Toward this, we estimate system (2.1) and (2.2) with data from the 62nd and 63rd NSS round.

Sample means for the 62nd NSS round are set out in Table 2.15. The results of this exercise are set out in Table 2.7. For all sub-samples, the point estimates are far from being statistically significant. The standard errors for the sub-sample of SC/ST households are around forty percent larger in the placebo than in our core analysis, which is due to the smaller number of observations in the 62nd NSS round relative to the 64th. This raises the issue whether the

Table 2.7: Regression Discontinuity Analysis of Consumption and Poverty, Placebo

	MPCE	HCR	PGR	MPCE	HCR	PGR	MPCE	HCR	PGR
	Sample: All Rural Households								
	All Year			**Fall**			**Spring**		
Year0607 * $\widehat{Phase2}$	−1.223	1.607	0.417	−2.905	8.186	1.331	−0.529	−3.259	0.925
	(5.692)	(6.471)	(1.666)	(7.033)	(7.609)	(2.062)	(8.931)	(9.713)	(2.666)
Households	19381	19381	19381	9630	9630	9630	9751	9751	9751
Clusters	402	402	402	400	400	400	396	396	396
Dist. in both years	201	201	201	199	199	199	195	195	195
	Sample: Rural Households Belonging to Scheduled Castes and Scheduled Tribes								
	All Year			**Fall**			**Spring**		
Year0607 * $\widehat{Phase2}$	−12.257	14.537	3.697	−21.159	24.209	7.663	−5.170	0.298	0.215
	(11.011)	(12.088)	(4.060)	(13.201)	(17.533)	(4.975)	(14.231)	(18.386)	(4.960)
Households	4405	4405	4405	2163	2163	2163	2242	2242	2242
Clusters	396	396	396	367	367	367	367	367	367
Dist. in both years	195	195	195	171	171	171	169	169	169
	Sample: Rural Laborers								
	All Year			**Fall**			**Spring**		
Year0607 * $\widehat{Phase2}$	4.226	−13.500	−1.955	−1.228	−5.681	3.805	0.856	−5.912	0.085
	(6.908)	(8.453)	(2.739)	(8.198)	(11.998)	(3.397)	(11.513)	(13.452)	(4.696)
Households	6275	6275	6275	3113	3113	3113	3162	3162	3162
Clusters	396	396	396	375	375	375	377	377	377
Dist. in both years	195	195	195	176	176	176	177	177	177

Notes: See Table 2.5, except for data: NSS rounds 62 and 63 for the years 2005-06 and 2006-07, respectively.

placebo analysis suffers from a lack of power. The absolute magnitude of the greatest point estimates obtaining in the placebo, SC/ST during fall, is still only about a half of those for SC/ST during spring in our main estimations, which we take as evidence in favor of the hypothesis that there is no discontinuity in a district's expected consumption growth rate at the $crank$-cutoff absent the NREGA.

Another potential issue with our placebo is that the NREGA started to operate in Phase II districts in April 2007. Hence, in our Phase II districts, the last three months of the 63rd round may be affected by the onset of the NREGA. As Figure 2.2 shows, however, this occurred at a very low intensity. In particular, no wage expenditures are recorded for the month of April 2007 and the somewhat greater expenditures during June 2007 are unlikely to affect June consumption as the consumption data are based on a mixed recall of thirty and 365 days. In line with this argument, all three point estimates for SC/ST households during spring are small and insignificant.

Table 2.17 sets out the results of a placebo experiment for a differences-in-differences version of (2.2), where $Phase2_{sd}$ is substituted for $\widehat{Phase2_{sd}}$. There are large and significant placebo effects for all rural households during the fall season and for SC/ST households during spring. Accordingly, consumption growth and poverty reduction between the spring seasons of 2006 and 2007 was about twice as large as between 2007 and 2008. Taken together, we conclude from the results of the two placebo experiments that the parallel time trend assumption underlying a differences-in-differences approach is clearly violated while the identifying assumptions of the fuzzy regression discontinuity design appear to be valid.

2.5.4 Sampling Weights and Two-stage Least Squares Implementation of Fuzzy Regression Discontinuity Design

As discussed in Section 2.3, our empirical specification as laid out in (2.1) and (2.2) assigns equal weights to all districts in the first stage while each district's weight in the second stage estimation is equal to its population share. This is the fundamental difference to a textbook implementation of a fuzzy regression discontinuity design, which amounts to two stage least squares estimation (Lee and Lemieux, 2010). The latter can be implemented by conducting an instrumental variables estimation of (2.2) with $Phase2_{sd}$ substituted for $\widehat{Phase2_{sd}}$, where $Phase2_{sd}$ is treated as endogenous regressor and $\mathbb{1}\{crank_{sd} \leq 0\} * D0708_t$ is used as identifying instrument. In such a specification, each district is assigned the same weight in each estimation stage, which equals its population share.

To illustrate the sensitivity of the Wald estimator of the program effect to the choice of sub-sample within this approach, columns 3 to 8 of Table 2.4 set out alternative first stage results of a standard instrumental variables version of system (2.1) and (2.2). The third column, which uses data from all rural households, gives results very similar to the first column. On the other hand, between the last two columns, which are for the sub-samples of SC/ST households during fall and spring, respectively, the difference in the estimated jump varies by almost a quarter.

As expected, the magnitude of estimated coefficients, which are set out in Table 2.8, is even more dramatic than in Table 2.5 for the sub-sample of SC/ST households during the spring season. On the other hand, the order of magnitude and the pattern of statistical significance across the different sub-samples is unchanged, at least as far as the five percent significance level is concerned. We take this as support for the validity of our procedure for calculating the standard errors in our preferred specification. As an additional robustness check, we also carry out a placebo estimation using instrumental variables estimation and data from the 62nd and 63rd NSS rounds. According to Table 2.18, as in Table 2.7, none of the estimated coefficients is statistically significant at conventional levels.

A third possibility of weighting districts in the two stages of the estimation is to give each district an identical weight in both stages. This corresponds to Zimmermann's (2012) approach, who carries out all estimations with district averages. Such an approach yields a program effect estimate which is representative for an average district at the cutoff of the centered rank, while the estimates set out in Table 2.5 are representative for the population in districts located around the cutoff. Asymptotically, the resulting coefficients of interest will be different if the local average treatment effect is heterogenous with regards to district population size. The results of this exercise are set out in Table 2.9 and confirm our previous findings qualitatively. The point estimates are much smaller with this alternative weighting scheme, however, and only logarithmic monthly per capita consumption of SC/ST households during the spring season increases in a statistically significant fashion.

2.5.5 Regression Discontinuity Design Applied to only Endline Data

Our estimation strategy in the main empirical analysis can be thought of as a fuzzy regression discontinuity design applied to changes in welfare outcomes between two years, where the relevant unit of observation is a district and district averages for each of the two years of data are calculated from household-level data in a first step. One key identifying assumption of such an approach is that the expected change in average household welfare in a district conditional on the district's backwardness index is continuous in that index absent the NREGA. Over the last ten years, panel RDD analyses have become common in empirical economics and have been applied fruitfully in many different contexts (see Lee and Lemieux, 2010, for references).

In this subsection we explore a simpler RDD specification using a cross section of districts with data from the endline survey only, that is from 2007-08. This corresponds to the fuzzy RDD textbook case. The underlying identifying assumption then is that the level of expected average household welfare in a district conditional on the backwardness index is continuous in that index absent the NREGA. The estimation continues to proceed in two steps. The first step (2.1) for predicting Phase II remains unaffected. The estimating equation for the second

Table 2.8: Two Stage Least Squares Regression Discontinuity Analysis of Consumption and Poverty

	MPCE	HCR	PGR	MPCE	HCR	PGR	MPCE	HCR	PGR
	Sample: All Rural Households								
	All Year			**Fall**			**Spring**		
Year0708 * $\widehat{Phase2}$	0.665	−7.285	−0.986	−2.396	−7.018	0.730	2.572	−8.117	−1.872
	(5.766)	(6.886)	(1.748)	(7.084)	(8.561)	(2.146)	(7.686)	(8.156)	(2.059)
Households	22929	22929	22929	11435	11435	11435	11494	11494	11494
Clusters	401	401	401	401	401	401	401	401	401
Dist. in both years	200	200	200	200	200	200	200	200	200
	Sample: Rural Households Belonging to Scheduled Castes and Scheduled Tribes								
	All Year			**Fall**			**Spring**		
Year0708 * $\widehat{Phase2}$	24.631***	−30.744**	−7.159**	−5.105	−3.972	1.617	40.969***	−49.664**	−12.833**
	(8.307)	(13.035)	(3.206)	(10.146)	(13.648)	(4.670)	(13.750)	(20.825)	(5.054)
Households	5285	5285	5285	2607	2607	2607	2678	2678	2678
Clusters	398	398	398	378	378	378	382	382	382
Dist. in both years	197	197	197	178	178	178	181	181	181

Notes: See Table 2.5.

Table 2.9: Regression Discontinuity Analysis of Consumption and Poverty, Equal District Weights

	MPCE	HCR	PGR	MPCE	HCR	PGR	MPCE	HCR	PGR
	Sample: All Rural Households								
	All Year			**Fall**			**Spring**		
Year0708 * $\widehat{Phase2}$	0.449	−3.287	−0.072	3.879	−5.016	−0.417	−2.990	−1.567	0.258
	(4.310)	(3.314)	(0.839)	(5.843)	(4.239)	(1.120)	(5.546)	(4.270)	(1.035)
Households	22929	22929	22929	11435	11435	11435	11494	11494	11494
Clusters	401	401	401	401	401	401	401	401	401
Dist. in both 2006-07 and 2007-08	200	200	200	200	200	200	200	200	200
	Sample: Rural Households Belonging to Scheduled Castes and Scheduled Tribes								
	All Year			**Fall**			**Spring**		
Year0708 * $\widehat{Phase2}$	8.925	−7.694	−1.797	−2.802	1.017	1.505	16.838**	−9.791	−2.661
	(5.791)	(7.330)	(1.743)	(9.095)	(9.712)	(2.666)	(7.890)	(10.533)	(2.404)
Households	5285	5285	5285	2607	2607	2607	2678	2678	2678
Clusters	398	398	398	378	378	378	382	382	382
Dist. in both 2006-07 and 2007-08	197	197	197	178	178	178	181	181	181

Notes: See Table 2.5, but instead of individual weights each district in each of the years is given the same weight.

step now becomes

$$y_{sdi} = \mu_s + \beta\,\widehat{Phase2}_{sd} + \delta_1\,crank_{sd} + \delta_2\,crank_{sd} * {}^1\{crank_{sd} \leq 0\} + \epsilon_{sdi},$$

where all observations for y are from the 64th NSS round. We expect this approach to have less power because pre-program differences between districts become unobserved heterogeneity in this cross-sectional approach.

The results are set out in Table 2.10. While the pattern of the signs of the estimated coefficients is the same as in Table 2.5, none of the estimated effects is statistically significant at the five percent level, which comes as no surprise given our just-mentioned reservations regarding the power of such an approach in our small sub-samples.

2.5.6 Alternative Baseline Year

In this subsection, we explore the 62nd NSS round as an alternative baseline round. We see two advantages and two disadvantages using the 62nd in place of the 63rd round as baseline. Turning to the disadvantages, we expect the residual variance to be greater because of a longer time spell between baseline and endline. Second, all estimates will be less precise as the sample size in the 62nd round is only about half of that of the 63rd round. On the other hand, unlike the 63rd, the 62nd round as a baseline is not affected by the onset of the NREGA in April of 2007. Finally, compared to the 63rd round, it has a sampling strategy more similar to that of the 64th round. As set out in Table 2.6, both the 62nd and 64th round follow the Indian NSSO's usual second stage stratification strategy, where an equal number of wealthy and non-wealthy households is interviewed in each block that has been drawn for inclusion in the NSS sample. It is only the definition of "wealthy" that varies across these two rounds. In particular, land ownership serves as criterion in the 62nd round while it is the possession of certain assets in the 64th. The 63rd round, on the other hand, has the singular feature of initially stratifying by participation in public works. If the sampling weights, which the NSS includes with each observation, were correct, variations in the second-stage stratification across survey rounds should not matter. Given the sensitivity of various findings derived from these surveys, e.g. regional poverty trends, to other survey features, such as the recall period (see, e.g., Deaton and Kozel, 2005) , we are somewhat skeptical about variations in the sampling methodology, however. In particular, since SC/ST households demand NREGA employment much more often than non-SC/ST households, we suspect that the stratification by public works employment in the 63rd round could lead to a misrepresentation of such households, even when using the weights supplied by the NSSO.

To assess this possibility, we estimate system (2.1) and (2.2) with the dependent variable equal to a dummy which takes the value of one if the interviewed household belongs to a scheduled caste or a scheduled tribe. We would like to stress that, as in all other regressions,

Table 2.10: Cross-sectional Regression Discontinuity Analysis of Consumption and Poverty

	MPCE	HCR	PGR	MPCE	HCR	PGR	MPCE	HCR	PGR
	Sample: All Rural Households								
	All Year			**Fall**			**Spring**		
Year0708 * $\widehat{Phase2}$	−8.032	3.587	0.151	−9.914	7.794	0.361	−6.070	−0.457	−0.090
	(7.149)	(6.404)	(1.572)	(8.101)	(7.698)	(1.910)	(7.823)	(7.850)	(1.803)
Households	10394	10394	10394	5196	5196	5196	5198	5198	5198
Clusters	201	201	201	201	201	201	201	201	201
Districts in 2007-08	201	201	201	201	201	201	201	201	201
	Sample: Rural Households Belonging to Scheduled Castes and Scheduled Tribes								
	All Year			**Fall**			**Spring**		
Year0708 * $\widehat{Phase2}$	1.630	−3.477	−0.089	−12.106	17.156	3.894	14.732*	−22.455	−4.022
	(7.458)	(10.646)	(2.696)	(9.958)	(13.090)	(3.302)	(8.267)	(13.661)	(3.149)
Households	2268	2268	2268	1116	1116	1116	1152	1152	1152
Clusters	199	199	199	189	189	189	188	188	188
Districts in 2007-08	199	199	199	189	189	189	188	188	188

Notes: Robust standard errors in parentheses, clustered at the district-year level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$
All measures in 2004-05 constant prices using monthly CPI-ALs, state-wise Tendulkar poverty lines for 2004-05.
Additional regressors whose coefficients are not displayed in the table:
State dummies, crank, and crank-above the crank cutoff (Dummy) interaction.
Weights: Individual weights as provided by the NSSO.
Data: NSS round 64 for the year 2007-08, sample trimmed to Phase II and Phase III districts with a crank no smaller than -10 and no greater than10.
"Fall" and "Spring" include observations from July to December and from January to June, respectively.

Table 2.11: Regression Discontinuity Analysis of the Incidence of Scheduled Castes and Scheduled Tribes and Laborers

Dependent Var.:	SC/ST[a] (1)	Laborer (2)	SC/ST[a] (3)	Laborer (4)	SC/ST[a] (5)	Laborer (6)
	Sample: All Rural Households in 2006-07 and 2007-08					
	All Year		Fall		Spring	
Year0708 * $\widehat{Phase2}$	−0.128***	0.084*	−0.151**	0.131*	−0.072	0.054
	(0.046)	(0.043)	(0.065)	(0.067)	(0.063)	(0.066)
Households	22928	22920	11435	11432	11493	11488
Clusters	401	401	401	401	401	401
Dist. in both years	200	200	200	200	200	200
	Sample: All Rural Households in 2005-06 and 2007-08					
	All Year		Fall		Spring	
Year0608 * $\widehat{Phase2}$	−0.036	0.073	−0.051	0.101	−0.010	0.089
	(0.053)	(0.050)	(0.079)	(0.063)	(0.071)	(0.083)
Households	17206	17202	8569	8567	8637	8635
Clusters	402	402	400	400	396	396
Dist. in both years	201	201	199	199	195	195

[a] Scheduled Castes and Scheduled Tribes.

Notes: See Table 2.5.

we use the weights provided by the NSSO. Hence, in principle, the estimated effects are representative for the entire rural population. For the baseline and endline years underlying our main analysis, the results are set out in columns 1, 3 and 5 of the upper panel of Table 2.11. According to column 1, the incidence of SC/ST individuals has dropped by 12.8 percentage points in response to NREGA's Phase II. This point estimate is significant at the five percent significance level and driven by the fall season, for which the point estimate equals more than fifteen percent. For the spring season, there is no statistically significant effect. We have carried out the same exercise with the dependent variable rural laborer, whose results are set out in columns 2, 4 and 6 of the upper panel. Again there are statistically significant effects of the NREGA, albeit of opposite sign. The lower panel of Table 2.11 sets out the results of the same exercise with the 62nd and 64th rounds of NSS data. For SC/STs, all estimated effects are small and statistically insignificant. Taken together, the pattern of results across the two panels is suggestive of differences regarding the populations that are represented in the 62nd and 64th round on the one hand, and the 63rd round on the other.

Sample means for the 62nd round are set out in Table 2.15 for SC/ST households. The results for system (2.1) and (2.2) with the 62nd round as baseline are set out in Table 2.12. They confirm our findings for SC/STs during the spring season both qualitatively and quantitatively. As expected, the precision of the point estimates deteriorates relative to our main results in Table 2.5.

Table 2.12: Regression Discontinuity Analysis of Consumption and Poverty, Alternative Base Year

	MPCE	HCR	PGR	MPCE	HCR	PGR	MPCE	HCR	PGR
	Sample: All Rural Households								
	All Year			**Fall**			**Spring**		
Year0608 * $\widehat{Phase2}$	−1.956	−3.795	−0.042	−8.612	6.995	2.135	6.390	−13.201	−1.765
	(5.672)	(6.119)	(1.682)	(6.942)	(7.707)	(2.000)	(7.463)	(8.562)	(2.322)
Households	17208	17208	17208	8571	8571	8571	8637	8637	8637
Clusters	402	402	402	400	400	400	396	396	396
Dist. in both years	201	201	201	199	199	199	195	195	195
	Sample: Rural Households Belonging to Scheduled Castes and Scheduled Tribes								
	All Year			**Fall**			**Spring**		
Year0608 * $\widehat{Phase2}$	11.207	−20.943*	−2.605	−15.987	19.514	7.382	38.575***	−52.924***	−14.811***
	(10.024)	(12.092)	(3.890)	(15.118)	(16.543)	(5.297)	(13.440)	(17.008)	(5.262)
Households	3647	3647	3647	1782	1782	1782	1865	1865	1865
Clusters	395	395	395	366	366	366	360	360	360
Dist. in both years	194	194	194	168	168	168	164	164	164

Notes: See Table 2.5, except for data: NSS rounds 62 and 64 for the years 2005-06 and 2007-08, respectively.

2.5.7 Timing of NREGA Onset and Consumption Survey Interviews

As mentioned in Section 2.2.2, the program commenced in Phase III districts in April 2008. While this occurred at a very low intensity, in principle this onset of the program in our control group of districts potentially biases our program effect estimates. This applies in particular to the spring season, for which consumption interviews take place between January and June. While we expect our program effect estimates set out in Table 2.5 to be downward-biased in this scenario, we repeat our main analysis for SC/ST households during the spring season with consumption interviews held only during the first quarter of 2007 and 2008. The results are set out in column 6 of Table 2.13. With less than 1,500 observations, for logarithmic MPCE we continue to find a statistically significant effect very similar in magnitude to the one in Table 2.5. The effects for the two poverty measures, on the other hand, are muted and insignificant.

2.5.8 Trimming, Functional Form of the Regression Discontinuity Design and Control Variables

As pointed out by Lee and Lemieux (2010), unlike in many instances of panel data fixed effects estimation, panel RDD regression equations do not require the inclusion of any controls or fixed effects to ensure consistent estimation of causal effects. The essential explanatory variables are a polynomial in the continuous forcing variable, here the centered rank, and a dummy for the discontinuity, each interacted with an endline dummy. In this subsection we explore alternative specifications of our system of estimating equations regarding the choice of trimming, fixed effects and control variables. For considerations of space, we discuss only results for SC/STs during spring. Columns 1 and 2 of Table 2.13 set out results for different extents of trimming. Neither widening nor narrowing the $crank$ window by five steps changes our main results in a remarkable way, though narrowing decreases the precision greatly. In this context, it is to be noted that further trimming, as in column 1, results in a loss of a third of the districts used in our main estimations.

We also explore a local polynomial regression with distinct quadratic polynomials to the left and right of the cutoff. To be precise, the first stage in this specification is

$$
\begin{aligned}
Phase2_{sd} \quad = \quad & c_s + \alpha\, {}^{1}\{crank_{sd} \leq 0\} + \eta_1\, crank_{sd} + \eta_2\, crank_{sd}^2 \\
& + \xi_1\, crank_{sd} * {}^{1}\{crank_{sd} \leq 0\} \\
& + \xi_2\, crank_{sd}^2 * {}^{1}\{crank_{sd} \leq 0\} + u_{sd}
\end{aligned}
$$

Table 2.13: Regression Discontinuity Analysis of Consumption and Poverty for Rural Households Belonging to Scheduled Castes and Scheduled Tribes during Spring, Alternative Specifications

	(1)	(2)	(3)	(4)	(5)	(6)
			Specifications for MPCE			
Year0708 * $\widehat{Phase2}$	40.373***	30.641***	48.481***	22.982***	30.700***	29.022**
	(14.805)	(9.989)	(9.184)	(8.352)	(9.015)	(11.488)
Households	1992	3045	2678	2678	2678	1406
Clusters	253	456	382	382	382	341
			Specifications for HCR			
Year0708 * $\widehat{Phase2}$	−33.340	−44.654***	−63.720***	−26.239*	−36.297**	−12.477
	(23.850)	(15.543)	(14.887)	(13.999)	(15.256)	(13.447)
Households	1992	3045	2678	2678	2678	1406
Clusters	253	456	382	382	382	341
			Specifications for PGR			
Year0708 * $\widehat{Phase2}$	−8.148	−11.747***	−16.900***	−6.833**	−9.631***	−3.585
	(6.338)	(3.714)	(3.679)	(3.393)	(3.673)	(3.356)
Households	1992	3045	2678	2678	2678	1406
Clusters	253	456	382	382	382	341
Trimming	±5	±15	±10	±10	±10	±10
Stage 1 State FE, Stage 2 State-Year Interactions	*Yes*	*Yes*	*Yes*	*No*	*Yes*	*Yes*
Polynomial Order	1	1	2	1	1	1
Household Size	*No*	*No*	*No*	*No*	*Yes*	*No*
January - March only	*No*	*No*	*No*	*No*	*No*	*Yes*

Notes: See Table 2.5. Household Size is a categorical variable. The seven categories are 1-2, 3, 4, 5, 6, 7, and 8 or more members.

and the second stage

$$\begin{aligned} y_{sdit} \;=\;& \mu_{sd} + \gamma_{st} + \beta\, \widehat{Phase2_{sd}} * D0708_t + \delta_1\, crank_{sd} * D0708_t \\ & + \delta_2\, crank^2_{sd} * D0708_t + \varkappa_1\, crank_{sd} * {}^1\{crank_{sd} \leq 0\} * D0708_t \\ & + \varkappa_2\, crank^2_{sd} * {}^1\{crank_{sd} \leq 0\} * D0708_t + \epsilon_{sdit}. \end{aligned}$$

According to column 3 of Table 2.13, our previous findings continue to obtain under this modification and the point estimates are larger.

Column 4 is as our main specification but without state-endline year interactions. To be precise, the terms c_s and γ_{st} in (2.1) and (2.2) are replaced by c and γ_t, respectively. As the point estimates show, our main results are robust to these two omissions but the estimated effects are muted. Figure 2.4 depicts the reduced form corresponding to system (2.1) and (2.2) with c

and γ_t substituted for c_s and γ_{st}, respectively,

$$\begin{aligned} y_{sdit} &= \mu_{sd} + \gamma_t + \beta\, ^1\{crank_{sd} \leq 0\} * D0708_t + \delta_1\, crank_{sd} * D0708_t \\ &\quad + \delta_2\, crank_{sd} * ^1\{crank_{sd} \leq 0\} * D0708_t + \epsilon_{sdit}, \end{aligned}$$

for logarithmic MPCE. Accordingly, there is an estimated downward jump at the discontinuity of 17.5 percentage points, which, once divided by the estimated jump in the probability of being notified under Phase II, 0.75 (see column 2 of Table 2.4), roughly gives the point estimate in the fourth column of the upper panel of Table 2.13, 22.98.

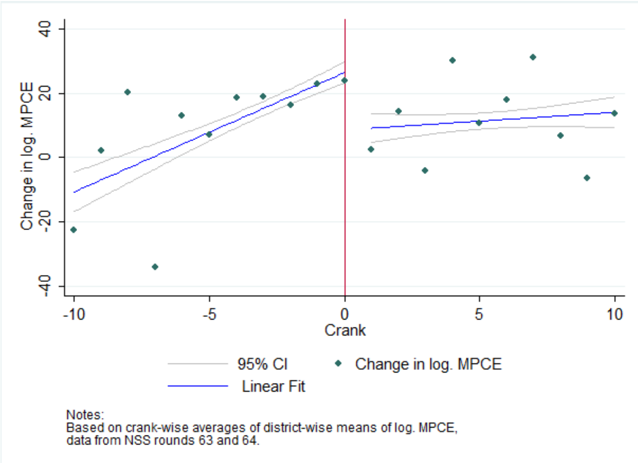

Figure 2.4: NREGA Effect on Mean Logarithmic Monthly per Capita Consumption Expenditures by Households Belonging to Scheduled Castes and Scheduled Tribes

Finally, in column 5 we have added dummies for different household sizes as explanatory variables, so the interpretation of the estimated program effect is conditional on household size. Our main findings continue to obtain, albeit slightly muted in magnitude.

2.6 Cost-Benefit Analysis

We first summarize the empirical findings obtained thus far. While we have not found statistically significant program effects for the sample of all rural households and the sub-sample of rural laborers residing in NREGA Phase II and Phase III districts, we have found very large and statistically significant local average treatment effects on consumption growth and poverty reduction for the subgroup of scheduled castes and scheduled tribes during spring, which is the agricultural lean season. While all point estimates in our disaggregated analyses suffer from a lack of precision, the pattern of the Act's welfare effects as elicited by our findings is clear. The main beneficiaries are households belonging to a particularly deprived subgroup of the rural population and the effects occur during the season in which the risk of consumption shortfalls is greatest. For the subgroup of SC/STs, consumption gains are especially large in the lower part of the consumption distribution. Given the lack of precision in the respective estimations, we view the pattern of welfare improvements generated by the NREGA as the major insight of our empirical analysis, rather than the point estimates, which we think should be taken with a grain of salt.

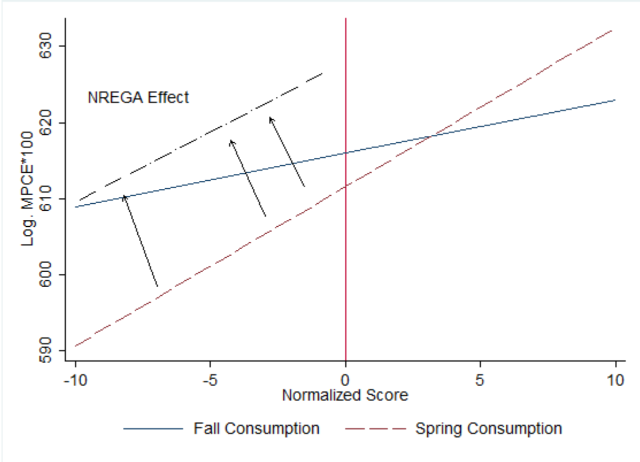

Figure 2.5: Estimated Effect of the NREGA on Seasonal Consumption Patterns

Figure 2.5 depicts the estimated effect on consumption expenditures among SC/ST households in a stylized fashion. The solid and the dashed line depict fall and spring consumption in 2006-07, respectively, by district backwardness. The location and slope of the two lines imply that, in backward districts, spring consumption falls considerably short of fall consumption, while fall and spring season consumption are similar in the less backward districts with a $crank$ greater than zero. This is in line with the sample means set out in the center left and bottom left panels of Table 2.3. Accordingly, Phase II districts experienced a consumption drop of about eighteen percent from fall 2006 to spring 2007 while Phase III districts enjoyed an increase of about two percent. In terms of Figure 2.5, our results imply a program effect resulting in an upward shift of the left part of the dashed line. To be precise, the estimated local average treatment effect only tells that there is an upward shift at zero, the cutoff value of the centered rank. For the figure we have implicitly assumed a homogeneous treatment effect of the NREGA with regards to a district's centered rank, which implies a parallel shift upwards of the dashed line to the left of zero. The resulting new situation clearly implies smoother consumption across the two seasons for SC/ST households in backward districts, and this is in fact what the sample means in the center right and bottom right panels of Table 2.3 imply. Accordingly, mean per capita consumption increased by about two percent for both the Phase II and III districts from the second half-year of 2007 to the first half-year of 2008.

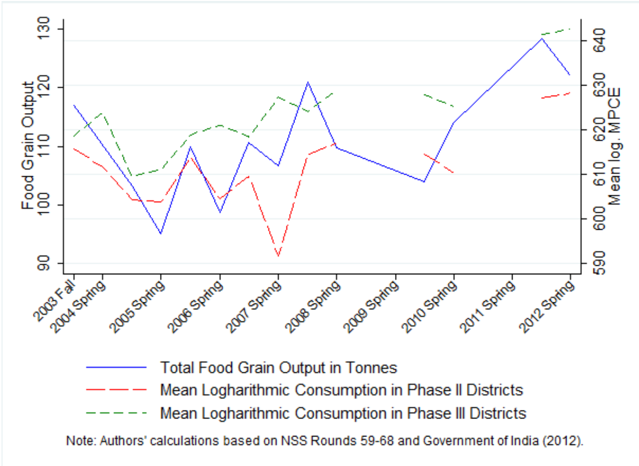

Figure 2.6: Mean Logarithmic Monthly per Capita Consumption Expenditures by Rural Households Belonging to Scheduled Castes and Scheduled Tribes in NREGA Phase II and III Districts and All-India Food Grain Production by Agricultural Season

To assess whether the NREGA has had a lasting impact on seasonal consumption patterns of SC/ST households, Table 2.15 sets out SC/ST consumption and poverty by NREGA phase and season for all NSS rounds featuring a consumption expenditure module since 2003. The upper panel covering the agricultural year 2003-04 is calculated from two rounds, the 59th and 60th, as the former covers the calendar year 2003 and the latter only the first half-year of 2004. Figure 2.6 depicts the time series of logarithmic MPCE among households belonging to scheduled castes and scheduled tribes by NREGA phase together with all-India agricultural production for each half-year from fall 2003 to spring 2012. Two stylized facts emerge from the table and figure. First, consumption averaged over an agricultural year tracks agricultural output closely in both groups of districts, that is consumption smoothing across years is far from complete irrespective of NREGA phase status. Second, prior to the NREGA, the risk of a consumption shortfall during the second half of an agricultural year is far greater in Phase II than in the less backward Phase III districts. To be precise, according to Table 2.15, average logarithmic consumption is lower in spring than in fall in Phase II districts in all years up to 2006-07, while Phase III districts enjoyed a moderate increase in logarithmic consumption at the same time. This seasonal consumption pattern in Phase II districts is in accordance with the seasonality in agricultural output, which is on average roughly ten percent larger in fall than in spring. Given an increase in logarithmic consumption between 2003-04 and 2011-12 of 14.5 and 20.1 in Phase II and Phase III districts, respectively, a perfectly smooth consumption path involves an increase in logarithmic consumption of 0.90 and 1.25 from fall to spring in each agricultural year, respectively.[7] It is evident from Table 2.15 that Phase III districts get much closer to such a pattern than Phase II districts prior to the NREGA. In particular, for the four agricultural years between 2003-04 and 2006-07, intra-year changes in logarithmic

[7]There are sixteen half-years between January 2004 and January 2012. The two numbers 0.90 and 1.25 are obtained from dividing 14.5 and 20.1 by sixteen, respectively.

consumption averaged at -8.1 in Phase II compared to +4.5 in Phase III districts with standard deviations equal to 7.5 and 3.4, respectively. In the three consumption surveys available since 2007-08, the mean changes between the two seasons of the same agricultural year are -0.1 and +1.1, respectively, with standard deviations equal to 3.5 and 3.8, respectively. A related fact that emerges from Figure 2.6 is that the consumption paths of Phase II and Phase III districts co-move much more closely from 2007-08 onward. To elaborate, the correlation coefficient between the two consumption time series is -0.15 up to the spring of 2007 and +0.96 afterwards. Together, we take these facts as suggestive evidence for a sustained effect of the NREGA on consumption smoothing among SC/ST households in backward districts.

The pattern of program effects that we find is consistent with the pattern of NREGA program expenditures. Regarding the beneficiaries of the program, Table 2.1 tells that almost half of all NREGA work days in our sample was performed by SC/STs. The figures imply that non-SC/ST individuals performed only 1.23 person days on average, about a third of the 3.51 person days performed by a representative individual from scheduled castes and scheduled tribes. Regarding seasonality, Figure 2.2 plots monthly NREGA wage expenditures in our sample's 92 Phase II districts relative to the rural population and wages paid to SC/STs relative to the rural SC/ST population. Accordingly, expenditures between January and June 2008 were on average three times the expenditures during the agricultural peak season in the fall of 2007. Combining the information on NREGA expenditures with our point estimates, we conclude that the estimated increases in SC/ST consumption are large relative to NREGA wage expenditures. The monthly wage expenditures of close to Rs. 60 per SC/ST capita during the spring season of 2008 come together with estimated consumption benefits of between Rs. 61 and Rs. 140, depending on whether we take the smallest of our point estimates for MPCE from Table 2.10 or the one from our preferred specification (Table 2.5). Hence, the Act appears to have been cost-effective in improving welfare among SC/ST households by reducing exposure to systematic seasonal consumption shortfalls. This conclusion continues to hold even if our point estimates overstated the true effect by a factor of two or four. A qualification that has to be made regarding the methodology of this cost benefit analysis is that we have compared our local average treatment effect as an estimate of the benefit of the program to the cost measured as an average difference between Phase II and III districts.

Deininger and Liu (2013) find similarly large short-term effects, of Rs. 140 per month, on SC/ST consumption in Phase II and III districts in the state of Andhra Pradesh. These authors' findings also imply that the welfare effects exceed the direct transfers to workers from the program. As their data cover only the agricultural peak season, however, their analysis does not address the seasonal pattern of program effects.

In principle, there are three channels by which income of poor rural households may benefit from a public employment program, first, wage income increases from more days of employment due to work on the NREGA sites, second, wage income increases from earnings in non-NREGA employment due to an increase in the equilibrium wage rate in the rural labor market and, third, income increases from wage labor and self-employed activity due to a higher marginal product of labor, which arises from the infrastructure put in place by NREGA work. As Berg et al. (2012) point out, the third of these channels appears to be negligible in the context of our analysis. Given that we consider only the first year of the program's second phase and that much of the activity unfolded not before January 2008, it is unlikely that household consumption benefited much from such infrastructure by the first half-year of 2008. Regarding the second channel, Berg et al. (2012) find that impacts on non-NREGA wage rates are lagged by about nine months, which is at odds with Zimmermann (2012), who finds a large instant, but imprecisely estimated, effect of the NREGA's Phase II on female casual wages during the fall season of 2007, that is when the program operated at a low intensity in the Phase II districts compared to the first half-year of 2008 (see Figure 2.2). Our empirical analysis leaves open the potential contributions of the just-mentioned three channels to the consumption increases that we estimate. Moreover, in principle, NREGA employment and the high female participation rate may also affect consumption through changes in household savings or intra-household decision making processes. Still, a rough calculation with Zimmermann's estimates suggests that the effect on female private-sector wages will result in a per capita monthly income increase of no more than Rs. 15 (this is based on a five person household with two female laborers) while the program expenditure data in Figure 2.2 implies that NREGA employment increases monthly per capita income by around Rs. 35 during the first half-year of 2008 (which is based on the assumption that no private sector employment is crowded out and that the program's wage expenditures fully reach the employed laborers). Hence, our impression is that the NREGA's short-term effect on consumption in Phase II districts is mostly attributable to the program's direct effect on households' labor incomes rather than any of the indirect, general equilibrium, effects.

2.7 Concluding Remarks

Governments of low and middle-income countries around the globe have been and are using large-scale public employment programs to provide livelihood security and combat poverty in their rural areas. Given that more than a third of the world's rural poor who live on less than a dollar per day resided in India in 2002 (Ravallion et al., 2007), assessing the costs and benefits of India's thus far largest public employment program is of immediate interest. We have embarked on our analysis of welfare and poverty effects of India's National Rural Employment Guarantee Act arguing that a pure labor market perspective is certainly important in its own right but not sufficient to judge an employment program's effect on rural households' livelihoods. Previous, often qualitative, field studies have claimed that many workers employed under India's NREGA use their public works' wages for goods and services which they previously considered prohibitive, like bicycles or children's education (Khera, 2011). In this paper, we have explored quantitatively whether NREGA employment opportunities have translated into higher levels and smoother patterns of consumption at an all-India level.

While we have not found statistically significant program effects in a sample representative for the entire rural population in the districts that we study, we have found economically and statistically significant poverty-reducing effects for the sub-sample of households belonging to scheduled castes and scheduled tribes during spring, which is the agricultural slack season. Our econometric findings for the time period 2006 to 2008 combined with patterns emerging from descriptive statistics for the years 2003 to 2012 suggest that the NREGA has helped this group of households in a sustained fashion to smooth consumption between the agricultural peak and slack seasons. Our main conclusion is hence that the NREGA has been successful not only in increasing consumption levels of particularly vulnerable households but also in reducing these households' exposure to the risk of seasonal drops in consumption. The pattern of these effects is consistent with the pattern of program expenditures. We have documented that, in our sample, about one in two workers on NREGA sites belongs to a scheduled caste or a scheduled tribe, and that the bulk of NREGA work is carried out during the spring season. Combining this information with our estimated welfare effects, we conclude that much of the public works' wages appear to have contributed to additional consumption by marginalized rural households during the agricultural off-season.

The text of the Act itself specifies among the main goals of the scheme "ensuring livelihood security for the poor" and "ensuring social protection for the most vulnerable people living in rural India" (Government of India, 2013b). In the language of economists, the former calls for risk reduction while the latter highlights the aspect of proper targeting. Our analysis suggests that the Act has successfully delivered on both of these two objectives.

In our view, the main shortcoming of our empirical analysis is the low precision of the estimated program effects, which is rooted in three reasons. First, we identify program effects from district-wise changes in consumption and there are only 255 districts available for our analysis. Second, our analysis relies on so-called thin rounds of India's National Sample Survey, where the sample size is comparatively small. Third, we conduct disaggregated analyses by agricultural seasons and population subgroups, which cuts the size of our sample further by a factor of up to ten. To deal with these complications, first, we have employed a modification of the usual instrumental variables implementation of a fuzzy regression discontinuity design, which substantially reduces the variability of program effect estimates in our small samples when program status is assigned at a higher than the individual level, in our case the district. Second, we have carefully examined the validity and robustness of our main findings by subjecting them to numerous robustness checks and extensions. Third, we have pointed out that we view the seasonal and subgroup-specific pattern of welfare improvements generated by the NREGA as our major insight, rather than the magnitude of the point estimates.

Finally, there are limitations to the scope of our analysis. Driven by the objective to identify causal program effects, we have examined only one, the first, year of that phase of the Act which was the smallest among the three phases of the NREGA roll-out, covering merely a fifth of India's rural population. Since then the NREGA's scale has further grown, from about 2.1 billion person-days in the fiscal year 2008-09 to 2.3 billion person-days in 2012-13. Moreover, several important design features, including mandatory bank payments and administrative processes such as linking the NREGA with India's Unique Identification Project have been added. Hence, a comprehensive analysis of the Act's welfare impacts since its inception is warranted, but the methodological challenges of such an endeavor appear to prevail.

Appendix

2.A Tables

Table 2.14: Summary Statistics for Rural Households whose Principal Occupation is Labor

	2006-07			2007-08		
	All Year	Fall	Spring	All Year	Fall	Spring
	Phase II and Phase III Sample Districts					
MPCE	513.49	517.71	509.28	549.31	540.36	557.95
Log. MPCE	612.34	613.87	610.82	621.66	620.45	622.81
HCR	51.41	52.09	50.72	42.83	43.75	41.94
PGR	12.33	11.99	12.67	8.47	8.89	8.06
HH-size	5.59	5.75	5.43	5.37	5.43	5.33
Crank	2.91	3.86	1.96	3.03	3.12	2.94
SC/ST[a] (in %)	43.40	43.06	43.74	42.84	40.86	44.75
Number of HHs	5299	2648	2651	2898	1405	1493
Districts	255	252	252	254	249	246
	Phase II Sample Districts					
MPCE	439.18	451.64	427.59	495.05	505.88	484.38
Log. MPCE	599.67	603.10	596.48	612.67	614.90	610.48
HCR	59.39	57.64	61.01	49.31	45.60	52.96
PGR	15.59	14.28	16.81	10.12	9.43	10.80
HH-size	5.64	5.91	5.39	5.35	5.35	5.34
Crank	−2.43	−1.65	−3.17	−2.12	−1.85	−2.40
SC/ST[a] (in %)	45.70	40.50	50.55	45.13	39.53	50.66
Number of HHs	2050	1039	1011	1254	616	638
Districts	92	89	91	92	91	89
	Phase III Sample Districts					
MPCE	578.14	571.68	584.96	589.60	566.46	611.55
Log. MPCE	623.36	622.66	624.10	628.32	624.66	631.80
HCR	44.46	47.55	41.19	38.02	42.36	33.90
PGR	9.50	10.12	8.84	7.25	8.49	6.07
HH-size	5.54	5.61	5.47	5.40	5.48	5.31
Crank	7.56	8.36	6.71	6.85	6.89	6.82
SC/ST[a] (in %)	41.40	45.16	37.43	41.14	41.86	40.45
Number of HHs	3249	1609	1640	1644	789	855
Districts	163	163	161	162	158	157

[a] Scheduled Castes and Scheduled Tribes

Notes: See Table 2.2.

Table 2.15: Sample Means for Various Years of NSS Consumption Surveys, Rural Households Belonging to Scheduled Castes and Scheduled Tribes

	Phase II			Phase III		
	All Year	Fall	Spring	All Year	Fall	Spring
	2003-04 (59th/60th Round)			2003-04 (59th/60th Round)		
MPCE	511.49	529.96	500.53	562.68	536.43	577.47
Log. MPCE	613.16	615.65	611.67	621.96	618.66	623.83
HCR	48.20	44.19	50.58	44.95	48.40	43.00
PGR	11.29	10.26	11.90	9.31	11.12	8.29
Observations	1641	756	885	1677	753	924
	2004-05 (61st Round)			2004-05 (61st Round)		
MPCE	462.22	461.45	463.00	489.74	488.41	491.07
Log. MPCE	604.07	604.46	603.68	610.33	609.48	611.18
HCR	57.69	57.72	57.67	56.80	57.64	55.95
PGR	14.32	14.12	14.52	13.49	14.09	12.88
Observations	3556	1807	1749	4390	2168	2222
	2005-06 (62nd Round)			2005-06 (62nd Round)		
MPCE	487.40	507.22	469.71	536.51	532.65	540.39
Log. MPCE	608.94	613.91	604.50	619.95	618.85	621.06
HCR	53.36	46.21	59.75	44.46	46.98	41.93
PGR	13.55	10.82	15.98	10.19	11.28	9.10
Observations	697	333	364	934	447	487
	2006-07 (63rd Round)			2006-07 (63rd Round)		
MPCE	446.23	494.02	412.67	553.33	526.26	582.13
Log. MPCE	599.00	609.55	591.58	622.64	618.25	627.31
HCR	61.44	50.25	69.31	43.02	48.14	37.57
PGR	17.25	13.60	19.80	9.33	10.73	7.84
Observations	1661	829	832	1918	947	971
	2007-08 (64th Round)			2007-08 (64th Round)		
MPCE	517.34	511.50	522.40	573.77	567.20	580.53
Log. MPCE	615.88	614.50	617.07	626.47	624.09	628.91
HCR	46.35	46.50	46.21	39.24	41.67	36.75
PGR	9.57	10.32	8.92	7.77	9.25	6.25
Observations	1341	643	698	1383	707	676
	2009-10 (66th Round)			2009-10 (66th Round)		
MPCE	506.14	519.56	492.04	576.50	588.12	564.10
Log. MPCE	612.47	614.55	610.30	626.66	627.98	625.25
HCR	50.20	50.12	50.29	38.05	38.09	38.00
PGR	11.87	11.26	12.52	7.49	7.56	7.42
Observations	2677	1295	1382	3490	1795	1695
	2011-12 (68th Round)			2011-12 (68th Round)		
MPCE	590.03	590.71	589.34	682.28	680.68	683.64
Log. MPCE	627.65	627.07	628.22	642.05	641.40	642.61
HCR	33.21	34.46	31.97	22.69	23.38	22.10
PGR	6.91	7.88	5.96	4.01	4.49	3.61
Observations	2462	1206	1256	3128	1521	1607

See Table 2.2, except for data.

Table 2.16: Differences-in-Differences Analysis of Consumption and Poverty

	MPCE	HCR	PGR	MPCE	HCR	PGR	MPCE	HCR	PGR
	Sample: All Rural Households								
	All Year			**Fall**			**Spring**		
Year0708 * Phase2	1.034	−3.877	−1.546**	2.071	−3.400	−1.683*	−0.715	−3.881	−0.967
	(2.388)	(2.747)	(0.758)	(3.268)	(3.386)	(0.950)	(2.778)	(3.284)	(0.829)
Households	22929	22929	22929	11435	11435	11435	11494	11494	11494
Clusters	401	401	401	401	401	401	401	401	401
Dist. in both years	200	200	200	200	200	200	200	200	200
	Sample: Rural Households Belonging to Scheduled Castes and Scheduled Tribes								
	All Year			**Fall**			**Spring**		
Year0708 * Phase2	10.110***	−9.690**	−4.943***	6.363	−5.527	−4.944***	8.405	−9.385	−2.543
	(3.210)	(4.769)	(1.310)	(4.012)	(5.296)	(1.817)	(5.173)	(7.134)	(1.679)
Households	5285	5285	5285	2607	2607	2607	2678	2678	2678
Clusters	398	398	398	378	378	378	382	382	382
Dist. in both years	197	197	197	178	178	178	181	181	181

Notes: See Table 2.5.

Table 2.17: Differences-in-Differences Analysis of Consumption and Poverty, Placebo

	MPCE	HCR	PGR	MPCE	HCR	PGR	MPCE	HCR	PGR
	Sample: All Rural Households								
	All Year			**Fall**			**Spring**		
Year0607 * Phase2	0.428	1.582	−0.190	−5.091	8.876**	2.309**	6.168	−3.823	−2.143
	(2.360)	(2.942)	(0.829)	(3.522)	(3.795)	(1.053)	(4.698)	(4.913)	(1.456)
Households	19381	19381	19381	9630	9630	9630	9751	9751	9751
Clusters	402	402	402	400	400	400	396	396	396
Dist. in both years	201	201	201	199	199	199	195	195	195
	Sample: Rural Households Belonging to Scheduled Castes and Scheduled Tribes								
	All Year			**Fall**			**Spring**		
Year0607 * Phase2	3.907	−5.525	−0.591	0.948	−3.975	1.625	13.579**	−15.010**	−5.911**
	(4.532)	(6.033)	(1.747)	(6.131)	(9.535)	(2.333)	(5.843)	(7.183)	(2.395)
Households	4405	4405	4405	2163	2163	2163	2242	2242	2242
Clusters	396	396	396	367	367	367	367	367	367
Dist. in both years	195	195	195	171	171	171	169	169	169

Notes: See Table 2.7.

Table 2.18: Two Stage Least Squares Regression Discontinuity Analysis of Consumption and Poverty, Placebo

	MPCE	HCR	PGR	MPCE	HCR	PGR	MPCE	HCR	PGR
	Sample: All Rural Households								
	All Year			**Fall**			**Spring**		
Year0607 * $\widehat{Phase2}$	−1.279	1.681	0.436	−2.999	8.453	1.374	−0.563	−3.472	0.985
	(5.940)	(6.760)	(1.743)	(7.176)	(7.654)	(2.093)	(9.515)	(10.359)	(2.857)
Households	19381	19381	19381	9630	9630	9630	9751	9751	9751
Clusters	402	402	402	400	400	400	396	396	396
Dist. in both years	201	201	201	199	199	199	195	195	195
	Sample: Rural Households Belonging to Scheduled Castes and Scheduled Tribes								
	All Year			**Fall**			**Spring**		
Year0607 * $\widehat{Phase2}$	−15.176	17.999	4.577	−20.931	23.949	7.580	−8.248	0.475	0.342
	(13.834)	(15.553)	(4.996)	(13.007)	(17.398)	(4.774)	(23.125)	(29.353)	(7.928)
Households	4405	4405	4405	2163	2163	2163	2242	2242	2242
Clusters	396	396	396	367	367	367	367	367	367
Dist. in both years	195	195	195	171	171	171	169	169	169

Notes: See Table 2.5, except for data: NSS rounds 62 and 63 for the years 2005-06 and 2006-07, respectively.

Chapter 3

Income Shocks, Consumption Smoothing, and Financial Market Transactions: Evidence from Indian Villages

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A large body of economic development literature finds that despite unstable income rural households' consumption remains relatively smooth, while categories of risk coping mechanisms are range real asset sales and credit to mutual insurance. In this paper, I examine changes in both consumption and financial market transactions as a response to changes in income in four South Indian villages over a span of four years. I combine self-collected local administrative data on India's public employment program with household-level data. Identifying monthly wage income shocks, I run high-frequency panel data regressions. I find that among the poorest households consumption and repayments of microfinance loans respond statistically significantly to changes in income, and in particular to changes in female wage income. I conclude that consumption is largely well-insured against moderate income shocks, except among the poorest households. Further, women empowerment via the provision of public works and innovative microfinance institutions helps to mitigate the risks of income volatility.

3.1 Introduction[1]

Poor households, in particular the rural poor in low income countries (LICs), are exposed to unsteady flows of income. The reasons are many, including seasonal unemployment related to the agricultural labor cycle, sickness or death in the family, weather shocks, or political unrest among many others. Furthermore, these households' access to formal financial institutions is limited or comes at exorbitant costs. In such a scenario it is crucial for researchers and policymakers to understand the response of rural households and their mechanisms to cope with such vulnerabilities. Most important to understand is whether households are able to foresee income shocks to some extent, save in advance and forego some consumption during good times. Do local arrangements within communities or villages help to insure against risk and thus smooth consumption? What forms of finance or public safety nets help best to smooth consumption?

Tests for consumption smoothing have been carried out in a variety of settings. Much of the vast body of empirical work is, in one way or another, based on the permanent income hypothesis (PIH) developed by Friedman (1957). The complete market hypothesis, implicit in the PIH, has been tested by several researchers. In one of the most prominent and early micro-economic studies, Mace (1991) tests this hypothesis using panel data on consumption from the Panel Study of Income Dynamics (PSID) survey for the entire US economy. While Mace largely fails to reject the complete market hypothesis, Cochrane (1991) demonstrates that idiosyncratic shocks of sickness and sudden unemployment do impact consumption. Other studies rejecting the complete market hypothesis and using PSID data include for example Zeldes (1989), Altonji et al. (1992) and Hayashi et al. (1996), whereas Altug and Miller (1990) fail to reject the null hypothesis.

In a different literature, several studies of efficient risk sharing test the null hypothesis that only average consumption of, for example, the village explains changes in individual consumption. Arguably the most prominent study is the seminal work by Townsend (1994). He shows that consumption does not react much to changes in income. Townsend (1994) uses yearly household panel data, collected during the 1970s and 1980s in three Indian villages by the International Crop Research Institute of the Semi-Arid Tropics (ICRISAT). He finds that individual consumption co-moves with average village consumption, but only to a limited extent with individual income. Utilizing the same data, Mazzocco and Saini (2012) show that risk sharing takes place at the caste level rather than at the village level. In contrast, Kazianga and Udry (2006) find almost no evidence for full insurance among rural households in Burkina

[1] I want to thank Sudha Narayanan for her ideas and the research collaboration. Also, I am very grateful to Abhiroop Mukhopadhay for advising me during my stay as a research visitor at the ISI, Delhi in February/March 2015 when most of this paper was developed. Further I would like to thank Christine Binzel, Jean Drèze, Magnus Hatlebakk, and in particular Stefan Klonner for their ideas and guidance. Field work was funded by the German Academic Exchange Service (DAAD). This paper benefited greatly from discussions, seminars, and conferences at the Indian Statistical Institute, Delhi, Heidelberg University, and Oxford University. All errors remain mine.

Faso during long periods of drought. Instead, Kazianga and Udry (2006) point out clearly that "village-level risk pooling mechanisms were not effective". There is additional empirical evidence that risk sharing is hard to accomplish among very poor communities in sub-Saharan Africa and Asia. For example, Harrower and Hoddinott (2005) study households in one of the poorest regions of Mali. They find that even though idiosyncratic shocks do not influence income growth, controlling for covariate shocks, total household income does impact consumption. Jalan and Ravallion (1999) also reject the full insurance model using six years of panel data on Chinese rural households. They emphasize the relatively greater vulnerability of the poorest households. In particular, Jalan and Ravallion (1999) find that "the marginal propensity to consume out of current income implied by the test equation is higher for less wealthy households." More recent studies testing risk sharing employ a large monthly panel data set on Thai households - the Townsend Thai Monthly Survey (e.g. Kinnan and Townsend, 2012; Karaivanov and Townsend, 2014; Alem and Townsend, 2014; Chiappori et al., 2014). Largely, risk sharing at the village level is not rejected by these studies. However, Kinnan and Townsend (2012) find that households that are not even indirectly connected to formal banking nor to a social network, are the most vulnerable to idiosyncratic changes in income. In the regional context of this paper, Gaurav (2015) tests for risk sharing, using yearly self-collected panel data for 120 households in five villages of one of India's poorest regions, Vidarbha, in Western India. Similar to Jalan and Ravallion (1999), his estimations yield a rejection of full risk sharing. He conjectures that wealthier, more land owning households are less exposed to idiosyncratic risks than poorer households.

Many studies on consumption smoothing in LICs find that at least some "smoothing takes place, and that consumption is not equal to income, even among very poor households" (Deaton, 1989). Mechanisms to mitigate risks are plenty, but are often difficult to identify given varying data constraints. Townsend (1994), for instance, cannot statistically determine "how households smooth so well." He can only speculate that "credit markets and gifts seem to smooth much of the fluctuations in income, and probably smooth as well fluctuations induced by erratic timing in asset purchases and sale." Using data for the same ICRISAT villages, Kochar (1995, 1999) finds that well-functioning labor markets serve as a mechanism to insure against idiosyncratic crop shocks, which is in line with the income-smoothing argument (Morduch, 1995).[2] In general, mechanisms to smooth consumption seem to be highly context dependent, and apart from smoothing labor they can be clubbed into five categories, which have been studied extensively.[3] In the following, I present four forms of consumption smoothing mechanisms, that can broadly be categorized as related to: 1) real assets , 2) financial assets , 3) financial credit, either formal or informal, 4) mutual insurance . The first three are related to the complete markets literature as these involve mostly individual and longitudinal-based

[2]For more research on changes in the supply of labor as a response to idiosyncratic risks see for example Saha (1994), Rose (2001), Lamb (2003), and Ito and Takashi (2009).

[3]For additional literature on consumption smoothing mechanisms, refer to the extensive literature review by Dercon (2002).

risk coping mechanisms. The fourth mechanism, mutual insurance, however, is concerned with cross-sectional rather than individual longitudinal risk-coping, making it a risk-sharing mechanism, as discussed above.

First, in times of distress, households could sell real assets in the form of accumulated buffer stocks. The buffer saving model proposed by Deaton (1989, 1991) provides for a theoretical framework. Accordingly, even households with no access to credit can smooth consumption over time as long as some assets are left as a buffer stock. Testing the buffer-stock model, Udry (1995) shows that households in northern Nigeria sell buffer stocks of grain to cope with adverse shocks such as sudden flooding of their lands. Fafchamps et al. (1998) find that in rural Burkina Faso at least 15 percent of income shortfalls are compensated with livestock sales as a response to adverse shocks for households. Rosenzweig and Wolpin (1993) examine the role of bullock sales as a mechanism to smooth consumption in the ICRISAT villages. They find that households do not invest sufficiently in bullocks to smooth income. This is surprising, given the farmers' risk aversion and the "importance of bullock ownership in producing crops efficiently and its value in mitigating consumption volatility" (Rosenzweig and Wolpin, 1993). In contrast to the null hypothesis of the buffer saving model, Kazianga and Udry (2006) find for households in Burkina Faso, during times of drought, traditional practices of risk sharing or buffer stock sales do not suffice to smooth consumption completely. Similarly, using panel data on Tanzanian farmers Dercon (1998) argues that investments in cattle as a form of buffer stock is "lumpy" and only possible for relatively richer households.

Second, financial assets in the form of precautionary savings serve as a cushion to fall back on during income shortfalls, as research on rural societies in LICs has shown. Deaton (1992a) provides evidence on households in the Ivory Coast, which anticipate income shortfalls and save in advance. While Deaton cannot measure to what extent households save in advance, Paxson's (1992) study of Thai rice farmers shows that the marginal propensity to save from transitory income is high. Dercon (1996) shows for rural Tanzanian households that savings in the form of liquid asset holdings help to smooth consumption and induce farmers to invest in riskier crops.

The third mechanism involves financial credit either from formal or informal institutions. Formal financial institutions have increasingly become an option even for rural households over the past decades. Recent government banking schemes, for example, a state-led bank branch expansion program in India (Burgess et al., 2005), or large scale government-led microfinance schemes like the Thai Baht Village Fund program in Thailand have tried to expand access to formal finance institution to a wider population (Kaboski and Townsend, 2011). Using the Townsend Thai data, Alem and Townsend (2014) examine the importance of formal financial institutions for consumption smoothing in Thai villages. They find that access to a government development bank helps in smoothing consumption and that such "commercial banks are smoothing investment, largely through formal savings accounts." Microfinance can be thought of as one subcategory of formal finance. Providing access to credit and formal finance institutions, often via some form of group liability, microfinance has much potential as a consumption smoothing mechanism (Morduch, 1999a,b). Kaboski and Townsend (2011), for example, underscore the role of microfinance in mitigating consumption volatility in the Thai villages. Similarly, Gertler et al. (2009) show that microfinance in Indonesia helps to smooth consumption after illness. In his study on microfinance and its indirect impacts on consumption in Bangladesh, Morduch (1999a) attributes the mitigated volatility in consumption to the reduction in "income variability across seasons, which is made possible by the employment diversification that [microfinance] credit affords."

The fourth mechanism concerns informal transactions as a form of mutual insurance to smooth consumption. Fafchamps and Lund (2003) find that borrowing among friends and relatives increases when households face adverse rainfall shocks in rural Philippines. Udry (1994), too, finds that gifts and transfers lead to smooth consumption for households in Nigerian villages; Chiappori et al. (2014) cannot statistically identify such mechanisms but consider these as potential mechanisms for consumption smoothing in the Thai villages. Using the same Thai data, Kinnan and Townsend (2012) are able to identify channels to establish the importance of kin and family networks in sharing risks. They find that "being indirectly connected to the financial system is as beneficial as a direct connection." This means that not everyone needs to be connected to formal banking as long as "interpersonal gifts and lending are widespread". Jacoby and Skoufias (1998) identify several insurance mechanisms at play to mitigate risk in the ICRISAT villages. These include both credits and gifts among households.

The major challenge to research on the literature on income risk, consumption and mechanisms to smooth consumption, either from a complete market or risk sharing perspective, is that income is a) measured with error and b) endogenous with respect to consumption. In the PSID data used for example by Mace (1991), there is a high chance of measurement error since income is self reported. Deaton (1992a) argues that "even if markets are far from complete, measurement error in income changes will bias the regression coefficient towards zero, apparently in favor of the complete markets model." Regarding the ICRISAT data for Indian villages Townsend (1994) acknowledges that "individual crop profits are no doubt measured with error, as are incomes generally." Deaton (1990) comments on the Ivory Coast data: "The consumption estimates are almost certainly a good deal more reliable than those for income." It is widely accepted that income data come with huge measurement errors - for that reason, they are usually not collected for the purpose of poverty estimations.

To circumvent both the measurement error problem and the endogeneity of income with respect to consumption or savings, various techniques have been proposed. Chaudhuri and Ravallion (1997) suggest using time dummies and the non-crop component of income as an instrument for income in their critique of Townsend (1994). Udry (1994) employs exogenous income shocks in the form of adverse transitory production shocks. He explains that "[t]he availability of this direct measure of transitory shocks at the household level means that shocks need not be inferred from the residual between actual income and some measure of permanent income." A number of studies on risk-sharing use positive or negative rainfall shocks as an instrument for income (Paxson, 1992; Fafchamps and Lund, 2003; Gaurav, 2015; Jacoby and Skoufias, 1998). Jacoby and Skoufias use rainfall data to proxy income shocks in the Indian ICRISAT villages. They argue that village-level rainfall impacts households of the same village differently and find that households are able to self-insure themselves against such idiosyncratic weather shocks. The above discussion of existing studies demonstrates how significant the strength of the instrument chosen is to the conclusions drawn.

In this paper, I test empirically a) how consumption of South Indian households responds to changes in wage income, and b) what financial mechanisms are in place to mitigate income volatility. I test all but the first of the above mentioned categories of consumption smoothing mechanisms. Accounting for the measurement error and endogeneity problem of self reported income, I depart from the methodology of existing literature and instead exploit an exogeneous income variable provided by a third party. To this end, I exploit an income variable provided by a third party and I show its exogeneity. The income variable I utilize is drawn from administrative wage payment records for ICRISAT households participating in a nationwide workfare program - the National Rural Employment Guarantee Act (NREGA). The administrative records include the date of payment and the amount paid, as well as the date and number of workdays. I show empirically to what extent the monthly NREGA wage payments can be considered as exogenous events. In particular, I demonstrate that the date of wage payments often does not coincide with the month of work - the month during which consumption decisions are made. This allows me to exploit the monthly variation in administrative wage payments to measure any changes in consumption and forms of financial transactions as a response to changes in wage income.

I merge this administrative data on NREGA worksites and wage payments with recently released ICRISAT monthly longitudinal household data. This data set was collected in four Indian villages in the state of Andhra Pradesh over 52 months between July 2010 and October 2014. Finally, I merge this combined data set with self-collected data from ICRISAT-NREGA households.

To expand the existing risk sharing related literature, I use household fixed effects to control for average village consumption and run village wise regressions similar to Townsend (1994). I test for consumption smoothing via high frequency panel estimations using the exogenous wage payment as an explanatory variable. I find that consumption is highly sensitive to changes in income in one of four villages, while I find no evidence against consumption smoothing in the other three villages. To test several financial mechanisms of consumption smoothing, I exploit the same identification strategy that is discussed above. In this way, I find that in the poorest village, in particular, microfinance institutions play an important role in the portfolio of financial transactions. My estimations for this village yield that the propensity to pay back loans to microfinance institutions is around .2. Estimates for payments into saving accounts are of similar magnitude. Thus, I am able to identify several mechanisms of consumption smoothing utilized by the poor. Findings from a self-conducted survey during months of field work in the sample villages echo the empirical results. Sixty percent of the sample households state that they utilize income from NREGA wages for loan repayments to microfinance institutions. In addition, I empirically identify gender-wise NREGA wage payments. This allows me to test whether changes in female wage income induce proportionately more or less a change in consumption or financial transactions. I find that higher female wage income leads to both higher household consumption expenditures and loan repayments to microfinance institutions.

The contribution of this paper to the literature on tests for risk sharing and on consumption smoothing mechanisms is fourfold. First, I use an income variable that does not contain the measurement error that self-reported income does, and it varies exogenously in time. In contrast to earlier studies based on ICRISAT data (Townsend, 1994; Chaudhuri and Ravallion, 1997; Mazzocco and Saini, 2012, among many others), using an exogenous income and no IV framework in the manner that I have, is an advantage because I measure a kind of reduced form effect, whose power of interpretation does not hinge on the strength of any instrument. Second, my results on consumption smoothing reiterate and extend earlier findings questioning the possibility of poor households to smooth consumption efficiently. On the one hand, my finding of no violation of the full risk sharing hypothesis in three villages reiterates work based on the Townsend Thai data (e.g. Chiappori et al., 2014). On the other hand, my findings on the poorest village echo the findings by Gaurav (2015) on Central Indian villages and earlier research by Jalan and Ravallion (1999) on Chinese households. By rejecting the null, and estimating propensities to consume of .66, I show that the consumption of the poor depends to a great deal on idiosyncratic changes in wage income.

Third, by testing a plethora of financial transactions as potential mechanisms to smooth consumption, I depart from studies testing just one major category of mechanisms, e.g. only savings (Paxson, 1992), and follow Fafchamps and Lund (2003) to test other categories separately. The financial transactions include borrowings and savings from formal and informal institutions, friends and relatives, and microfinance institutions in the form of self-help groups (SHGs). Especially the latter have not been studied much in the context of mitigating the potential consequences of volatile income.[4] My analyses provide new insights on the effectiveness of microfinance in smoothing consumption (Morduch, 1995; Chiappori et al., 2014; Kinnan and Townsend, 2012). In this aspect, too, it is advantageous in comparison to other microfinance-consumption smoothing studies, to employ a unique form of income to identify effects on microfinance outcomes without any threat of reverse causality. Fourth, disaggregating wage income shocks by gender, I contribute to the dimension of intra-household economics and allocations, as well as the literature on the role of women empowerment in LICs (see e.g. Pitt et al., 2006; Siwan Anderson, 2002; Duflo, 2012). In the context of the NREGA, it

[4]Studies on SHGs in Africa include for example recent work by Greaney et al. (2016), who evaluate the effects of a cost reduction experiment on several performance indicators of SHGs.

has been argued and shown that female employment has positive welfare impacts (Narayanan, 2008; Khera and Nayak, 2009), for example in education and health (Afridi et al., 2012; Das and Singh, 2013). However, it has been difficult to identify female wage income empirically, which is a well-known problem (Haddad, 1999; Hopkins et al., 1994). In this paper, I identify gender-wise payments in a unique fashion, and thus add a valuable contribution to the larger literature in the field of gender and intra-household allocations (Thomas, 1990; Bourguignon et al., 1993; Browning et al., 1994; Browning and Chiappori, 1998, see for example).

Based on these four major contributions, I conclude the following. First, the null-hypothesis of full risk sharing at the village level cannot be rejected in three of the four villages. Second, the poorest village is the least well-insured, as consumption is very sensitive to changes in wage income. Three, households in this village are induced to depend to a great extent on microfinance loans. Fourth, my estimation technique allows me to track almost financial path ways. For the poorest village, for instance, I find that from a positive wage income shock of Rs. 100, about Rs. 60 are spent directly on consumption, Rs. 20 on the repayment of microfinance loans, and another Rs. 20 are deposited into saving accounts. I conjecture that the portfolio choice of the poor is multifaceted. Given that my study only tracks financial transactions, and not real asset sales or agricultural investments aimed at smoothing consumption during phases of distress, it is very likely that the extent and variety of the options are not fully captured.

The structure of the paper is as follows. Section 3.2 introduces the theoretical background of the study, focusing on the standard predictions of the PIH framework following Deaton (1992b). In addition, Townsend's (1994) version of a test for mutual insurance is presented as it will be the basis for this paper's empirical strategy. Section 3.3 gives an overview of the key features of the NREGA in the state of Andhra Pradesh. Section 3.4 introduces the three data sets and establishes that the date of wage payments can be considered as exogenous events. In Section 3.5, the methodology to test for consumption smoothing and risk coping mechanisms are presented. This is followed by a discussion of the results in Section 3.6, robustness checks in Section 3.7 and a conclusion in Section 3.8.

3.2 Theoretical Background

In this section, I present the permanent income hypothesis (PIH) as modeled by Deaton (1992b) and a typical test for full insurance as modeled by Townsend (1994). Both frameworks yield testable implications. The main argument under the PIH is that consumption is a function of life-time income and should not react to any changes in current income. First hypothesized by Friedman (1957), who applied it to macro-data on consumption and income, tests of the PIH show that consumption is much smoother than income. In the PIH framework, the focus is on the longitudinal perspective of individuals' income and consumption paths, it is concerned with today's idiosyncratic shocks given expectations about future income. In contrast, the full insurance framework is concerned with idiosyncratic shocks in the cross-section of households. That is, given average consumption of a community how does individual consumption react to idiosyncratic shocks? The hypothesis is that idiosyncratic shocks do not matter as consumption co-moves with average consumption of the community.

I do not attempt to either advance the PIH or full insurance model nor prove them empirically. Instead, the possible predictions hypothesized by the models shall provide yardsticks for the results of my empirical analyses. In the latter, I test how consumption and other outcome variable react to changes in wage income using monthly household panel data in four village-wise fixed-effects regressions. Thus, I deal with a cross-sectional component, namely the changes in income and consumption across households within a village, which is controlled for by household fixed effects. Also, the regressions include a longitudinal component, namely monthly variations in household consumption and income over the span of four years, which is controlled for by month fixed effects.

3.2.1 Permanent Income Hypothesis (PIH)

Hand to Mouth

Before thinking of consumption as a function of expected future incomes, I consider a situation in which any income is immediately consumed irrespective of any future or past income flows. Metaphorically speaking, income moves directly from "hand to mouth." Consumption c of person i in time t is then just a function of y, so that

$$c_{it} = y_{it}, \tag{3.1}$$

with the prediction of

$$\frac{\partial c_{it}}{\partial y_{it}} = 1. \tag{3.2}$$

Thus, any change in income should be entirely reflected in the change of consumption. Given equation 3.1, and assuming that savings s_{it} are equal to disposal income ($y_{it} - c_{it}$), savings are zero in the hand to mouth model:

$$s_{it} = y_{it} - c_{it} = y_{it} - y_{it} = 0 \tag{3.3}$$

Therefore, with predictions for savings being

$$\frac{\partial s_{it}}{\partial y_{it}} = 0, \tag{3.4}$$

changes in income are predicted not to induce changes in savings. I present such a simple thought experiment here, as it may be quite an accurate prediction of the relationship between consumption, savings and income for very poor households.

Permanent Income Hypothesis

Following Deaton's (1992b) version of the PIH, consumption is a function of net present value of expected income, $E_t y_{it}$. Under assumptions of quadratic preferences, infinite life, and a constant real interest rate r equal to time preference

$$c_{it} = \frac{rA_{it}}{1+r} + \frac{r}{1+r}\sum_{k=0}^{\infty}(1+r)^{-k}E_t y_{it+k}, \tag{3.5}$$

consumption equals the "annuity value of lifetime wealth," which is the sum of by expected income $E_t y_{it}$ and assets A_{it} of household i in period t. It is evident that consumption in t does not depend on realized income, as it only depends on changes in expected income. According to (3.5), the prediction for any changes in realized income on consumption conditional on expected incomes is:

$$\frac{\partial c_{it}}{\partial y_{it}} = 0, \tag{3.6}$$

Thus, testing the PIH in a regression framework one expects betas of zero for any idiosyncratic changes in current income or characteristics. Savings, s_{it}, on the other hand, are a function of realized income, following (Deaton, 1992b):

$$s_{it} = y_{it} + \frac{rA_{it}}{1+r} - c_{it}, \tag{3.7}$$

Any changes in realized income should be fully absorbed by changes in savings. Conditional on expected incomes the prediction according to (3.7) is:

$$\frac{\partial s_{it}}{\partial y_{it}} = 1 \tag{3.8}$$

Now, one may object that savings and consumption are not only a function of realized income but also of wage income claims or expected wage income, e.g. delayed payments. In the following, I show the case for savings. For consumption an analogous argument holds. Any estimation of the form:

$$s_{it} = \gamma + \delta \ wage_{it} + u_{it}, \tag{3.9}$$

would underestimate the effect of expected wage income on savings as only changes of realized wages ($wage_{it}$) are in the regression equation. The true effect should instead be measured via the following specification:

$$s_{it} = \alpha + \beta_1\, wage_{it} + \beta_2\, wageEXP_{it} + v_{it}, \tag{3.10}$$

with $wageEXP$ being expected wage income. Then, according to the PIH:

$$\begin{aligned} \beta_1 &= 1 \\ \beta_2 &< \frac{r}{1+r}, \end{aligned} \tag{3.11}$$

since expected wages enter the equation with a discount factor of $\frac{r}{1+r}$.

I want to argue, however, that any estimation which disregards wage claims comes close to predicting the true effect. I consider two scenarios: a) $wage$ and $wageEXP$ are uncorrelated, and b) there is perfect correlation between $wage$ and $wageEXP$.

In the case of a), the prediction for equation 3.9 according to the PIH is:

$$\delta = 1 \tag{3.12}$$

while $wageEXP_{it} + v_{it}$ are fully absorbed in u_{it} since the error terms are orthogonal. Hence, this is the same as when only realized wage income is included in the regression equation.

In case b) of perfect correlation, the prediction is:

$$\delta = \beta_1 + \beta_2 < 1 + \frac{r}{1+r} \tag{3.13}$$

With $\frac{r}{1+r}$ as an upper bound and assuming that r is very small[5]

$$\delta \approx 1 \tag{3.14}$$

Therefore, both cases (equations 3.12 and 3.14) yield the same estimates as the specification of equation 3.9. In any estimation one can thus ignore wage claims and focus on realized wage income.

3.2.2 Mutual Insurance

One of the most influential works on mutual insurance in village economies is the one by Townsend (1994). Based on assumptions by Wilson (1968) and Diamond (1967) that preferences are time separable and display weak risk aversion, if all individuals discount the future at the same rate, and if all information is held in common (Townsend, 1994), individual

[5] In the empirical analyses, where I employ monthly data on wages and consumption, I can assume that the monthly interest rate is no larger than 5 per cent, given that yearly interest rates for loans are at the most 30 or 40 per cent. Thus, $\frac{r}{1+r}$ is at the most around 0.05 in magnitude.

consumption co-moves with aggregate consumption, independent of idiosyncratic shocks. In other words, in a village economy, individual consumption should not react to any idiosyncratic changes in income when average village consumption is controlled for.

The basic specification to test for mutual insurance at the village level is the following reduced form version tested by Townsend (1994):

$$c_{it} = \alpha + \beta \bar{c_t} + \delta H_{it} + \zeta y_{it} + u_{it} \tag{3.15}$$

with average village consumption for N households is

$$\bar{c_t} = \frac{1}{N} \sum_{j=1}^{N} c_{tj} \tag{3.16}$$

and where H_{it} captures demographic components and y_{it} is income for household i in time t. Full insurance implies that individual consumption is only dependent on changes in average consumption, as follows:

$$\beta = \frac{\partial c_{it}}{\partial \bar{c_t}} = 1 \tag{3.17}$$

At the same time, according to the null hypothesis, idiosyncratic changes should not matter at all, so that consumption remains insensitive to changes in income as follows:

$$\zeta = \frac{\partial c_{it}}{\partial y_{it}} = 0 \tag{3.18}$$

To reject the null hypothesis of full insurance requires $\zeta \neq 0$. In his paper on three ICRISAT villages, Townsend's (1994) major finding is that consumption responds to individual changes in income, albeit to a very low degree. Even though full insurance is rejected, his estimates of ζ are very small in magnitude and thus he concludes that households come close to full insurance. It is important to note that Townsend does not use the monthly ICRISAT data, but yearly aggregates. In Section 3.5, I show how the basic predictions of the mutual insurance model can be considered using month and household fixed effects.

3.3 NREGA Background and Modus Operandi

3.3.1 Background on the NREGA

India's first United Progressive Alliance (UPA I) government passed several laws between 2004 and 2009. These laws aimed to improve the livelihood of the poor "ensuring inclusive growth in rural India" through its "impact on social protection, [and] livelihood security."[6] The National Rural Employment Guarantee Act (NREGA) is one of them, it guarantees 100 days of employment to every rural household whose members are willing to do unskilled manual labor at the statutory minimum wage.[7] The NREGA was originally designed as a demand-driven program, in which workers self-select themselves for manual labor at the minimum wage. However, many studies show that, effectively, participation in NREGA works is supply-driven rather than demand-driven (Chopra, 2014). For example, research on the state of Rajasthan reveals that the allocation of NREGA funds is often diverted to worksites situated closely to the residence of local leaders, say, the village head (Himanshu et al., 2015). Related research on Rajasthan shows that competition among political parties influences the flow of NREGA funds at the block level (Gupta and Mukhopadhyay, 2014). Furthermore, Dutta et al. (2014) establish that rationing of workdays exists in the state of Bihar, which means that works do not respond to the existing demand, which in turn means that the demand for work is higher than the supply of workdays. Das (2013) provides for similar, albeit weaker evidence of rationing for the state of West Bengal during 2009-10 and 2011-12.

At the time of writing, the NREGA has been studied widely. National-level labor market studies include works by Azam (2012) and Imbert and Papp (2015) whose analyses are based on National Sample Survey (NSS) data and difference-in-difference estimations.[8] They show that the Act resulted in an increase of rural wages ranging between 4 and 8 per cent. Berg et al. (2012) find similar effects using district-level wage data. Further, female workers and marginalized groups belonging to scheduled castes and scheduled tribes (SC/ST) are among the main beneficiaries. These studies underscore that the demand for NREGA employment varies seasonally and is highest during the lean season. The NREGA is shown to be a safety net during the lean season when agricultural work opportunities are scarce. Estimates of a regression discontinuity design (RDD) by Zimmermann (2014), however, somewhat mitigate the above mentioned findings as she finds only a very small, positive wage impact for female workers during the fall season - and not during the spring season.

Work on aggregate welfare effects by Klonner and Oldiges (2014) using NSS data on monthly per capita consumption expenditure (MPCE) suggest large seasonal effects for SC/ST households during spring. Raghunathan and Hari (2014) study the program's effects on behavioral choices of farmers and find that farmers who participate in the NREGA adopt riskier and higher productivity crops. In contrast to the studies employing difference-in-difference es-

[6]See MGNREGA Guidelines 2013: `http://nrega.nic.in/netnrega/WriteReaddata/Circulars/Operational_guidelines_4thEdition_eng_2013.pdf/`

[7]As shown by Klonner and Oldiges (2014), the NREGA stands in line with similar workfare programs around the globe (Subbarao, 2003). In sub-Saharan Africa alone, around 150 public works programs are currently active (World Bank, 2013). For research on the theory of of self-selection inherent to most workfare programs to ensure targeting of those in need see among many others Datt and Ravallion (1995), Besley and Coate (1992), Basu (1981). See Galasso and Ravallion (2004) on Argentina's Jefes program from 2002, and Berhane et al. (2011) on the Ethiopian Productive Safety Net Program (PSNP) from 2005.

[8]The cited studies exploit the phase-wise role-out of the NREGA across Indian districts over a three year time period.

timations, Raghunathan and Hari (2014) follow Zimmermann's (2014) identification strategy of an RDD, whereas Klonner and Oldiges (2014) employ a sharp RDD in their latest working paper. Deininger and Liu (2013) demonstrate similar evidence to findings by Klonner and Oldiges (2014). Using longitudinal data of 4,000 households residing in Andhra Pradesh for the years 2004, 2006 and 2008 and employing double and triple differences as well as propensity score matching estimations they find large short-term effects on SC/ST consumption in the state of Andhra Pradesh. Similarly, based on propensity score matching estimations Ravi and Engler (2009) use a smaller panel of 320 households in Andhra Pradesh and find that the Act did increase consumption expenditures.

3.3.2 The NREGA in Andhra Pradesh: Modus Operandi

Praised as the *Andhra Model*, the NREGA in the state of Andhra Pradesh[9] has received a lot of attention from academia, from civil society organisations and the media. The state's performance and its well-functioning state machinery of employment generation is well established (Maiorano, 2014; Drèze and Oldiges, 2009). At the same time, the Andhra model is known for its transparency mechanisms which entail, chiefly among others, the mandatory undertaking of so called *social audits* by civil society organizations (Aakella and Kidambi, 2007a,b; Afridi, 2008; Afridi and Iversen, 2014). By employing mostly female workers and thereby improving educational outcomes of children the Andhra model has gained further credit (Afridi et al., 2012). At the same time, however, it is known that the Andhra model intentionally circumvents important provisions of the NREGA's Guidelines. In particular, as Maiorano (2014) thoroughly explains, the Andhra model is in effect supply-driven rather than demand-driven, preventing workers to provide their labor as per their request. The entire system is organized in a top-down fashion from the state's chief minister to the ultimate implementing agent, the Field Assistant. The latter has the crucial role of forming labor-groups[10] at the village level. Once assigned to such a labor-group, workers remain in the very same group during the subsequent years. The FA is also in charge of supervising the worksites and posting labor-groups to worksites as per his or her judgment. Keeping this in mind, workers in the states of Andhra Pradesh and Telangana cannot demand work as stipulated in the Act. They need to wait for the FA's assignment. In section 3.4, the uncertainty involved in the timing of NREGA-worksites and the timing of NREGA wage payments is presented. Establishing this feature is crucial to consider the group-wise wage payments as exogenous events.

[9] Andhra Pradesh was divided into two states Telangana and Andhra Pradesh with effect from June 2, 2014 when the first phase of the NREGA had already been in place for 8 years. A note on the data and the partition is provided in Section 3.4.

[10] These labor-groups are called Shrama Shakti Sanghas (SSS) and were formed in 2010.

3.4 Data, Summary Statistics, Exogenous Variation

Among the second generation of ICRISAT's Village Level Studies, the ICRISAT has collected monthly panel data from four villages in Andhra Pradesh via its resident field investigators between July 2010 and June 2015. While the two villages of Aurepalle and Dokur belong to the district of Mahbubnagar, the villages of JC Agraharam and Pamidipadu belong to the district of Prakasam.[11] The districts are depicted in Figure 3.8, which shows that Prakasam is situated closer to the coast, whereas Mahbubnagar is in the interior of India.[12] Village-wise information on demographics and key institutions situated in each village is presented in Table 3.1. Among the four villages, Pamidipadu is the most populated with more than 1,200 households, whereas JC Agraharam and Dokur are the smallest with about 500 and 400 households, respectively. In terms of castes, three caste groups, namely Scheduled Castes (SC), Other Backward Castes (OBC), and Upper Castes (UC) are more or less evenly distributed in Pamidipadu. In the other three villages, the OBC group dominates (between 50 and 60 per cent), followed by SC in Aurepalle (32 per cent) or UC in JC Agraharam. In Pamidipadu, 50 per cent of the households are landless, which is quite remarkable especially when compared to the other three villages, where the share of landless households is at most 22 per cent (JC Agraharam).

With stratification based on land ownership, in each village 40 households are interviewed monthly. Since households in Aurepalle and Dokur have been interviewed since the 1970s, the total number of households interviewed has increased due to family growth and the subsequent splitting of households (Dercon et al., 2013). All data are based on a monthly recall, so that irrespective of the interview date households provide information regarding the preceding month. The data include information on household demographics, consumption, income, financial transactions, land holding, and agriculture related topics.

I combine these monthly data with self collected data at the household level. The self collected data include each household's NREGA job card number if it exists and information retrieved from qualitative questions regarding the NREGA. I collected the data in research collaboration with Sudha Narayanan (IGIDR, Mumbai) and Krushna Ranawale (IGIDR, Mumbai)[13] during September and October 2014. We visited each ICRISAT household which, according to ICRISAT's detailed records, had at least one member employed under the NREGA. We asked each ICRISAT-NREGA household various questions regarding the NREGA and its process of implementation within the village. Crucially for this paper, we asked about the formation of labor groups and who was in charge of deciding on the composition of groups.

[11] Until June 2014 the two districts belonged to the same state, Andhra Pradesh. Since June 2014 Prakasam has been part of to the newly formed state of Andhra Pradesh, and Mahbubnagar of the state of Telangana. In the paper we only refer to Andhra Pradesh, since most of the sample period is covered under the old regime.

[12] More information on the villages of Aurepalle and Dokur based on the 1980s can be found in Walker and Ryan (1990).

[13] Monica Saranya and Srilatha Jinne were part of the survey team, and I am very grateful for their excellent assistance during the survey. Further, I want to thank the ICRISAT staff, in particular the resident field investigators in Aurepalle and Dokur who have been very helpful and accommodating throughout the time.

Table 3.1: Four Villages at a Glance

	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Households	984	545	382	1,214
Households belonging to (in %):				
Scheduled Castes	32	17	16	29
Scheduled Tribes	1	1	0	2
Other Backward Castes	59	64	53	32
Upper Castes	11	18	31	38
Households by Landownership (in %)				
Landless	15	10	22	49
Marginal (< 1 ha)	27	44	34	29
Small (≥ 1 ha & < 2 ha)	38	31	21	11
Medium (≥ 2 ha & < 4 ha)	19	10	20	7
Large (≥ 4 ha)	8	4	4	4
Village has:				
Banking Facility	*no*	*no*	*no*	*yes*
Post Office	*yes*	*yes*	*yes*	*yes*
Public Health Facility	*yes*	*yes*	*no*	*yes*
Primary School	*yes*	*yes*	*yes*	*yes*
Higher Secondary School	*yes*	*yes*	*no*	*yes*

Notes: Based on ICRISAT Census data (December 31, 2010).
Sources: Reddy et al. (2011), Krishna et al. (2011), Ramesh et al. (2012), Siddappa et al. (2012).

Further, we asked key stake holder such as the Field Assistant, the village head, and block and district officials about the procedures of providing work and paying wages on time. We also met officials at the state level and the data processing unit who explained us the various bureaucratic steps. In summary, a picture emerged that the potential for delay caused by system inherent failures is considerable and that the demand-driven aspect of the Act is largely circumvented.

Using the job card number allows me to merge those ICRISAT households who have ever been employed under the NREGA with administrative records as provided by the Government of Andhra Pradesh.[14] The administrative data include each worker's job card number along with a vast array on information including, crucially for this paper, the worker's group, the exact opening and closure dates of group-wise worksites and the date and amount of group-wise wage payments. In total, I am able to merge three data sets using the job card number as a link: ICRISAT panel data, administrative program data, and primary data collected from households belonging to the ICRISAT panel. An illustration of merging the three data sets is

[14]The Society for Social Audit, Accountability and Transparency (SSAAT, http://www.socialaudit.ap.gov.in/) was very helpful in obtaining the data and explaining the inherent processes of the "Andhra model."

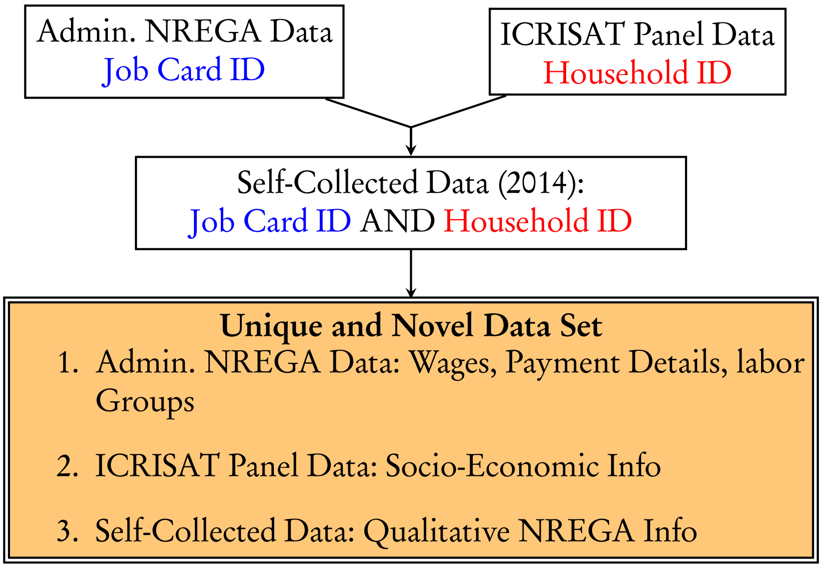


Figure 3.1: Merging of Three Data Sets

depicted in Figure 3.1. The final data set includes 82 ICRISAT-NREGA households, spanning four villages interviewed monthly over five years. While ICRISAT's monthly interviews took place between July 2010 and June 2015 administrative data from the Government of Andhra Pradesh are only available up to October 2014. As explained below, each village-wise sample period is trimmed depending on the village-wise NREGA activity.

3.4.1 Sample Summary Statistics

Trimming of Sample

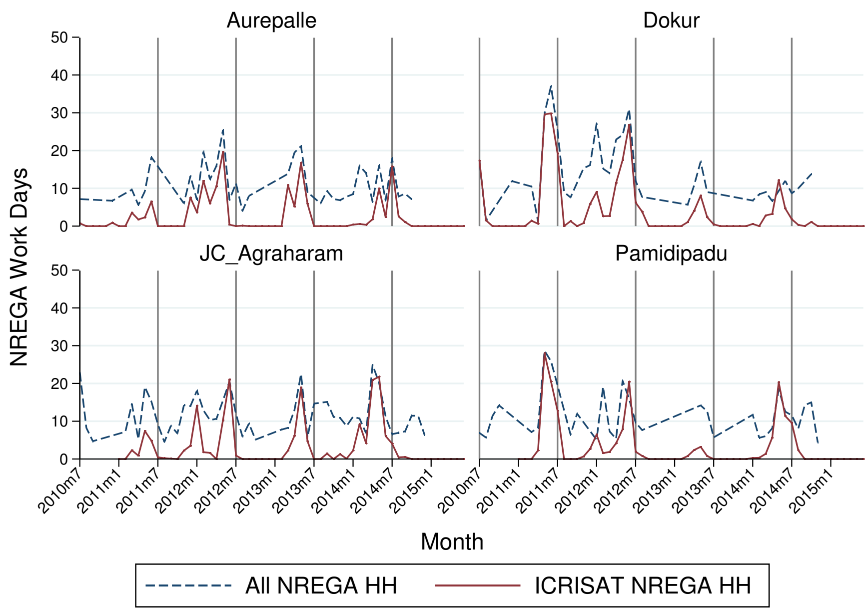


Figure 3.2: Seasonality of Days Worked under the NREGA

To introduce the village-wise sample periods I begin by presenting the actual timing of NREGA activity in the sample villages according to which the sample will be trimmed. Figure 3.2 depicts the monthly variation of the average number of work days per NREGA household[15] and per ICRISAT-NREGA household[16] over the time span for which ICRISAT data are available. Across the four villages it is evident that NREGA work days normally take place during the agricultural lean season, i.e. during the months between January and July with peaks in NREGA activity normally in June of each year. However, certain deviations from this rule are apparent. For example, in Aurepalle the real activity in terms of NREGA work days seems to begin only by January 2012 with the last peaks observed in July 2014. In Dokur, the more prominent peaks are only visible for the period between March 2011 and July 2012, whereas in JC Agraharam the period between March 2011 and July 2014 is the most relevant time span. In Pamidipadu we observe two intervals of activity, one between March 2011 and July 2012 and the other between January 2014 and July 2014. We use these village-wise intervals to trim the sample for the subsequent analyses accordingly. Also, we take into account that wage payments may come with a delay of up to three months. Hence, the latest month included for all villages is October 2014, whereas the initial month of each interval varies by village.

Consumption Expenditure

Table 3.2 presents sample summary statistics by village. The sample data adheres to the trimming of time spans according to NREGA activity with the beginning of each sample period indicated by "Min Month" and the end of each period indicated by "Max Month". The unit of analysis is a household. All prices are deflated to July 2010 prices using the monthly and state-wise consumer price index for agricultural laborers (CPI-AL) (Government of India, 2013a). According to the sample means, Pamidipadu accounts for the highest mean consumption per household and month (INR 8,794), which is almost twice as large as the average monthly consumption for JC Agraharam. In between the two are Aurepalle and Dokur with both household consumption expenditure of around INR 5,500. To put into perspective, average monthly per capita consumption expenditure in 2009-10 in rural Andhra Pradesh is INR 1,234 (National Sample Survey Organisation, 2011). Hence, with an average household size of four, consumption of sample households is close to the state's average. Complementing the sample summary statistics, Figure 3.9 depicts the monthly variation in household consumption expenditure. Regular peaks occur during the festive or harvest season around October. However, some potential outliers can be observed. For example, in the village of Pamidipadu unusual peaks in consumption occur in the early months of 2014. These peaks can be corroborated in the data and it becomes evident that these consumption

[15] An NREGA household is a household employed under the NREGA as reported by the administrative data.

[16] An ICRISAT-NREGA household is a household holding an NREGA job card while also being part of the ICRISAT sample.

peaks are driven by very high expenses for marriage ceremonies or education. These seem to happen for a number of households in Pamidipadu at the same time.

Financial Transactions

Table 3.2 reports four major categories of borrowing (loans) and and three for saving: Formal, informal (only for borrowing), microfinance, friends and relatives (loans) or loans to other (savings). Formal borrowing and saving considers all transactions with formal institutions such as banks, co-operatives and the like. According to the sample means formal borrowing is highly prevalent in Pamidipadu, somewhat less in Aurepalle and Dokur, but as good as non-existent in JC Agraharam. Informal loans entail loans borrowed from a money lender. In Pamidipadu, this practice seems to have faded away, whereas in Dokur and JC Agraharam it is still quite prevalent. In Aurepalle, the sample mean of informal loans is about 75 percent the size of the sample mean for formal loans (repaid).

Borrowing from friends and relatives seems to top all of the financial channels. Even though monthly average repayments in Dokur and JC Agraharam are not as high as in the other two villages, loans received from friends and relatives are higher than loans from any other categories. Microfinance loans and savings, too, seem to play a major role in financial transactions for households across villages, albeit to varying degrees. Average monthly repayments and receipts of microfinance loans are the highest in Pamidipadu, followed by Aurepalle, JC Agraharam and Dokur.

Microfinance - Self Help Groups

In the sample villages, microfinance loans and savings are predominantly transactions with Self Help Groups (SHGs) which are part of the Government's SHG-bank linkage program. According to Basu and Srivastava (2005), the latter is "[...] somewhat unique to India, particularly given its preponderance in the country's microfinance landscape. The model evolved so that the SHG-bank linkage today involves having the group save, and then linking it to a bank. Banks typically provide the group a loan amounting to four times the group's savings but, as the group matures, and based on the group's track record, banks are ready to lend more. Borrowed and saved funds are rotated through lending within the group using flexible repayment schedules (usually monthly repayment); SHGs thus save, borrow and repay collectively." It is important to stress here that repayment schedules are flexible. At the same time, members "decide the terms of loans to their own members" while "peer pressure ensures timely repayments" (Puhazhendi and Badatya, 2002). Such a framework induces members "to recycle loans within the group, as the bank loans are often taken for longer duration of 3 years" (National Bank for Agriculture and Rural Development, 2013). Most of the SHGs are formed by women, and according to Parida and Sinha (2010) female groups adhere to "financial management practices" of much higher standards than male groups.[17]

[17]Suda and Bantilan (2014) use a special survey on SHG groups in the sample village of Aurepalle and Maha-

Table 3.2: Sample Summary Statistics

	Aurepalle		Dokur		JC Agraharam		Pamidipadu	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Consumption								
Hh. Consumption Expenditure	5820	9629	5414	24732	4764	7948	8794	16876
Loan Repaid								
Formal	432	3291	361	5247	30	394	825	5529
Informal	295	4281	606	9149	376	4444	6	121
Microfinance	494	482	337	533	310	438	700	628
Friends & Rel.	1511	10094	455	3502	308	2990	773	3703
Loan Received								
Formal	1189	15447	817	6865	47	980	2401	15297
Informal	590	6041	322	2844	589	6969	140	2101
Microfinance	165	1445	331	1987	246	1980	910	4378
Friends & Rel.	1791	10542	928	6150	1147	9710	1484	13818
Savings Paid								
Formal	218	926	125	940	255	1351	979	3833
Microfinance	1290	1863	487	1270	36	27	942	1720
Loan to Other	161	1834	.	.	156	1730	0	0
Savings Received								

Formal	179	2530	240	2598	89	916	558	3716
Microfinance	404	4986	65	1153	0	0	435	4140
Loan to Other	270	5501	530	4322	18	438	17	178
Wages								
Admin. NREGA Wage	272	560	652	1383	321	929	541	1004
Self Reported NREGA Wage	466	805	266	670	507	920	432	1029
Self Reported Total Wage	4900	4593	4665	4091	4795	3037	10601	7224
Work Days								
Admin. NREGA Work Days	4	8	7	14	4	11	6	11
Self Reported NREGA Work Days	7	12	4	10	8	14	5	10
Self Reported Total Work Days	42	30	42	33	44	24	52	26
Female Work Days								
Share in Admin. NREGA Work Days (in %)	89	27	67	35	45	25	60	34
Household Size	4.07		3.79		4.36		3.81	
Households	26		19		20		17	
Number of Months	34		28		44		27	
Number of Observations	884		532		868		458	
Min Month	2012m1		2010m7		2011m3		2011m3	
Max Month	2014m10		2012m10		2014m10		2014m10	

Notes: Author's calculations of monthly household averages from ICRISAT data. The sample is restricted to ICRISAT-NREGA households.

Since the most frequent financial transactions undertaken are monthly loan repayments to microfinance institutions we take a closer look at the monthly fluctuation in Figure 3.10. With several spikes across varying seasons, there does not seem to exist a particular period for such loan repayments. Instead, while microfinance loan repayments in Aurepalle seem to begin only in January 2012 they follow a stable path with minor peaks here and there. For JC Agraharam, microfinance loan repayments decline continuously from the end of 2013 onwards. In Dokur, there is a decline between 2010 and 2013 before these loan repayments pick up again in 2014. Only in Pamidipadu they remain constant at a certain level - at a level much higher than in the other three villages. Only one steep decline can be observed in May 2014 before the earlier level is reached again.

Wage Income and Work Days

According to Table 3.2, village-wise self reported total wage income is of a similar magnitude as the village-wise consumption expenditure. Hence, equivalent to the consumption-based ranking of villages, Pamidipadu accounts for by far the highest average wage income with INR 10,000. The average wage income is not even half as much in the other three villages. Looking at income from NREGA wages, there are two sources: a) self reported, meaning as reported by households during the monthly ICRISAT interviews, and b) administrative, meaning as recorded by the Government of Andhra Pradesh. Self reported NREGA wage is the highest in JC Agraharam (approx. INR 500), followed by Aurepalle (INR 466), Pamidipadu (INR 432) and Dokur, where average NREGA wages are only around INR 260. The latter is probably due to much less NREGA work days in Dokur. In fact, self reported NREGA work days (4) in Dokur are half as much as those in JC Agraharam (8). The self reported NREGA wage of around INR 500 in JC Agraharam is quite substantial given that it is the average amount over all months, including months when no NREGA wages are paid. Therefore, one may consider that monthly NREGA wage income reach up to INR 1,000 during months of the spring season. This would correspond to one fifth of total household consumption expenditure. Since total wage income and consumption expenditure are of similar magnitude NREGA wage income can be quite substantial with regards to total wage income. The monthly variation of the share of NREGA wage income in total wage income is depicted in Figure 3.11. For one, the seasonality in NREGA activity is revealed also by administrative data on NREGA wage payments. And second, peaks of up to 20 per cent corroborate the point that NREGA wages can be of considerable importance for households in certain months.

Table 3.2 also lists the number of self reported NREGA work days and total work days. These yield ratios of NREGA to total work days similar to those based on wages indicating that NREGA work days may take up between 20 to 30 per cent of all work days in a month when NREGA works occur. Interestingly, however, self reported and administrative data on work days seem to tally only for the sample of Pamidipadu. As observed for the data on

rashtrian villages to discuss potential welfare effects of the SHG-bank linkage program.

NREGA wage payments, the self reported figures are higher than the figures obtained from administrative records on NREGA work days in Aurepalle and JC Agraharam. There may be at least two conceivable reasons for this mismatch: a) a reporting problem during the ICRISAT interview, or b) the possibility that the household holds more jobcards than reported to us. The latter results in matching less work days from administrative records to a given ICRISAT household. In Dokur, on the other hand, the pattern is reversed: self reported NREGA days (4) are much less than administrative NREGA days (8). In contrast to the other case this may potentially indicate a scam at the supply side, meaning for example, that bogus days are reported in administrative records. In Pamidipadu, too, the ratio of administrative NREGA wages to self reported NREGA wages hints towards such a scenario. Therefore, any results depending on administrative data for Dokur and Pamidipadu should be taken with a grain of salt.

Qualitative Data
Linking NREGA wage income with consumption and financial transactions - the main focus of this paper - it is worthwhile to take a look at some of the qualitative data self-collected from ICRISAT-NREGA households in 2014. Table 3.16 reports frequencies of answers to general questions regarding the use of NREGA wages. Accordingly, NREGA wages are often spent on consumption and frequently utilised to repay loans to microfinance institutions. As per ICRISAT data a large proportion of all loans taken up are from such informal or semi-formal institutions, as reported in Table 3.17.

3.4.2 Financial Market Access of Sample Households by Village

The ICRISAT data allow us to take a closer look at the portfolio of financial market transactions from two angles. First, yearly balance sheets taken on July 1 of each year illustrate the stock of borrowings and savings (Tables 3.18 and 3.19). Thus, the yearly balance sheet highlights access to finance in general. Second, by observing monthly incidences and monthly average transactions of payments and receipts we gain information about the flow of borrowings and savings (Table 3.3). These also tell us about the general access to finance but also highlight the monthly exposure to formal and informal financial markets.

Monthly Incidences and Yearly Balance Sheets
To begin with a general view on the flows (Table 3.3), the most frequently undertaken monthly transactions are microfinance loan repayments. These occur at least every other month in each village, followed by financial transactions with friends and relatives. All other borrowing transactions occur only a few times in the sample period indicating that other loans mature probably after one year or more and are not to be repaid in monthly instalments.

In terms of general access to formal finance institutions, approximately 60 per cent of all households across villages are connected to formal banking, as inferred from the yearly data on

Table 3.3: **Financial Transactions: Monthly Incidences**

	Aurepalle		Dokur		JC Agraharam		Pamidipadu	
	Rec.	Rep.	Rec.	Rep.	Rec.	Rep.	Rec.	Rep.
Borrowing (Incidence in %):								
Formal	1.70	4.64	2.26	3.20	0.23	0.81	4.59	5.24
Informal	1.92	1.13	2.63	2.07	3.46	2.88	1.31	0.22
SHG	1.92	76.92	3.76	61.09	1.73	47.93	4.80	76.86
Friends & Rel.	9.50	5.32	9.96	5.45	7.14	2.19	5.02	5.68
Others	50.79	49.10	1.50	1.69	37.44	37.44	35.15	34.06
Households	26	26	19	19	20	20	17	17
Months	34	34	28	28	44	44	27	27
Number of Observations	884	884	532	532	868	868	458	458
Savings (Incidence in %):								
Formal	0.68	4.41	2.07	4.51	1.15	23.16	3.71	27.95
SHG	0.90	92.19	0.38	73.87	0.00	83.76	1.75	97.60
Loan to Other	0.45	0.90	3.38	0.00	0.35	0.35	1.09	0.00
Households	26	26	19	19	20	20	17	17
Months	34	34	28	28	44	44	27	27
Number of Observations	884	884	532	532	868	868	458	458

Notes: Author's calculations of monthly household averages from ICRISAT data.
The sample is restricted to ICRISAT-NREGA households.

borrowings (Table 3.18). However, some yearly variation is visible, especially so in JC Agraharam and Pamidipadu where during the years 2010 and 2011 average access hovers around 30 per cent. In Dokur, a decline to such a low level can be noted only in 2014. The monthly data (Table 3.3) underscore the broad access to formal banking as monthly savings (received or paid) via formal banking institutions happen regularly and about every two months, with Dokur being the exception. Borrowings from formal institutions do not happen as frequently, which is visible both in the yearly as well as in the monthly data. The latter suggests that on average households take up and pay back such a loan once in a year or so.

Access to microfinance loans is on average even higher than access to loans from formal institutions, as one can infer from incidences of the yearly data which hover around 70 per cent (Table 3.18). Exceptions are Dokur in 2013 and JC Agraharam in 2014. In terms of magnitudes, loans from microfinance institutions are much smaller than loans borrowed from formal institutions. Importantly, monthly loan repayments to microfinance institutions occur in 60 per cent of all sample months (Table 3.3), underscoring the nature of flexible microfinance repayments in monthly instalments. Even higher frequencies for microfinance savings indicate monthly commitments to local microfinance groups (Table 3.3). On the other hand, microfinance loans are received usually only about once a year.

In all villages access to loans borrowed from friends and relatives is equally important and of similar magnitude as loans taken from formal institutions (Table 3.18). This may vary from village to village and from year to year but the general access to such loans from this network is quite prominent. Such loans are taken and repaid quite frequently (Table 3.3). Loans received and repaid to friends and relatives are relatively huge in magnitude (Table 3.2). However, such transactions take place only three to four times during the sample period (Table 3.3).

In summary, the following stylised facts emerge: households in Dokur have the least access to formal banking in terms of saving behaviour. In JC Agraharam formal borrowing is abysmally low while informal borrowing is relatively high. In comparison, households in Aurepalle and Pamidipadu are the most frequent borrowers from formal institutions. In all villages saving and borrowing via microfinance institutions is very prominent. Borrowing from friends and relatives is also of considerable magnitude across villages.

3.4.3 Labor Groups in ICRISAT Villages

Among the sample households who are both part of the ICRISAT panel and work under the NREGA we identify 58 SSS groups: 16 in Aurepalle, 14 in Dokur, 15 in JC Agraharam, and 13 in Pamidipadu. In self-conducted interviews we asked ICRISAT-NREGA households about the formation of groups, as presented in Table 3.16. Overwhelmingly, they had no say which group they join. The reason cited - in more than 60 percent of all answers - for being in a particular group was given as "Field Assistant", followed by "neighborhood" and "caste". Further and crucially, in more than 70 percent of all cases it was not the household's decision to be in the particular group, but instead the Field Assistant's.

The evidence highlighted here shows that there is no room for self-selection into labor groups. Therefore, self-selection into worksites can be ruled out as well if the demand for NREGA work always meets the supply of NREGA works. The extent to which this may be assumed at the village level is explained in the following subsections via the variation in worksites per group, and the extent of workday smoothing.

3.4.4 Group-wise Variation in Open Worksites

The number of monthly worksites available per group and month are depicted as an example for Aurepalle and Dokur in Figures 3.3 and 3.4, respectively. During Spring 2011 (for illustrative purposes this season only is depicted here) the number of open worksites per group varies greatly. Clearly, some groups have higher chances of receiving work than others. Thus, rationing of labor as discussed for example by Das (2013) in the context of West Bengal or by Dutta et al. (2014) in the context of Bihar does seem to happen in our sample villages as well. Since workers do not have any say about when their group should receive work but are solely dependent on the field assistant, one may consider the timing of open worksites as exogenous events.

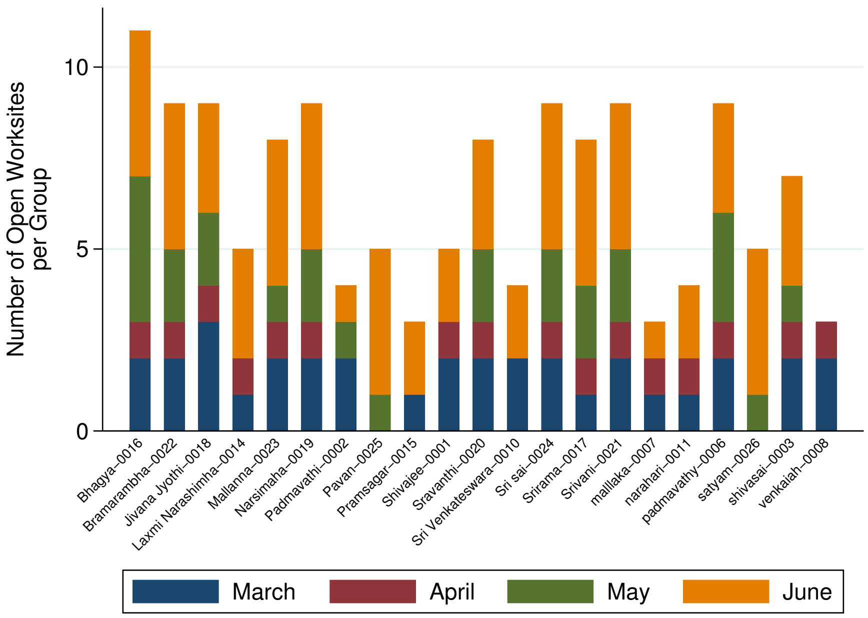


Figure 3.3: Variation of Open Worksites in Aurepalle by Month and Group

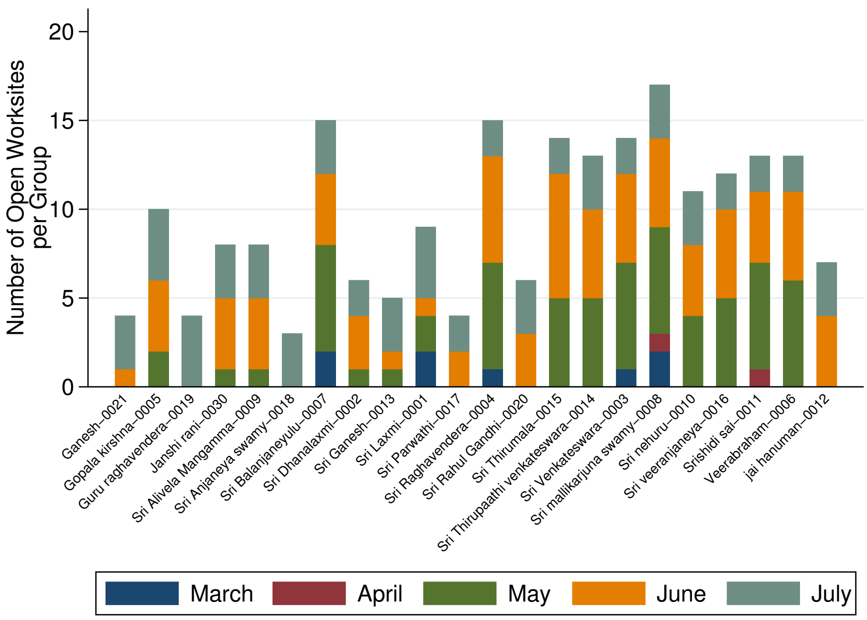


Figure 3.4: Variation of Open Worksites in Dokur by Month and Group

3.4.5 Supply Shocks of NREGA Work Days?

In this section, I test whether the supply of NREGA work days can be considered as a supply-driven shock to total working days. For this purpose, I regress self reported total work days on self reported NREGA days in a two-stage-least-squares (2SLS) framework, where self reported NREGA days are instrumented by administrative NREGA days. The regression equations for the OLS (3.19), the first stage (3.20), and second stage (3.21)are specified as

$$TWD_{it} = \mu_i + \gamma_t + \sum_{\tau=0}^{3} \beta_\tau \, SND_{it-\tau} + \epsilon_{it} \tag{3.19}$$

$$SND_{it} = \mu_i + \gamma_t + \sum_{\tau=0}^{3} \beta_\tau \, ADMIN_{it-\tau} + \epsilon_{it} \tag{3.20}$$

$$TWD_{it} = \mu_i + \gamma_t + \beta \, \widehat{SND_{it}} + \epsilon_{it}, \tag{3.21}$$

where TWD_{it} corresponds to the number of total self reported work days, SND_{it} to the number of self reported NREGA work days, and $ADMIN_{it}$ to NREGA work days as recorded in administrative data, each for household i in month t. μ_i is a household fixed effect and γ_t a month fixed effect. ϵ_{it} is a stochastic error term. Standard errors are clustered at the group-month level. Each summation term in equation 3.19 and 3.20 includes one contemporaneous and three lagged forms of the explanatory variable, which thus yield four betas in total. If NREGA days are a true and fully utilized supply shock, the coefficient in the 2nd stage should be positive and relatively high, so that any additional NREGA work day positively impacts total work days. In other cases of statistically significant but smaller coefficients in magnitude, NREGA work days might still be considered as a supply shock, albeit one which is of no great relevance to the households. For instance, household might undertake a form of workday smoothing, utilize NREGA days when needed or substitute them for other work days.

Regression results are set out in Table 3.4, where three columns for each village present the first stage, OLS, and second stage results. According to the 2nd stage results, NREGA work days impact the total number of monthly work days in Dokur, Pamidipadu, and Aurepalle. The coefficient of interest is highly statistically significant in the village-wise regressions in these three village-wise regressions. The first stage results corroborate impressions from the sample summary statistics: for Dokur and Pamidipadu, administrative data do not tally with self-reported data and since the former are higher than the latter, suspicions for a supply-side scam may be warranted. In accordance, the first stage estimates for Dokur and Pamidipadu are not statistically significant.[18] Hence, the second stage results for Dokur and Pamidipadu should be considered with caution, not least because of the smaller sample size. The regression results for Aurepalle and JC Agraharam on the other hand look promising, although they yield different interpretations. For Aurepalle, the highly significant coefficient of .6 in magnitude can be interpreted as a supply-side related increase of total work days. This, however, cannot be found in JC Agraharam, since the coefficient of interest is not statistically significant at conventional levels. Hence, there does not seem to be evidence for a supply-side shock but rather for work day smoothing.

[18]For illustrative purposes, the ratio of self reported to administrative NREGA days is depicted in Figure 3.12.

Table 3.4: 2SLS: Total Self Reported Work Days on Self Reported NREGA Days, Administrative NREGA Days as Instrument

	Aurepalle			Dokur			JC Agraharam			Pamidipadu		
	1st	OLS	2nd	1st	OLS	2nd	1st	OLS	2nd	1st	OLS	2nd
	DV: Total Self Reported Work Days											
Administrative NREGA Days												
Cont.	0.323***			0.093			0.229***			0.127		
	(0.088)			(0.057)			(0.055)			(0.089)		
Lagged 1	0.139**			0.073			0.083**			0.127		
	(0.063)			(0.052)			(0.040)			(0.083)		
Lagged 2	0.073			−0.040			−0.001			−0.034		
	(0.061)			(0.049)			(0.033)			(0.053)		
Lead 1	0.144**			0.069			0.214***			−0.015		
	(0.073)			(0.058)			(0.052)			(0.061)		
Lead 2	0.077			0.072			0.015			−0.023		
	(0.081)			(0.061)			(0.036)			(0.046)		
Self Reported NREGA Days												
Cont.		0.605***	0.567***		0.215*	1.021***		0.474***	0.180		0.761***	0.821**
		(0.087)	(0.200)		(0.131)	(0.309)		(0.057)	(0.130)		(0.138)	(0.325)
Lagged 1		−0.060			0.183			0.033			0.005	
		(0.093)			(0.124)			(0.064)			(0.143)	
Lagged 2		0.093			0.309***			0.108**			−0.137	
		(0.077)			(0.090)			(0.054)			(0.126)	
Lead 1		−0.029			0.094			0.038			0.170	
		(0.078)			(0.173)			(0.059)			(0.121)	
Lead 2		−0.052			0.134			0.110**			0.043	
		(0.070)			(0.145)			(0.053)			(0.097)	
Household FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Month FE	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
1st Stage F	9.27			4.80			14.91			2.27		
Dep.V. Mean	6.84	42.21	42.21	3.69	41.77	41.77	7.81	43.69	43.69	4.84	52.42	52.42
Ind.V. Mean	3.70	6.84		6.49	3.69		4.44	7.81		6.36	4.84	
Observations	884	884	884	494	494	494	862	862	862	458	458	458
Households	26	26	26	19	19	19	20	20	20	17	17	17
Min Month	2012m1	2012m1	2012m1	2010m9	2010m9	2010m9	2011m3	2011m3	2011m3	2011m3	2011m3	2011m3
Max Month	2014m10	2014m10	2014m10	2012m10	2012m10	2012m10	2014m10	2014m10	2014m10	2014m10	2014m10	2014m10

Notes:

Robust standard errors in parentheses, clustered at the group month level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$

Sample: ICRISAT-NREGA Sample. Month and household fixed effects are included. The dependent variable of the 1st stage regression (1st) is Self Reported NREGA Days.

In support of the above findings, the density graphs depicted in Figure 3.5 illustrate that there is evidence for a supply-side shock in Aurepalle and evidence for work day smoothing in JC Agraharam. Using group-wise information from administrative data on the total number of possible NREGA work days for each ICRISAT-NREGA household we calculate the ratio of monthly realised work days by a household to monthly supplied work days for a group. In Figure 3.5 frequencies of such a demand-supply ratio are plotted for each village. In the case of Aurepalle a bunching towards the 100 per cent mark is visible whereas in JC Agraharam there is an even distribution around that threshold, which indicates smoothing of work days. For Dokur and Pamidipadu a clear bunching towards the 100 per cent mark cannot be found.

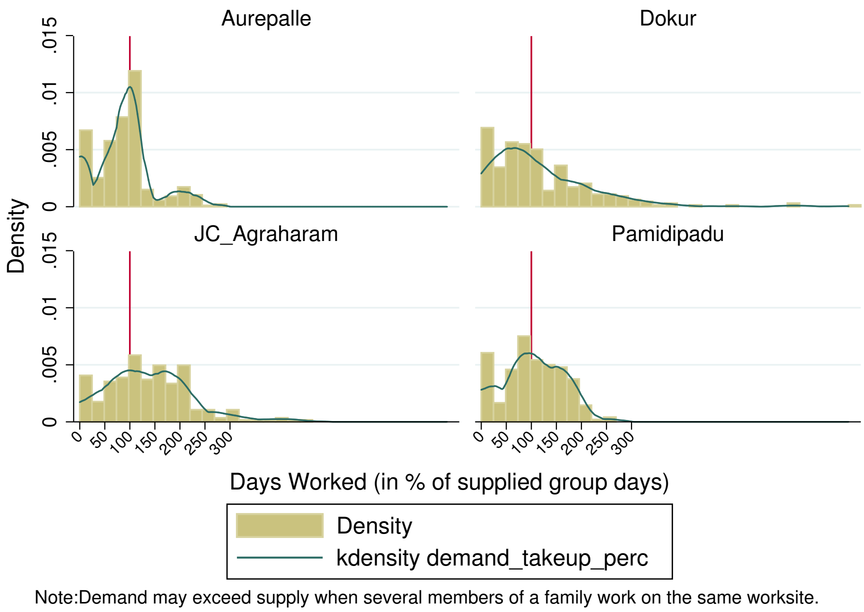


Figure 3.5: Percentage of NREGA Work Days in Supplied Group Days per Month

3.4.6 Variation in Monthly Wage Payments

While NREGA work days may not come as a surprise or may be smoothed as shown above, workers might still face some uncertainty regarding the exact timing of wage payments. According to the Act NREGA wages are supposed to be paid within 15 days after work. But across India, most often wage payments reach workers much later for a variety of reasons including inherent problems with the payment system(Khera, 2010). Based on a survey of NREGA laborers conducted in 10 states during the year 2008, more than 50 percent of the respondents complain about a delay in wage payments (Drèze and Khera, 2009).[19] Basu and

[19]For all-India figures on payment delay since 2012-13 see the following insightful report in the *Hindustan Times*: http://www.hindustantimes.com/india-news/sharp-rise-in-timely-wage-payment-to-mgnrega-workers/story-jj01pMVXeXmMZk9lIUWUUP.html

Sen (2015) provide for a theoretic model conceptualizing how a delay in wage payment can be a multifaceted welfare loss.

Our interviews with the sample households also indicate that workers may have to wait for several months to get paid. As listed in Table 3.16, a large proportion of ICRISAT-NREGA households (about 40 percent) complain about a delay in wage payments. From administrative records, too, such evidence emerges. As shown in Figure 3.6, even though ICRISAT-NREGA households do not face delays in 60 to 70 per cent of all cases, when delays occur these may take up to three months. Wage payments may then be considered as random events as the delays are due to bureaucratic obstacles and the banking system. Both are beyond the reach of the ordinary worker or field assistant.

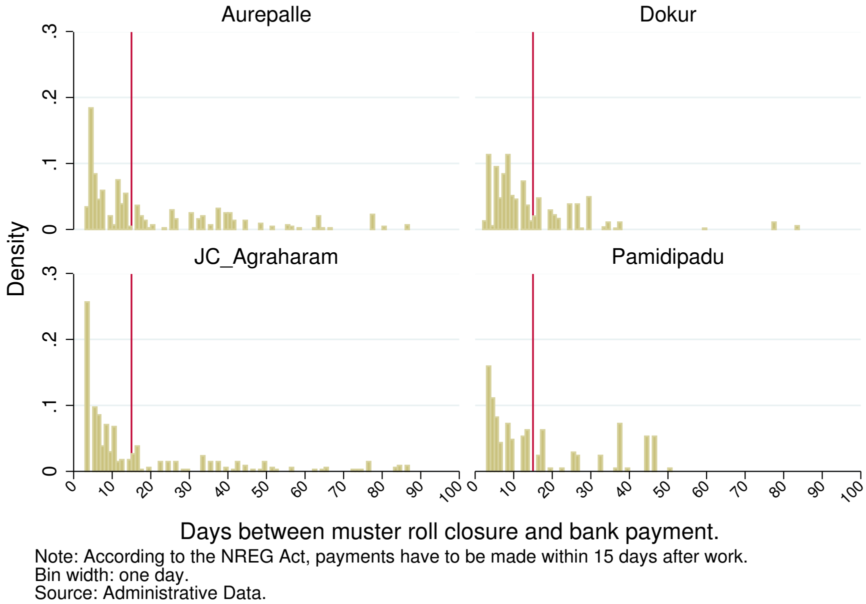


Figure 3.6: Uncertainty of Date of Payment

For purposes of identifying the NREGA wage payments and classifying them as potential "income shocks", it is important to establish that the date of wage payment does not occur in the same month when NREGA work days take place and consumption decisions are made. In fact, if one were to rely on the self-reported ICRISAT data, one would identify wage claims rather than actual wage payments in most cases. That is because during the interview households are first asked about the number of work days and then about their wages. So one would expect households to first report the number of work days followed by the expected and not necessarily the real wage income, as the latter can be paid out later. Figure 3.7 depicts administrative data on NREGA wage payments and its timing. It illustrates that wage payments are often paid in the month after NREGA works took place. Hence, self-reported data on wage payments would likely be wage claims rather than actual payments. Therefore, to identify the true wage payment and exploit the monthly variation and uncertainty in the timing of wage payments the administrative data on monthly payments is employed in the empirical analyses of this paper. So, even if work days can be smoothed, in for example JC Agraharam, the date of payment may still vary and is still somewhat uncertain.

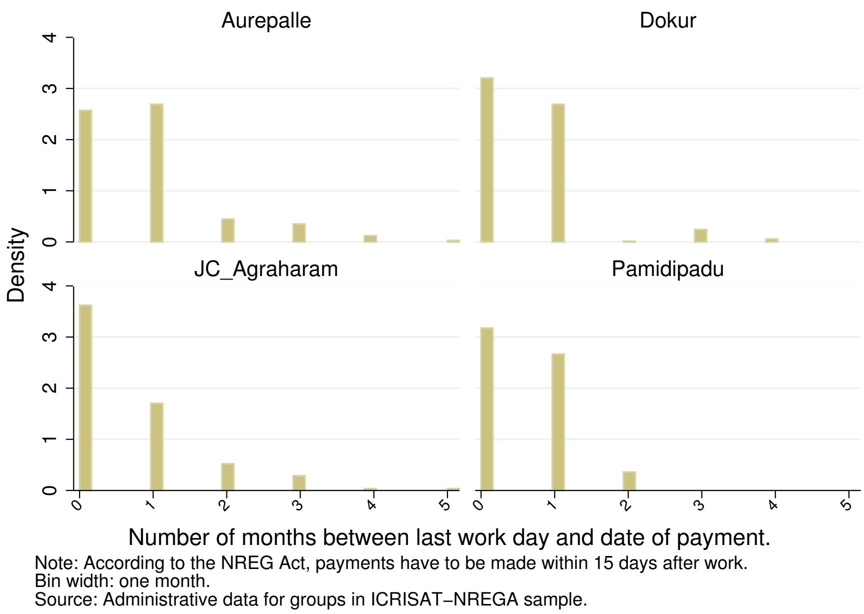


Figure 3.7: Month of Wage Payment

3.5 Regression Model

In this section, I present the regression model and possible predictions. The aim of the regression analysis is to estimate a) whether households are able to smooth consumption and b) what kind of financial transactions are utilised. The regression estimates depend heavily on the identification of income shocks and to what degree these can be considered as exogenous events. From the discussion in Section 3.4 the major take-away is that at least the timing of wage payments can be considered as exogenous to consumption behaviour and financial transactions. The variation in the monthly timing of wage payments as per administrative records - wage payments may or may not happen in the month when works take place - is important to identify exogenous income shocks. To clarify, the main explanatory variable is wage income as recorded in administrative records which is not equal to the self reported wage income. As discussed for example by Deaton (1990) and Townsend (1994), self reported income is often measured with error. This measurement error correlates with the error of the self reported outcome variable, say consumption. To avoid this, one can either use an instrumented variable (IV) framework or exploit the exogenous variation in another variable which also captures household income. The latter is often hard to get by and hence IV frameworks are the most common approaches. In this paper, I consider NREGA wage payments as recorded in administrative data to capture reasonably well the income from NREGA activities.[20] During the spring season such income from NREGA activities may be substantial for a household.

3.5.1 Regression Model

Townsend (1994) argues that the ICRISAT villages are very heterogeneous in nature. They are more than 100 kilometres apart and differ in agricultural activities and in their socio-economic setting. Therefore, we follow Townsend (1994) and subsequent empirical studies by for example Mazzocco and Saini (2012) on some of the same villages and run village-wise estimations. As Mazzocco and Saini (2012), we exploit the nature of the high-frequency panel data set by employing the monthly data. In contrast to Townsend we do not need to aggregate at the yearly level, and in contrast to Mazzocco and Saini (2012) we do not need to adjust the monthly data as the recall periods are constant and always refer to the previous month, even though the interview date might vary. Thus we can employ month fixed effects without any tweaking of the monthly data. To account for the heterogeneity across households within a village we use household fixed effects.

The basic panel OLS regression with household and month fixed effects is of the form

$$c_{it} = \mu_i + \gamma_t + \sum_{\tau=0}^{3} \beta_\tau ADMIN_{it-\tau} + \epsilon_{it}, \tag{3.22}$$

where $ADMIN_{it}$ is the NREGA wage as recorded in administrative records for household i in month t. μ_i is a household fixed effect, γ_t is a month fixed effect, and ϵ_{it} is a stochastic error term. Standard errors are clustered at the group-month level. As before, the summation term contains one contemporaneous and three lagged forms of the explanatory variable, which thus yield four betas in total. Equation 3.22 follows equation 3.15 quite closely. Household and month fixed effects cancel out all household demographics captured in H_{it}, while the household fixed effects also cancel out village average consumption, $\bar{c_t}$. To test for consumption smoothing, the outcome variable c_{it} is household consumption expenditure for household i in month t. To test for mechanisms of consumption smoothing in separate regressions, c_{it} captures several forms of borrowings and savings. Doing so, I follow Fafchamps and Lund (2003), who regress gifts, loans, and change in assets on negative income shocks for rural households in the Philippines to test which of the three serves to smooth consumption. As discussed in Section 3.2 I ignore wage claims and only include realized wage income as regressors of interest. Since the primary data (Table 3.16) suggest that NREGA wages are likely to

[20]Still, one may think of several occasions when the wage payment as recorded on bank statements may not be wage earned of households. For instance, it could be that due to corrupt official at the bank or post office only some part of the wage is paid out. Or it could be that powerful Field Assistants open their hands after the wage was paid out. Such cases have been told to us during our field work. However, it is likely that such inherent corruption does not vary across households. In contrast to self reported income, such measurement error would not be correlated with the measurement error in the self reported outcome variables.

be utilized for purposes of savings and repayments of loans to microfinance groups, if not for direct consumption, I focus on those forms of financial transactions, in particular. The sample is restricted to ICRISAT-NREGA households, so that only households who have ever been part of any NREGA labor group are included in the sample. For logarithmic transformations of outcome and explanatory variables ones are added to every non-missing observation.

3.5.2 Gender-wise Payments and Intra-household Allocations

In South India, and in particular in the state of Andhra Pradesh, women constitute the majority of the NREGA workforce. Since the beginning of the NREGA in 2006, annually more than 60 per cent of all workers in Andhra Pradesh are female workers (Drèze and Oldiges, 2011). There are numerous studies on female employment under the NREGA, which highlight the beneficial effects on women empowerment, women's bargaining power, and child education (Narayanan, 2008; Khera and Nayak, 2009; Afridi et al., 2012). Under the NREGA female workers are entitled to the same minimum wage as male workers. Also, female workers are entitled to collect wages at the bank or post office. Thus, as some of the above mentioned studies highlight, NREGA employment of women has the potential to directly impact intra-household finance decisions. Such intra-household allocations are often difficult to statistically identify and have not been studied much in the context of the NREGA.

Doing so, I contribute to a larger literature in the field of gender and intra-household allocations (Thomas, 1990; Bourguignon et al., 1993; Browning et al., 1994; Browning and Chiappori, 1998, see for example). It is widely accepted that women and men "spend income differently," measurement error problems (female income may have a higher measurement error than male income) and endogeneity issues have, however, complicated much research in this field (Haddad, 1999) and induced many to instrument labor income with non-labor income Hopkins et al. (1994). The latter estimate the response of seasonal household consumption to seasonal male and female wage income on in rural Niger and find that the gender of income matters.

In this paper, I contribute to the literature by exploiting gender-wise data on wage payments and ICRISAT's rich data on financial transactions. The share of female workers varies by village, according to the administrative data on work days (Table 3.2). The female share is almost 90 per cent in Aurepalle, about 70 per cent in Dokur, 45 per cent in JC Agraharam, and 60 per cent in Pamidipadu. The administrative data on gender-wise work days allow me to infer the share of female wages in total NREGA wage payments. Based on that I impute female and male NREGA wages and include these as separate regressors in the regression equation.

However, since I cannot statistically distinguish wage shares of zero from monthly wages of zero[21] my framework departs from the often used technique of using female and male wage

[21]Recall that in many winter months the NREGA is not operating or that in some cases households chose not to participate. For such months wage payments of zero go into the regression. If at the same time but for other months wage shares of zero enter the regression no distinction between the two cases would be possible.

shares along with total household income as regressors of interest (Bourguignon et al., 1993; Browning et al., 1994; Browning and Chiappori, 1998). The regression equation only includes the imputed gender-wise wage incomes as separate regressors in log form. In fact, my regression equation is similar to the specification adopted by Hopkins et al. (1994). Using household and month fixed effects as before in equation 3.22, the regression equation is then

$$c_{it} = \mu_i + \gamma_t + \sum_{\tau=0}^{3} \beta_\tau \, FEM_{it-\tau} + \sum_{\tau=0}^{3} \beta_\tau \, MAL_{it-\tau} + \epsilon_{it}, \tag{3.23}$$

where $FEM_{it-\tau}$ and $MAL_{it-\tau}$ are female and male NREGA wage payments, respectively. We include four time periods for each, yielding eight betas of interest in total.

3.6 Main Results and Discussion

In this section, I present the main results of tests for consumption smoothing and for mechanisms of consumption smoothing. After highlighting the key findings, an attempt is made to place these into the context of the village economies and the village-wise access to finance.

3.6.1 Results

Consumption Smoothing

Table 3.5 presents the village-wise regression results for the tests on consumption smoothing. Each column corresponds to one regression as specified in equation 3.22 with both the dependent variable (DV) and each independent variable (IV) in log terms. Therefore, the coefficients can be interpreted as elasticities. The table also reports the p-value of the F-test for joint significance of the explanatory variables. I include two F-tests, one to test for the joint significance of only the lagged variables and one for the joint significance of both the lagged variable and the contemporaneous term.

The results indicate that only in JC Agraharam consumption responds to changes in income. In the other three village-wise regressions, coefficients are statistically insignificant and very small in magnitude. This is evidence for consumption smoothing. These results are in line with those of Townsend (1994) who finds that consumption responds only in rare cases to changes in income, and if so at very low degrees. For JC Agraharam, on the other hand, the magnitude of the sum of the point estimates (.045) is quite considerable, since it implies a propensity to consume of .66. This means that a INR 100 increase in wages leads to an increase in consumption of INR 66. In the context of possible predictions, the results for JC Agraharam are somewhat between the predictions of the PIH and the "hand to mouth" model (see equations ?? and 3.8).

Financial Transactions: Borrowings

Table 3.5: Consumption Regressed on NREGA Income

	DV: HH Consumption Expenditure (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Admin. NREGA Income (in logs)				
Contemporaneous	−0.003	0.004	−0.001	−0.002
	(0.006)	(0.012)	(0.006)	(0.010)
Lag 1	−0.004	−0.005	0.025***	0.007
	(0.008)	(0.009)	(0.007)	(0.015)
Lag 2	−0.008	−0.003	0.003	−0.012
	(0.007)	(0.008)	(0.008)	(0.012)
Lag 3	−0.010	0.002	0.017**	−0.002
	(0.007)	(0.008)	(0.007)	(0.018)
P-value (F): Lagged Income	0.20	0.89	0.00	0.73
P-value (F): Contemp. & Lagged Income	0.27	0.96	0.00	0.81
Mean: DV	5820	5517	4806	8795
Mean: Admin. Income	272	605	329	561
Months	34	25	43	26
Households	26	19	20	17
Observations	884	475	842	441
Min Month	2012*m*1	2010*m*10	2011*m*4	2011*m*4
Max Month	2014*m*10	2012*m*10	2014*m*10	2014*m*10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Table 3.7 set out regression results for tests on mechanisms of consumption smoothing in the form of borrowing. Each column represents one village-wise regression with a given loan category in logs as the dependent variable. As before, the explanatory variables are in logs as well, so that the coefficients may be interpreted as elasticities. The regression specification is according to equation 3.22. Also, p-values of the F-test on joint significance are reported for each regression.

In order to get an overview of the many results, I let p-values of the F-tests guide us in focusing on the most conservative results. From such a conservative view, it appears that only loan repayments to microfinance groups respond to changes in income as identified by NREGA wage payments. In particular, for the two villages of Dokur and JC Agraharam positive elasticities can be observed which are statistically significant. In the case of Dokur, the third lag is highly statistically significant with an elasticity of 0.086. The sum of the coefficients is near 0.1, yielding a propensity to repay loans of about 0.05. Thus, five per cent of an income increase is diverted to the repayment of microfinance loans. For JC Agraharam, the propensity to repay microfinance loans to is much higher (.21).

In terms of interpreting the results, one has to keep in mind the small sample size for Dokur and Pamidipadu. Thus, the propensities for Dokur are to be treated with caution. The ratio between the mean of the dependent variable and the mean of the independent variable (administrative income) is the key multiplier for the calculation of propensities. In Dokur, however, as shown in Section 3.4, wage income based on administrative records is much higher than self reported wage income. As this might point towards a supply-side scam any results for Dokur should be treated with an additional grain of salt. In fact, such high values for administrative income in the ratio's denominator reduce the multiplier substantially. Thus the low propensities might be underestimates given the elasticities.

Financial Transactions: Savings

Regression results for savings are presented in Tables 3.20 to 3.24. Analogous to results discussed above, coefficients can be interpreted as elasticities. As in the preceding interpretation of results we let the p-values of the F-test be the conservative guide for analyzing only the most robust results. Recall that incidences for most forms of Saving (Received) are very low, hence it is very difficult to run meaningful regressions. In the case of savings from microfinance institutions in JC Agraharam the incidences are so low that no regression can be run, and hence the blank space in the respective column of Table 3.21.

In JC Agraharam, savings received from formal institutions respond to changes in wage income. However, the estimated propensity is very low with a magnitude of 0.03. Related to this finding, savings deposited at formal institutions react to a much greater extent in JC Agraharam. Propensities to save at formal institutions are around 0.17, meaning that INR 17 of a INR 100 increase in wages are deposited into saving accounts. At the same time, in JC Agraharam informal savings reduce as a response to wage increases. The corresponding propensity, however, is relatively small at 0.025. For Aurepalle, too, I find that informal savings reduce as a response to an increase in wage income. With informal savings being much more prevalent in Aurepalle (higher mean), the propensity of .92 to reduce informal savings is much higher than in JC Agraharam. As the last finding to be discussed, I focus on microfinance Saving (Paid) in Dokur. The sum of coefficients yield an elasticity of about .8, which yields a propensity to deposit such savings of about .6.

3.6.2 Discussion of Main Results

At the outset of this discussion of results, it is important to note one caveat of the study. For two reasons, I can only test a limited number of consumption smoothing mechanisms. First, financial transactions need to occur with a reasonable frequency in order to be measured in a regression framework. Therefore, even though gifts, for example, might play an important part in consumption smoothing, I cannot include these as potential outcome variables as they happen much too rarely. Second, by focusing only on financial transactions I ignore other investments, for example investments in agriculture-related activities or products which are also aimed at smoothing consumption. Thus, this paper provides insights and evidence of several mechanisms at work, albeit no claim is made to portray them all. From the findings presented above a few patterns emerge. Sticking to the conservative focus on regarding only regression results with p-values of smaller than 0.10, I come to the following four conclusions.

First, only households in JC Agraharam utilize income from NREGA wages immediately

Table 3.6: Borrowings via Formal and Microfinance Institutions Regressed on NREGA Income

	Received				Repaid			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu	Aurepalle	Dokur	JC Agraharam	Pamidipadu
	DV: Formal Loan (in logs)							
Admin. NREGA Income (in logs)								
Contemporaneous	−0.021	−0.084**	−0.004	0.014	−0.035	−0.002	−0.009	−0.016
	(0.027)	(0.041)	(0.003)	(0.055)	(0.031)	(0.027)	(0.007)	(0.029)
Lag 1	0.000	0.011	−0.001	−0.017	−0.009	0.021	0.004	−0.014
	(0.022)	(0.040)	(0.003)	(0.047)	(0.025)	(0.031)	(0.007)	(0.033)
Lag 2	0.014	0.020	0.002	0.021	0.030	−0.015	0.001	−0.040
	(0.032)	(0.037)	(0.006)	(0.052)	(0.030)	(0.025)	(0.008)	(0.035)
Lag 3	−0.022	−0.016	−0.002	−0.069	−0.004	0.032	0.003	0.001
	(0.029)	(0.037)	(0.003)	(0.048)	(0.027)	(0.022)	(0.006)	(0.030)
P-value (F): Lagged Income	0.90	0.94	0.77	0.34	0.79	0.39	0.86	0.42
P-value (F): Contemp. & Lagged Income	0.91	0.11	0.77	0.49	0.76	0.43	0.58	0.34
Mean: DV	1189	915	48	2493	432	404	25	857
Mean: Admin. Income	272	605	329	561	272	605	329	561
	DV: SHG Loan (in logs)							
Admin. NREGA Income (in logs)								
Contemporaneous	−0.059*	−0.012	−0.014	0.018	0.027	−0.061	0.024	−0.023
	(0.033)	(0.029)	(0.013)	(0.038)	(0.037)	(0.039)	(0.040)	(0.049)
Lag 1	0.054**	−0.018	0.012	0.133**	0.035	0.026	0.054	−0.082
	(0.027)	(0.034)	(0.018)	(0.058)	(0.038)	(0.038)	(0.038)	(0.057)
Lag 2	0.017	0.035	0.013	0.060	−0.056	0.068	0.075*	−0.002
	(0.017)	(0.033)	(0.014)	(0.047)	(0.036)	(0.043)	(0.040)	(0.055)
Lag 3	−0.021	−0.001	−0.018	−0.084	0.015	0.086**	0.076*	0.139**
	(0.022)	(0.028)	(0.023)	(0.072)	(0.037)	(0.039)	(0.040)	(0.059)
P-value (F): Lagged Income	0.15	0.76	0.54	0.10	0.41	0.00	0.01	0.12
P-value (F): Contemp. & Lagged Income	0.26	0.88	0.45	0.18	0.45	0.00	0.02	0.21
Mean: DV	165	370	253	945	494	319	308	688
Mean: Admin. Income	272	605	329	561	272	605	329	561
Months	34	25	43	26	34	25	43	26
Households	26	19	20	17	26	19	20	17
Observations	884	475	842	441	884	475	842	441
Min Month	2012m1	2010m10	2011m4	2011m4	2012m1	2010m10	2011m4	2011m4
Max Month	2014m10	2012m10	2014m10	2014m10	2014m10	2012m10	2014m10	2014m10

Notes: All regressions include month and household fixed effects. The sample is restricted to ICRISAT-NREGA households.

Table 3.7: Borrowings via Informal Institutions Regressed on NREGA Income

	Received				Repaid			
	Aurepalle	**Dokur**	**JC Agraharam**	**Pamidipadu**	**Aurepalle**	**Dokur**	**JC Agraharam**	**Pamidipadu**
	DV: Friends & Rel. Loan (in logs)							
Admin. NREGA Income (in logs)								
Contemporaneous	0.002	−0.015	0.033	0.022	0.029	0.048	−0.036**	0.037
	(0.044)	(0.050)	(0.034)	(0.040)	(0.023)	(0.034)	(0.018)	(0.053)
Lag 1	0.045	0.040	−0.012	0.119**	−0.001	0.009	0.001	0.041
	(0.050)	(0.046)	(0.040)	(0.054)	(0.030)	(0.038)	(0.023)	(0.073)
Lag 2	−0.001	−0.013	0.036	−0.074	0.008	−0.048	−0.020	−0.014
	(0.051)	(0.046)	(0.043)	(0.055)	(0.032)	(0.051)	(0.025)	(0.041)
Lag 3	0.006	0.003	−0.012	−0.031	0.028	−0.001	−0.009	−0.073
	(0.040)	(0.046)	(0.039)	(0.063)	(0.036)	(0.046)	(0.021)	(0.055)
P-value (F): Lagged Income	0.82	0.84	0.86	0.13	0.76	0.69	0.80	0.54
P-value (F): Contemp. & Lagged Income	0.90	0.91	0.81	0.20	0.55	0.57	0.29	0.67
Mean: DV	1791	949	1182	923	1511	494	318	751
Mean: Admin. Income	272	605	329	561	272	605	329	561
	DV: Money Lender Loan (in logs)							
Admin. NREGA Income (in logs)								
Contemporaneous	−0.020	−0.056**	−0.024	−0.005	0.021	−0.009	0.005	−0.001
	(0.021)	(0.027)	(0.026)	(0.013)	(0.013)	(0.010)	(0.028)	(0.002)
Lag 1	−0.027	−0.019	0.031	0.015	0.005	0.011	−0.009	−0.006
	(0.018)	(0.019)	(0.024)	(0.022)	(0.014)	(0.020)	(0.027)	(0.006)
Lag 2	−0.004	−0.006	−0.029	−0.061	−0.024*	−0.037	0.031	−0.001
	(0.029)	(0.019)	(0.020)	(0.044)	(0.014)	(0.039)	(0.020)	(0.002)
Lag 3	−0.005	−0.020	0.031	0.032	−0.017	−0.030	−0.049**	0.004
	(0.027)	(0.029)	(0.021)	(0.025)	(0.018)	(0.032)	(0.022)	(0.004)
P-value (F): Lagged Income	0.46	0.39	0.21	0.48	0.30	0.24	0.10	0.82
P-value (F): Contemp. & Lagged Income	0.52	0.09	0.33	0.37	0.30	0.29	0.18	0.92
Mean: DV	590	294	586	145	295	245	388	6
Mean: Admin. Income	272	605	329	561	272	605	329	561
Months	34	25	43	26	34	25	43	26
Households	26	19	20	17	26	19	20	17
Observations	884	475	842	441	884	475	842	441
Min Month	2012m1	2010m10	2011m4	2011m4	2012m1	2010m10	2011m4	2011m4
Max Month	2014m10	2012m10	2014m10	2014m10	2014m10	2012m10	2014m10	2014m10

Notes: All regressions include month and household fixed effects. The sample is restricted to ICRISAT-NREGA households.

for consumption expenditures. Thus, there is evidence for consumption smoothing in Aurepalle, Dokur, and Pamidipadu, but not in JC Agraharam. Second, from all forms of borrowings loan repayments to microfinance institutions are the only mechanisms identified to be responding to changes in wage income. It is worth noting, that I find such behavior for JC Agraharam - the only village where consumption is not insured against income shocks. Recall that JC Agraharam is also the village with the least exposure to formal banking (see Table 3.18 or Section 3.4.2). Hence, new forms of insurance in the form of an employment guarantee (NREGA) and microfinance might be vital to increase consumption. Besides this, JC Agraharam is the poorest village of the four in terms of household consumption expenditure. From this perspective, the regression results underscore the immediate benefits public initiatives like the NREGA or new forms of finance may bring about. Overall, for JC Agraharam, I can track the utilization of an additional INR 100 almost entirely; at least in so far as about INR 66 are used for consumption, INR 20 are used to pay back microfinance loans and INR 17 are deposited into saving accounts while INR 3 are deducted from informal saving accounts. Third, in the slightly richer villages, consumption does not react to changes in wage income from the NREGA. This may be so, since NREGA income is relatively small in comparison to consumption expenditure in these villages. At the same time, I find that certain financial market transactions can be statistically identified in these villages. Aurepalle, the most diverse village in terms of financial means, sees savings deposited at informal institutions being reduced as a response to positive changes in wage income. While it is certainly an interesting finding, I cannot statistically identify other mechanisms or outflows to track where the savings are invested. Even though the statistical properties for the sample of Aurepalle speak for the possibility of identifying mechanisms - such as sample size, supply-side shocks in NREGA works - the huge portfolio of financial options may be a constraint in itself. For instance, if a household diverts tiny amounts of the small increase in wages to every single kind of loan repayment or saving option the statistical framework employed cannot identify such movements. In addition, there may be other financial transactions such as investments in agriculture or education which are not captured in this analysis. And finally, in Dokur, the second poorest village of the four sample villages, I see an increase in microfinance loan repayments as a response to changes in wage income. As discussed in Section 3.4.2 both Dokur and JC Agraharam are the least exposed to formal banking as inferred from either their saving or borrowing behaviour. Hence, one may reason that these households are particularly vulnerable and depend even more on microfinance institutions as estimated in the regression analyses.

3.6.3 Results and Discussion of Gender-wise Payments

Recall that women account for at least 50 per cent of all NREGA workers in the sample villages, and depending on the village, for example Aurepalle, the share may even reach

Table 3.8: Consumption Regressed on Gender-wise NREGA Income

	DV: HH Consumption Expenditure (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Imputed Male Income (in logs)				
Contemporaneous	−0.011	0.022	−0.014*	−0.005
	(0.011)	(0.018)	(0.009)	(0.010)
Lag 1	−0.009	0.007	0.014	0.015
	(0.012)	(0.016)	(0.015)	(0.017)
Lag 2	0.022	0.003	0.015	−0.001
	(0.014)	(0.014)	(0.016)	(0.012)
Lag 3	0.006	−0.003	0.002	−0.012
	(0.011)	(0.014)	(0.009)	(0.014)
Imputed Female Income (in logs)				
Contemporaneous	−0.004	−0.008	0.019**	−0.001
	(0.006)	(0.017)	(0.009)	(0.010)
Lag 1	−0.000	−0.008	0.016	−0.018
	(0.008)	(0.017)	(0.016)	(0.014)
Lag 2	−0.015**	−0.012	−0.012	0.013
	(0.007)	(0.013)	(0.015)	(0.015)
Lag 3	−0.013*	−0.004	0.017*	0.010
	(0.008)	(0.012)	(0.009)	(0.019)
P-value (F): Lagged Male Income	0.34	0.97	0.45	0.63
P-value (F): Contemp. & Lagged Male Income	0.27	0.07	0.29	0.75
P-value (F): Lagged Female Income	0.03	0.51	0.20	0.31
P-value (F): Contemp. & Lagged Female Income	0.06	0.34	0.02	0.47
P-value (F): Male & Female Income	0.07	0.21	0.00	0.73
Mean: DV	5820	5517	4806	8795
Mean: Male Income	44	195	181	226
Mean: Female Income	229	409	148	336
Months	34	25	43	26
Households	26	19	20	17
Observations	884	475	842	441
Min Month	2012m1	2010m10	2011m4	2011m4
Max Month	2014m10	2012m10	2014m10	2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

90 per cent. In this section, I present and discuss the results based on regression equation 3.23 where imputed gender-wise wage payments are included as explanatory variables. For briefness, I focus in this discussion on the results for consumption smoothing (Table 3.8) and the results for microfinance loan repayments (Table 3.9).[22] In each table, I report two separate blocks of coefficients: one for imputed male wage payments and one for imputed female wage payments, along with block-wise p-values of the F-test on joint significance.

Consumption Smoothing

The F-test is our guide for the most conservative estimates. Based on that, I find for JC Agraharam that consumption responds positively to changes in female wage income but not to changes in male wage income. With a propensity of higher than one (1.29) female wage income is fully utilized for consumption. Therefore, I conjecture that the evidence against consumption smoothing in JC Agraharam (Section 3.6.2) is largely driven by female

[22] Tables 3.26 to 3.32 present results for all other outcome variables. Mostly, the p-values of the F-tests are very high.

wage income. To put the results in context, think of the total propensity to consume (.6) as the sum of the wage-share-weighted female and male propensities to consume. The female wage-share-weighted propensity to consume is $1.29 * (148/329) = 0.6$. Hence, female wage payments alone suffice to explain the propensity in consumption. For Aurepalle, on the other hand, negative coefficients for female wage income point towards a different direction and possibly a different scenario altogether. Here, an increase in female wage income reduces expenditures for consumption as the corresponding propensity is negative and similarly huge in magnitude (-1.3).

Financial Transactions: Microfinance

In Table 3.9, the statistically significant results for JC Agraharam indicate that repayments of microfinance loans respond to female wages. Propensities are relatively huge (1.01), so that the wage-share-weighted propensity to pay back microfinance loans (0.45) overshoots the total propensity (0.2). Since the wage-share-weighted propensity for male wages is negative (-.23) in total the propensity of 0.2 can be established. In Dokur, the relationship is reversed. Here, male NREGA income is largely used to repay microfinance loans instead of female income. In fact, an increase in female wage payments lowers repayments to microfinance institutions. In Pamidipadu, several statistically significant point estimates for male wage income with negative and positive signs add up to an elasticity of -0.03 and yield a propensity of -0.09. For Pamidipadu, I also find that female wages and not male wages are used to pay back loans borrowed from friends and relatives. As these effects cancel out, no effects can be found when wage payments are not dis-aggregated by gender (see Table 3.7).

Discussion

The gender-wise results yield that especially in JC Agraharam female wages seem to have a great impact on intra-household financial decision making. Female workers appear to have autonomy over their wages and decide that they be spent on consumption and microfinance groups, which happen to be largely populated by women. However, such high propensities on both consumption and microfinance repayments seem puzzling as they add up to much more than one. Consider though, that the ratio of administrative to self reported NREGA work days is about one half, implying that the administrative work days are under-reported by 50 per cent.[23] This leads to biased results in the propensities. A lower denominator in the multiplier of the elasticity - and one may argue this case especially for female wages - increases the multiplier and thus increases the propensity. Therefore, to yield conservative estimates for JC Agraharam one would have to divide all propensities by a factor of two.

[23]There is a variety of reasons for such a mismatch. One may be that additional job cards used by households were not reported to us during the survey.

Table 3.9: Microfinance Loan Repayments Regressed on Gender-wise NREGA Income

	DV: Microfinance Loans (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Imputed Male Income (in logs)				
Contemporaneous	−0.036	0.063	−0.086	−0.063
	(0.056)	(0.041)	(0.060)	(0.051)
Lag 1	0.021	0.065*	−0.084	−0.097*
	(0.065)	(0.040)	(0.062)	(0.059)
Lag 2	−0.046	0.069*	−0.039	−0.010
	(0.068)	(0.042)	(0.062)	(0.055)
Lag 3	0.123**	0.074*	−0.022	0.140**
	(0.058)	(0.044)	(0.064)	(0.061)
Imputed Female Income (in logs)				
Contemporaneous	0.041	−0.091**	0.108	−0.001
	(0.038)	(0.043)	(0.066)	(0.053)
Lag 1	0.040	−0.010	0.149**	−0.028
	(0.040)	(0.037)	(0.068)	(0.058)
Lag 2	−0.044	0.044	0.123*	−0.008
	(0.039)	(0.041)	(0.067)	(0.053)
Lag 3	−0.005	0.067	0.106	0.037
	(0.038)	(0.043)	(0.065)	(0.055)
P-value (F): Lagged Male Income	0.18	0.00	0.50	0.05
P-value (F): Contemp. & Lagged Male Income	0.20	0.00	0.32	0.02
P-value (F): Lagged Female Income	0.54	0.17	0.01	0.91
P-value (F): Contemp. & Lagged Female Income	0.40	0.07	0.01	0.97
P-value (F): Male & Female Income	0.30	0.00	0.02	0.13
Mean: DV	494	319	308	688
Mean: Male Income	44	195	181	226
Mean: Female Income	229	409	148	336
Months	34	25	43	26
Households	26	19	20	17
Observations	884	475	842	441
Min Month	2012m1	2010m10	2011m4	2011m4
Max Month	2014m10	2012m10	2014m10	2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

3.7 Robustness Checks

3.7.1 Serial Correlation in Wage Income

Based on the PIH equation 3.5 one may conjecture that realized income is correlated with income of the preceding period. I test for serial correlation in the main explanatory variable, wage income as recorded in administrative records by regressing wage income in month t on wage income of eight preceding periods. The panel data regressions are similar to the main specification of equation 3.22, such that:

$$ADMIN_{it} = \mu_i + \gamma_t + \sum_{\tau=1}^{8} \beta_\tau ADMIN_{it-\tau} + \epsilon_{it}, \tag{3.24}$$

where μ_i is a household fixed effect, γ_t a month fixed effect, and the summation includes eight betas of interest. As before ϵ_{it} is a stochastic error term. Table 3.10 presents the village-wise regression results for the test of serial correlation in wage income. Even though in every village-wise regression the coefficient for the first lag is statistically significant, it is quite small in magnitude and far below one, indicating that there is no evidence for serial correlation.

3.7.2 Sample Period Extension

One may argue that the main results depend heavily on the sample period chosen, and that the village-wise trimming has been hand-picked. In this section, we present evidence against this argument. As a robustness check I change the trimming of sample months to a uniform period across villages, i.e. to the period applied in tests for JC Agraharam. Results for tests on consumption smoothing are reported in Table 3.11. While the number observations for JC Agraharam remains the same as before, I now include more observations in every other village-wise regression. The sample period now begins earlier in Aurepalle, April 2011 instead of January 2012; it ends later in Dokur, October 2014 instead of October 2012; and no intervals occur for Pamidipadu.

Results in Table 3.11 show that the main results remain robust to the inclusion of additional months. Evidence for consumption smoothing in three villages remains stable. In Tables 3.12 and 3.13, I report results for the untrimmed sample analogous to Table 3.7, where results for the trimmed sample are set out. The majority of results remains stable, as most of the p-values of the F-tests remain high, except as before for regressions with loan repayments to microfincance groups as the outcome variable, in JC Agraharam and Dokur. The only change occurs for Dokur: the estimates for formal borrowings (received) are now jointly significantly different from zero according to the F-test. This is due to a lower standard error of the coefficient for contemporaneous income which is probably induced by the increased sample size, and thus the higher precision of the estimate.

3.8 Conclusion

Much research on testing full insurance in village economies yields that consumption is largely insured against idiosyncratic income shocks. Like Townsend (1994), however, while providing evidence for almost full insurance, many studies conjecture that especially the poorest cannot compensate for the risks of volatile income sufficiently. Jalan and Ravallion (1999) show in their study of rural Chinese households that the poorest are the least able to smooth consumption. Gaurav (2015) finds such “wealth differentiated heterogeneity” in the ability of coping with risk for rural households in central India.

In this paper, tests for consumption smoothing in Indian villages extend the above arguments. On the one hand, the results echo earlier findings in support of quasi-full insurance: consumption is robust to changes in income in the majority (three of four) of sample villages. On the other hand, in the smallest and poorest sample village, consumption reacts strongly to changes in income. Furthermore, and in particular in this village, while formal borrowing

Table 3.10: Test for Serial Correlation in Admin. NREGA Wage

	DV: Admin. NREGA Wage , contemporaneous (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Admin. NREGA Income (in logs)				
Lag 1	0.245***	0.318***	0.115***	0.177***
	(0.043)	(0.061)	(0.042)	(0.065)
Lag 2	0.111***	0.162***	−0.051	0.192**
	(0.042)	(0.054)	(0.043)	(0.081)
Lag 3	−0.007	0.007	0.025	−0.004
	(0.037)	(0.066)	(0.042)	(0.076)
Lag 4	−0.051	−0.193***	−0.051	0.076
	(0.035)	(0.067)	(0.036)	(0.078)
Lag 5	−0.069*	0.090	−0.059	−0.234**
	(0.036)	(0.066)	(0.043)	(0.091)
Lag 6	0.015	0.020	−0.029	0.044
	(0.029)	(0.057)	(0.042)	(0.083)
Lag 7	−0.040	−0.028	0.011	0.140
	(0.030)	(0.063)	(0.041)	(0.101)
Lag 8	−0.017	−0.200***	−0.083**	−0.014
	(0.035)	(0.069)	(0.040)	(0.087)
P-value (F): Sum of Lagged Income = 0	0.02	0.13	0.29	0.02
Mean: DV	272	756	346	373
Months	34	20	38	21
Households	26	19	20	17
Observations	884	380	742	356
Min Month	2012m1	2011m3	2011m9	2011m9
Max Month	2014m10	2012m10	2014m10	2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households. All regressions include household and month fixed effects.

Table 3.11: Consumption Regressed on NREGA Income with "Untrimmed" Sample

	DV: HH Consumption Expenditure (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Admin. NREGA Income (in logs)				
Contemporaneous	−0.002	0.011	−0.001	−0.003
	(0.006)	(0.008)	(0.006)	(0.009)
Lag 1	−0.005	−0.002	0.025***	0.008
	(0.007)	(0.007)	(0.007)	(0.013)
Lag 2	−0.006	−0.005	0.003	−0.004
	(0.007)	(0.007)	(0.008)	(0.011)
Lag 3	−0.008	0.002	0.017**	−0.008
	(0.006)	(0.006)	(0.007)	(0.013)
P-value (F): Lagged Income	0.30	0.88	0.00	0.84
P-value (F): Contemp. & Lagged Income	0.45	0.71	0.00	0.93
Mean: DV	6148	4947	4806	8887
Mean: Admin. Income	248	427	329	358
Months	43	43	43	43
Households	26	19	20	17
Observations	1118	813	842	730
Min Month	2011m4	2011m4	2011m4	2011m4
Max Month	2014m10	2014m10	2014m10	2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Table 3.12: Borrowings via Formal and Microfinance Institutions Regressed on NREGA Income with "Untrimmed" Sample

	Received				Repaid			
	Aurepalle	**Dokur**	**JC Agraharam**	**Pamidipadu**	**Aurepalle**	**Dokur**	**JC Agraharam**	**Pamidipadu**
	DV: Formal Loan (in logs)							
Admin. NREGA Income (in logs)								
Contemporaneous	−0.026	−0.078***	−0.004	−0.005	−0.036	−0.012	−0.009	−0.009
	(0.022)	(0.026)	(0.003)	(0.045)	(0.025)	(0.028)	(0.007)	(0.028)
Lag 1	−0.012	0.010	−0.001	−0.001	0.001	−0.001	0.004	0.032
	(0.019)	(0.028)	(0.003)	(0.046)	(0.021)	(0.031)	(0.007)	(0.037)
Lag 2	0.033	0.003	0.002	−0.002	0.042	0.004	0.001	−0.033
	(0.029)	(0.023)	(0.006)	(0.040)	(0.027)	(0.029)	(0.008)	(0.028)
Lag 3	−0.020	−0.008	−0.002	−0.044	0.014	0.029	0.003	−0.036
	(0.023)	(0.022)	(0.003)	(0.034)	(0.024)	(0.028)	(0.006)	(0.027)
P-value (F): Lagged Income	0.67	0.97	0.77	0.43	0.32	0.73	0.86	0.23
P-value (F): Contemp. & Lagged Income	0.68	0.02	0.77	0.60	0.35	0.85	0.58	0.36
Mean: DV	1041	822	48	2632	384	550	25	1019
	DV: SHG Loan (in logs)							
Admin. NREGA Income (in logs)								
Contemporaneous	−0.005	0.010	−0.014	0.004	0.007	−0.028	0.024	−0.011
	(0.032)	(0.022)	(0.013)	(0.035)	(0.030)	(0.033)	(0.040)	(0.041)
Lag 1	0.045	0.012	0.012	0.130***	0.036	0.043	0.054	−0.046
	(0.030)	(0.024)	(0.018)	(0.047)	(0.032)	(0.035)	(0.038)	(0.044)
Lag 2	0.023	−0.019	0.013	0.051	−0.054*	0.066*	0.075*	0.009
	(0.025)	(0.025)	(0.014)	(0.036)	(0.031)	(0.035)	(0.040)	(0.040)
Lag 3	−0.026	0.018	−0.018	−0.040	0.019	0.074**	0.076*	0.086**
	(0.024)	(0.024)	(0.023)	(0.051)	(0.031)	(0.032)	(0.040)	(0.040)
P-value (F): Lagged Income	0.16	0.82	0.54	0.03	0.30	0.00	0.01	0.16
P-value (F): Contemp. & Lagged Income	0.14	0.83	0.45	0.07	0.44	0.00	0.02	0.26
Mean: DV	297	383	253	968	422	236	308	720

Notes: All regressions include month and household fixed effects. The sample is restricted to ICRISAT-NREGA households.

Table 3.13: Borrowings via Informal Institutions Regressed on NREGA Income with "Untrimmed" Sample

	Received				Repaid			
	Aurepalle	**Dokur**	**JC Agraharam**	**Pamidipadu**	**Aurepalle**	**Dokur**	**JC Agraharam**	**Pamidipadu**
	DV: Friends & Rel. Loan (in logs)							
Admin. NREGA Income (in logs)								
Contemporaneous	−0.015	−0.052	0.033	0.016	0.040*	0.001	−0.036**	0.006
	(0.040)	(0.044)	(0.034)	(0.037)	(0.023)	(0.029)	(0.018)	(0.043)
Lag 1	0.054	−0.048	−0.012	0.083*	0.009	0.007	0.001	0.012
	(0.046)	(0.045)	(0.040)	(0.048)	(0.028)	(0.029)	(0.023)	(0.056)
Lag 2	0.005	−0.025	0.036	−0.079	0.016	−0.048	−0.020	0.027
	(0.046)	(0.043)	(0.043)	(0.051)	(0.029)	(0.038)	(0.025)	(0.041)
Lag 3	0.026	0.047	−0.012	0.001	0.038	−0.026	−0.009	−0.097**
	(0.040)	(0.044)	(0.039)	(0.052)	(0.032)	(0.034)	(0.021)	(0.041)
P-value (F): Lagged Income	0.48	0.52	0.86	0.23	0.32	0.28	0.80	0.09
P-value (F): Contemp. & Lagged Income	0.65	0.13	0.81	0.37	0.09	0.43	0.29	0.16
Mean: DV	1750	1304	1182	1723	1343	423	318	954
	DV: Money Lender Loan (in logs)							
Admin. NREGA Income (in logs)								
Contemporaneous	−0.013	−0.001	−0.024	−0.007	0.017	0.005	0.005	−0.003
	(0.025)	(0.020)	(0.026)	(0.009)	(0.016)	(0.010)	(0.028)	(0.002)
Lag 1	0.003	0.001	0.031	0.015	−0.005	0.023	−0.009	−0.004
	(0.026)	(0.013)	(0.024)	(0.016)	(0.016)	(0.017)	(0.027)	(0.004)
Lag 2	0.009	−0.007	−0.029	−0.041	−0.025*	−0.015	0.031	0.001
	(0.029)	(0.014)	(0.020)	(0.031)	(0.015)	(0.027)	(0.020)	(0.002)
Lag 3	−0.033	−0.012	0.031	0.018	0.002	−0.003	−0.049**	0.001
	(0.023)	(0.018)	(0.021)	(0.017)	(0.022)	(0.022)	(0.022)	(0.003)
P-value (F): Lagged Income	0.54	0.52	0.21	0.60	0.40	0.61	0.10	0.81
P-value (F): Contemp. & Lagged Income	0.55	0.68	0.33	0.35	0.50	0.76	0.18	0.83
Mean: DV	718	258	586	93	502	144	388	10
Mean: Admin. Income	248	427	329	358	248	427	329	358
Months	43	43	43	43	43	43	43	43
Households	26	19	20	17	26	19	20	17
Observations	1118	813	842	730	1118	813	842	730
Min Month	2011m4	2011m4	2011m4	2011m4	2011m4	2011m4	2011m4	2011m4
Max Month	2014m10	2014m10	2014m10	2014m10	2014m10	2014m10	2014m10	2014m10

Notes: All regressions include month and household fixed effects. The sample is restricted to ICRISAT-NREGA households. Time periods as indicated in Table 3.13.

practices are not common, microfinance institutions provide a vital tool for accessing finance. Findings for the said village reveal that wage income gains from public works translate almost entirely into consumption expenditure and the repayment of microfinance loans. Thus, this paper provides empirical evidence to substantiate that the poorest depend on at least two institutions to cope with volatile income: public safety nets for wage income and microfinance institutions for credit. In addition, changes in the same outcome variables as a response to gender-wise wage payments shed light on intra-household allocations of income and the positive effects women empowerment has on household welfare.

Furthermore, this study highlights that a plethora of financial means may exist to varying degrees in Indian villages, ranging from formal banking, microfinance, borrowing and lending among friends and relatives to borrowing from the traditional money lender. The adoption of these is highly context dependent. In panel estimations, several of them respond statistically significantly to changes in income, contributing to the literature on consumption smoothing mechanisms in developing countries (e.g. Fafchamps and Lund, 2003; Chiappori et al., 2014). Village-wise data on financial access indicate the importance of mutual insurance in the form of borrowing and lending among relatives and friends.

While previous studies on consumption smoothing are either potentially biased towards the null hypothesis of complete markets due to measurement error in self reported income or need to rely on instruments for income, this paper's estimation strategy exploits a unique source for income data. Administrative records on monthly wage payments from a public works program provide for an ideal income measure. It is shown empirically that the date of monthly wage payments varies exogenously due to inherent delays in the administrative setting. The empirical strategy of applying high-frequency panel data to household and month fixed effects estimations circumvents both the measurement error problem and commonly faced endogeneity issues. Since the administrative data may carry other reporting problems and may thus bias propensities upwards, I propose conservative estimates for propensities to consume and pay back loans.

In summary, the results of this paper suggest that innovations in access-to-finance policies as well as in social safety nets benefit from a holistic and context-dependent view. It is evident that households rely both on public employment as well as on innovative microfinance institutions to mitigate the risks of volatile income flows.

Appendix

3.A Figures

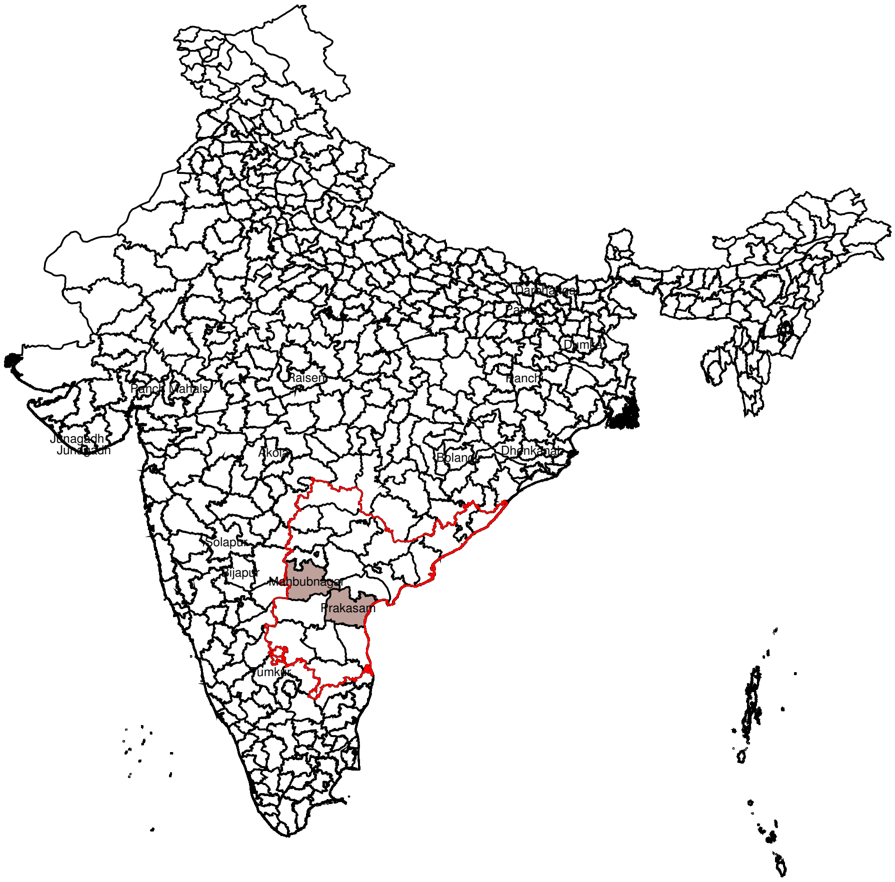
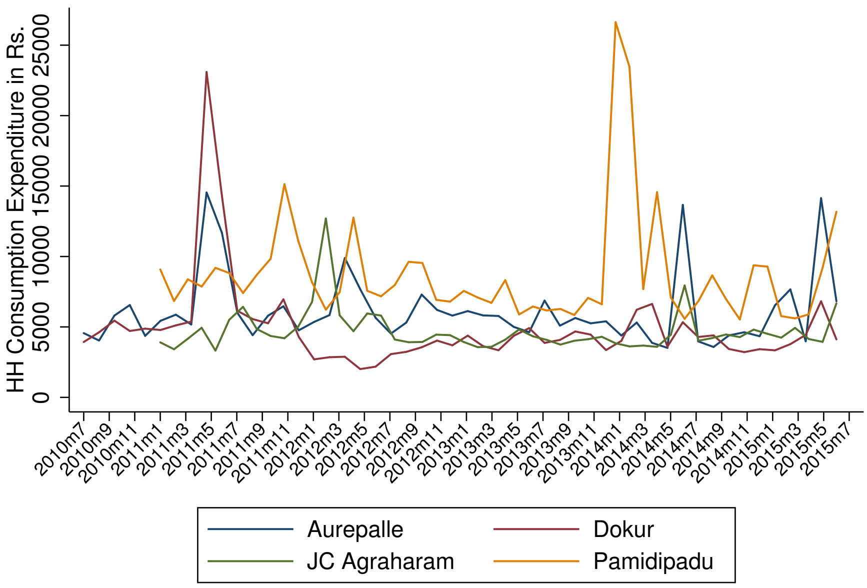
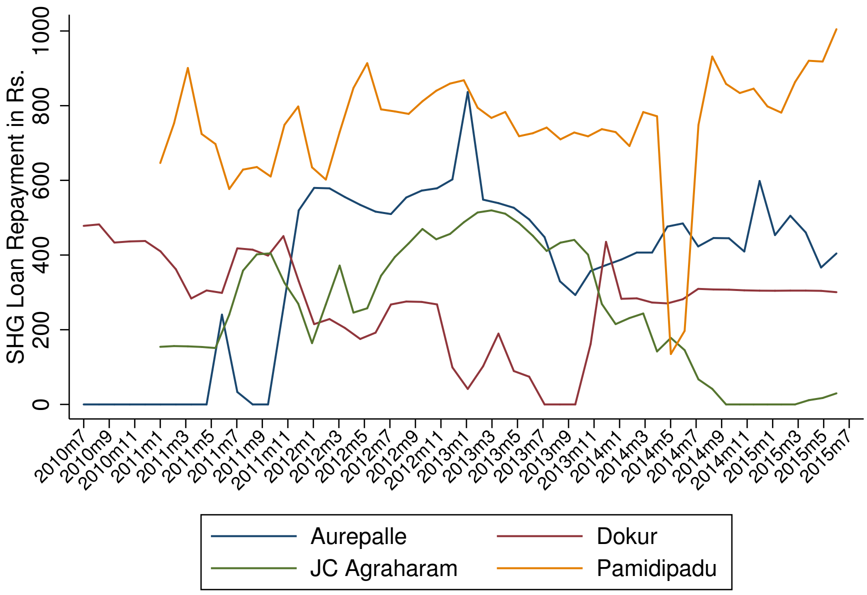


Figure 3.8: District Map of India with Districts of Sample Villages



Based on ICRISAT data; all in July 2010 prices using the CPI−AL.

Figure 3.9: Variation of Monthly Household Consumption Expenditure by Village



Based on ICRISAT data; in July 2010 prices using the CPI−AL.

Figure 3.10: Variation of Monthly Loan Repayments by Village

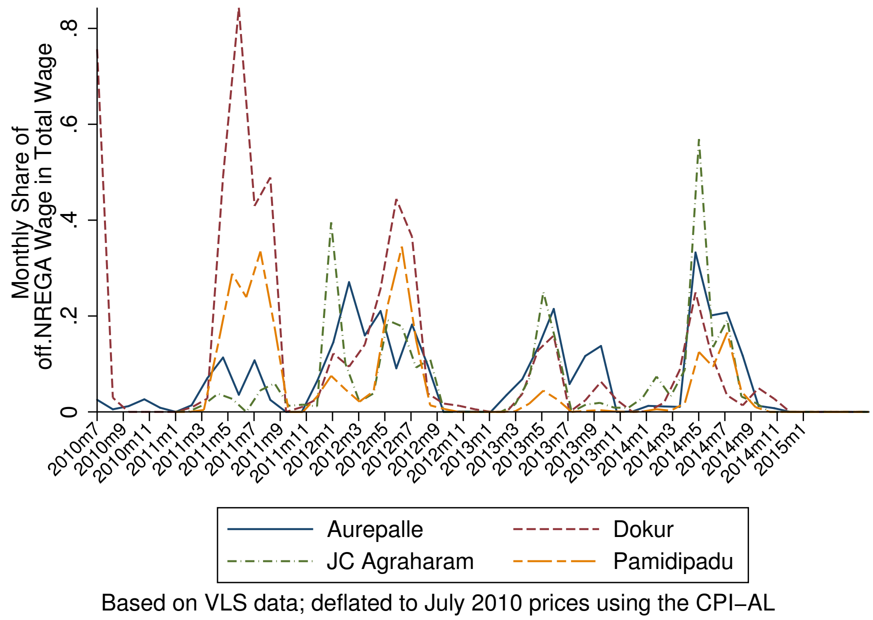


Figure 3.11: Monthly Share of Official Wage in Total Wage

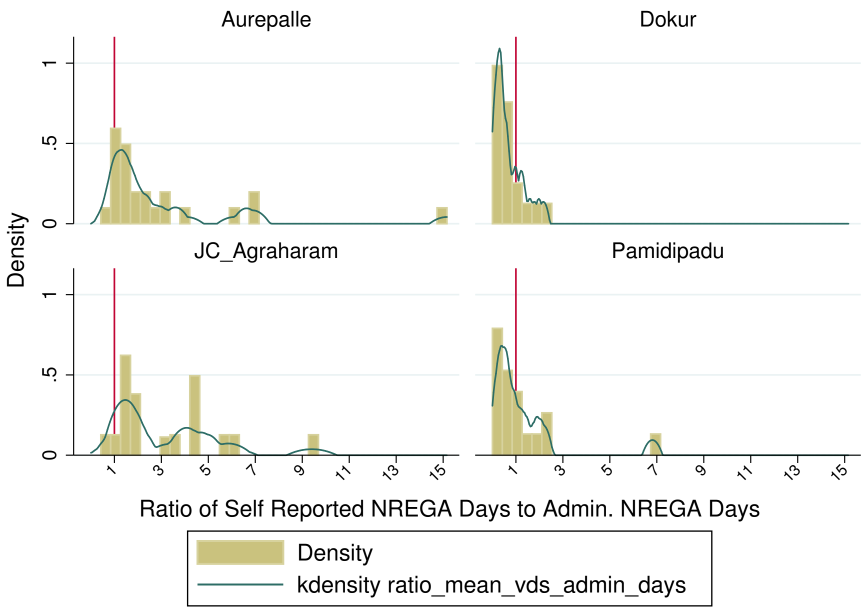


Figure 3.12: Ratio of Self Reported to Admin. NREGA Days

3.B Tables

Table 3.14: Summary Statistics by Village and Calendar Year

	Aurepalle		Dokur		JC Agraharam		Pamidipadu	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
					2011			
Self Reported NREGA Wage	241	543	83	355	256	662	535	1308
Admin. NREGA Wage	130	359	687	1336	120	414	575	1084
Total Self Reported Wage	4661	3906	3973	3362	5364	3641	11076	7909
Consumption Expenditure	6965	17101	7915	37469	4601	7272	9254	14744
Loan (Institutional) Repaid	292	1809	272	2260	64	695	9	93
Loan to Self Help Group Repaid	112	559	367	452	258	292	704	662
Loan to Friends Repaid	552	2973	680	5044	28	301	1124	3776
Loan to Money Lender Repaid	1393	6847	485	4468	39	586	0	0
Loan (Institutional) Received	438	4421	192	2081	0	0	2103	10808
Loan from Self Help Group Received	649	2863	332	2348	39	583	913	4102
Loan from Friends Received	1593	5641	1503	9111	288	2529	2227	19318
Loan from Money Lender Received	916	5769	480	4002	440	5447	309	3144
Number of Observations	312		228		222		204	
					2012			
Self Reported NREGA Wage	429	732	427	809	530	1053	161	590
Admin. NREGA Wage	332	616	584	1165	342	881	352	904
Total Self Reported Wage	5089	4583	6198	4867	5170	3211	10629	7302
Consumption Expenditure	6292	8092	3011	2024	5775	11943	8151	10276
Loan (Institutional) Repaid	297	2922	586	7708	49	338	1677	9688
Loan to Self Help Group Repaid	557	348	218	284	353	497	781	461
Loan to Friends Repaid	640	3365	147	753	230	1731	714	3106
Loan to Money Lender Repaid	242	1849	4	38	1323	8371	13	182
Loan (Institutional) Received	1312	16611	1631	10156	72	1109	2471	14748
Loan from Self Help Group Received	232	1635	165	1231	624	3080	1001	4696
Loan from Friends Received	934	4500	447	2378	989	5233	1181	6819
Loan from Money Lender Received	1100	8164	4	55	1722	12117	4	60
Number of Observations	312		228		240		203	

Notes: Author's calculations of monthly household averages from ICRISAT data.
Administrative NREGA wage and NREGA group membership is collected from administrative records.
The sample is restricted to ICRISAT-NREGA households.

Table 3.15: Summary Statistics by Village and Calendar Year

	Aurepalle		Dokur		JC Agraharam		Pamidipadu	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
2013								
Self Reported NREGA Wage	359	756	125	455	501	892	0	0
Admin. NREGA Wage	251	582	123	402	206	594	61	350
Total Self Reported Wage	5385	4785	5394	4351	4365	2455	9745	6744
Consumption Expenditure	5581	5060	4112	4300	4059	2500	6683	5377
Loan (Institutional) Repaid	505	2388	568	4381	0	0	1320	6186
Loan to Self Help Group Repaid	481	663	112	281	440	482	752	375
Loan to Friends Repaid	2583	13732	390	1836	205	2183	1705	18341
Loan to Money Lender Repaid	271	4063	81	1005	0	0	0	0
Loan (Institutional) Received	1643	19340	1110	9195	97	1498	3099	17973
Loan from Self Help Group Received	158	1633	871	4042	228	2049	739	3746
Loan from Friends Received	2949	14744	1274	5994	2560	17398	1358	14296
Loan from Money Lender Received	243	2107	354	5102	0	0	0	0
Number of Observations	312		228		240		204	
2014								
Self Reported NREGA Wage	535	867	0	0	567	882	274	598
Admin. NREGA Wage	189	418	139	367	504	1337	294	630
Total Self Reported Wage	4124	4279	4793	3683	4112	2373	10256	6495
Consumption Expenditure	5316	13157	4475	10435	4465	5703	11350	44242
Loan (Institutional) Repaid	569	4557	684	1800	0	0	753	3212
Loan to Self Help Group Repaid	451	494	292	311	109	311	677	615
Loan to Friends Repaid	1274	9706	469	2150	654	4941	408	3609
Loan to Money Lender Repaid	321	5668	32	202	0	0	24	346
Loan (Institutional) Received	682	5736	0	0	0	0	2287	18185
Loan from Self Help Group Received	79	762	159	1706	0	0	908	4925
Loan from Friends Received	1542	9091	1692	7076	591	2316	2875	30194
Loan from Money Lender Received	327	5669	87	771	0	0	21	297
Number of Observations	312		222		240		204	

Notes: Author's calculations of monthly household averages from ICRISAT data.
Administrative NREGA wage and NREGA group membership is collected from administrative records.
The sample is restricted to ICRISAT-NREGA households.

Table 3.16: Summary Statistics of Primary Data

Percentage of Households responding that	All Villages	Aurepalle	Dokur	Pamidipadu	JC Agraharam
NREGA Income is spent on Normal HH Expenses	81.48	84.62	89.47	87.50	65.00
NREGA Income is spent on SHG or Chit Fund	48.15	61.54	52.63	37.50	35.00
NREGA Income is spent on Food	35.80	26.92	36.84	43.75	40.00
NREGA Income is spent on Medical Expenses	25.93	19.23	31.58	18.75	35.00
NREGA Income is spent on School Fees	4.94	3.85	10.53	0.00	5.00
NREGA Income is spent on Dowry	1.23	0.00	5.26	0.00	0.00
NREGA Income is spent on Transport Expenses	0.00	0.00	0.00	0.00	0.00
NREGA Income is spent on Debt	0.00	0.00	0.00	0.00	0.00
NREGA Income is spent on House related Expenses	0.00	0.00	0.00	0.00	0.00
NREGA-Wages are Delayed	40.74	42.31	57.89	37.50	25.00
Neighbourhood is reason for being in this group	24.69	19.23	5.26	68.75	15.00
Caste is reason for being in this group	12.35	11.54	5.26	25.00	10.00
FA is reason for being in this group	61.73	69.23	84.21	6.25	75.00
I decided that I be in this group	12.35	7.69	26.32	12.50	5.00
Caste decided that I be in this group	14.81	23.08	0.00	25.00	10.00
FA decided that I be in this group	71.60	69.23	68.42	62.50	85.00
Number of Households	82	26	19	17	20

Source: From own survey of ICRISAT-NREGA households in September-November 2014.

Table 3.17: Sources of Loans to be Repaid (in %)

Type	Non-NREGA	NREGA Groups	Total
Self Help Group (SHG)	28	83	38
Bank or Finance Company	5	5	5
Cooperatives	1	0	1
Friends/Relatives	23	5	20
Money Lender	3	4	3
Shopkeeper	30	0	24
Other	11	2	9
Total	100	100	100

Source: ICRISAT data and self collected data on NREGA groups

Table 3.18: Financial Balance Sheet, Borrowings (Yearly)

	Sample: ICRISAT-NREGA							
	Aurepalle		Dokur		JC Agraharam		Pamidipadu	
Source:	Inci. (%)	Amt.	Inci. (%)	Amt.	Inci. (%)	Amt.	Inci. (%)	Amt.
	1st July, 2010							
Formal	69	19935	58	19368	24	3588	29	17435
SHG	69	4975	79	3084	94	10000	71	8118
Rosca	12	1592	5	1316	0	0	0	0
Informal								
Friends & Relatives	62	19135	47	12368	88	47882	29	15588
Money Lender	50	26923	37	7158	0	0	0	0
Others	54	4929	11	1368	0	0	6	588
Households	26	26	19	19	17	17	17	17
	1st July, 2011							
Formal	88	24371	63	21505	35	18007	35	21603
SHG	77	4383	68	6281	60	5420	65	5550
Rosca	23	9132	0	0	0	0	0	0
Informal								
Friends & Relatives	73	20281	58	19329	25	8714	29	27723
Money Lender	42	8756	32	21529	45	29345	6	209
Others	42	3188	11	1498	10	2579	12	889
Households	26	26	19	19	20	20	17	17
	1st July, 2012							
Formal	62	19825	53	29236	65	22519	71	31743
SHG	85	6105	53	4390	55	9049	82	9248
Rosca	23	2149	21	7024	0	0	0	0
Informal								
Friends & Relatives	77	26497	68	37006	65	32528	65	29732
Money Lender	38	17355	47	24583	0	0	0	0
Others	54	5280	16	2546	0	0	29	6623
Households	26	26	19	19	20	20	17	17
	1st July, 2013							
Formal	58	18825	53	23171	62	22005	88	45105
SHG	73	3265	26	249	48	2607	76	7953
Rosca	0	0	5	1343	0	0	0	0
Informal								
Friends & Relatives	31	21208	84	47761	81	53902	59	44247
Money Lender	19	12012	5	5754	0	0	0	0
Others	62	21726	16	2302	0	0	12	2401
Households	26	26	19	19	21	21	17	17
	1st July, 2014							
Formal	61	25142	32	9739	59	20208	79	63569
SHG	75	5759	63	4338	9	1132	68	11630
Rosca	.	.	.	.	.	.	.	.
Informal								
Friends & Relatives	46	25762	79	51528	86	64443	53	44569
Money Lender	18	1226	0	0	0	0	0	0
Others	32	12353	0	0	5	673	5	531
Households	28	28	19	19	22	22	19	19

Notes: Author's calculations of household averages from ICRISAT data as reported on 1st July of every year.
The sample is restricted to ICRISAT-NREGA households. All amounts in July 2010 prices.

Table 3.19: Financial Balance Sheet, Savings and Lendings (Yearly)

	Sample: ICRISAT-NREGA on 1st July, 2011							
	Aurepalle		Dokur		JC Agraharam		Pamidipadu	
	Inci. (%)	Amt.	Inci. (%)	Amt.	Inci. (%)	Amt.	Inci. (%)	Amt.
	1st July, 2010							
Formal	62	20985	32	15340	35	5555	76	47188
SHG	85	2456	79	2043	88	1576	94	3988
Rosca	8	1577	47	10763	0	0	12	2647
Informal								
Friends & Relatives	19	7692	63	55053	0	0	71	39588
Others (Informal)	0	0	5	1842	0	0	0	0
Others	4	4808	21	1053	0	0	0	0
Households	26	26	19	19	17	17	17	17
	1st July, 2011							
Formal	62	22773	42	14221	60	6166	82	51942
SHG	88	2999	74	1722	75	2014	88	2171
Rosca	19	3882	21	1170	0	0	24	6852
Informal								
Friends & Relatives	23	17956	32	12402	5	978	71	59578
Others (Informal)	0	0	0	0	0	0	0	0
Others	0	0	32	828	5	133	6	340
Households	26	26	19	19	20	20	17	17
	1st July, 2012							
Formal	62	19806	26	9864	55	7252	82	53313
SHG	92	2913	74	2313	80	2152	94	783
Rosca	31	6432	5	658	0	0	29	5348
Informal								
Friends & Relatives	31	13473	16	3292	25	2877	65	55931
Others (Informal)	0	0	0	0	0	0	0	0
Others	69	1317	21	1712	0	0	12	1251
Households	26	26	19	19	20	20	17	17
	1st July, 2013							
Formal	54	13122	26	9660	67	10869	100	60914
SHG	88	3029	74	1052	81	2183	82	617
Rosca	50	27703	11	1688	0	0	35	11791
Informal								
Friends & Relatives	35	28875	11	3836	33	4061	71	47216
Others (Informal)	.	.	.	.	.	.	.	.
Others	0	0	21	1726	0	0	6	468
Households	26	26	19	19	21	21	17	17
	1st July, 2014							
Formal	50	15310	5	1062	64	11677	100	50074
SHG	96	1973	63	2107	82	2289	100	891
Rosca	.	.	.	.	.	.	.	.
Informal								
Friends & Relatives	21	13698	16	3896	32	3640	53	30102
Others (Informal)	.	.	.	.	.	.	.	.
Others	0	0	0	0	0	0	0	0
Households	28	28	19	19	22	22	19	19

Notes: Author's calculations of household averages from ICRISAT data as reported on 1st July of every year.
The sample is restricted to ICRISAT-NREGA households. All amounts in July 2010 prices.

Table 3.20: Formal Saving (Received) Regressed on NREGA Income

	DV: Formal Saving (Received) (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Admin. NREGA Income (in logs)				
Contemporaneous	−0.016*	0.057**	0.023	−0.066*
	(0.009)	(0.028)	(0.019)	(0.038)
Lag 1	−0.014*	−0.019	0.021	0.043
	(0.008)	(0.023)	(0.019)	(0.032)
Lag 2	−0.006	−0.047	−0.018	0.040
	(0.007)	(0.033)	(0.022)	(0.037)
Lag 3	−0.000	0.007	0.011	0.012
	(0.007)	(0.021)	(0.016)	(0.040)
P-value (F): Lagged Income	0.35	0.31	0.53	0.45
P-value (F): Contemp. & Lagged Income	0.42	0.27	0.35	0.47
Mean: DV	175	268	85	416
Mean: Admin. Income	272	605	329	561
Months	34	25	43	26
Households	26	19	20	17
Observations	884	475	842	441
Min Month	2012m1	2010m10	2011m4	2011m4
Max Month	2014m10	2012m10	2014m10	2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Table 3.21: Microfinance Saving (Received) Regressed on NREGA Income

	Microfinance Saving (Received) (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Admin. NREGA Income (in logs)				
Contemporaneous	0.027	−0.004		−0.020
	(0.020)	(0.007)		(0.025)
Lag 1	0.016	0.001		−0.007
	(0.014)	(0.004)		(0.037)
Lag 2	0.003	−0.001		−0.015
	(0.010)	(0.004)		(0.043)
Lag 3	0.001	−0.001		0.006
	(0.012)	(0.006)		(0.034)
P-value (F): Lagged Income	0.37	0.99		0.99
P-value (F): Contemp. & Lagged Income	0.36	0.98		0.91
Mean: DV	404	72		452
Mean: Admin. Income	272	605		561
Months	34	25		26
Households	26	19		17
Observations	884	475	4825	441
Min Month	2012m1	2010m10		2011m4
Max Month	2014m10	2012m10		2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Table 3.22: Loan to Other (Received) Regressed on NREGA Income

	Loan to Other(Received) (in logs)			
	Aurepalle	**Dokur**	**JC Agraharam**	**Pamidipadu**
Admin. NREGA Income (in logs)				
Contemporaneous	−0.004	0.006	−0.017	0.008
	(0.006)	(0.019)	(0.010)	(0.011)
Lag 1	−0.002	−0.007	0.003	−0.002
	(0.004)	(0.030)	(0.004)	(0.008)
Lag 2	0.001	−0.007	−0.010	0.015
	(0.004)	(0.024)	(0.007)	(0.010)
Lag 3	−0.000	−0.013	−0.001	0.004
	(0.004)	(0.032)	(0.003)	(0.010)
P-value (F): Lagged Income	0.95	0.59	0.51	0.40
P-value (F): Contemp. & Lagged Income	0.92	0.73	0.59	0.40
Mean: DV	270	469	19	18
Mean: Admin. Income	272	605	329	561
Months	34	25	43	26
Households	26	19	20	17
Observations	884	475	842	441
Min Month	2012m1	2010m10	2011m4	2011m4
Max Month	2014m10	2012m10	2014m10	2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Table 3.23: Formal Saving (Paid) Regressed on NREGA Income

	DV: Formal Saving (Paid) (in logs)			
	Aurepalle	**Dokur**	**JC Agraharam**	**Pamidipadu**
Admin. NREGA Income (in logs)				
Contemporaneous	0.018	−0.015	0.043	−0.105**
	(0.030)	(0.037)	(0.028)	(0.046)
Lag 1	−0.019	0.015	0.052**	0.056
	(0.026)	(0.041)	(0.026)	(0.068)
Lag 2	0.001	0.007	0.061**	0.047
	(0.024)	(0.038)	(0.027)	(0.069)
Lag 3	−0.010	0.007	0.055**	0.011
	(0.025)	(0.038)	(0.026)	(0.066)
P-value (F): Lagged Income	0.80	0.92	0.00	0.62
P-value (F): Contemp. & Lagged Income	0.89	0.95	0.00	0.20
Mean: DV	174	136	233	791
Mean: Admin. Income	272	605	329	561
Months	34	25	43	26
Households	26	19	20	17
Observations	884	475	842	441
Min Month	2012m1	2010m10	2011m4	2011m4
Max Month	2014m10	2012m10	2014m10	2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Table 3.24: Microfinance Saving (Paid) Regressed on NREGA Income

	Microfinance Saving (Paid) (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Admin. NREGA Income (in logs)				
Contemporaneous	0.007	−0.020	0.015	−0.004
	(0.029)	(0.029)	(0.014)	(0.027)
Lag 1	0.010	−0.007	0.006	0.043
	(0.030)	(0.031)	(0.012)	(0.027)
Lag 2	−0.046	0.067**	−0.017	0.056*
	(0.029)	(0.034)	(0.013)	(0.029)
Lag 3	−0.034	0.036	0.003	−0.041
	(0.029)	(0.029)	(0.012)	(0.034)
P-value (F): Lagged Income	0.13	0.03	0.63	0.10
P-value (F): Contemp. & Lagged Income	0.22	0.06	0.42	0.13
Mean: DV	1290	445	36	944
Mean: Admin. Income	272	605	329	561
Months	34	25	43	26
Households	26	19	20	17
Observations	884	475	842	441
Min Month	2012m1	2010m10	2011m4	2011m4
Max Month	2014m10	2012m10	2014m10	2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Table 3.25: Loan to Other (Paid) Regressed on NREGA Income

	Loan to Other(Paid) (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Admin. NREGA Income (in logs)				
Contemporaneous	0.005	−0.029	−0.011	−0.023
	(0.021)	(0.028)	(0.016)	(0.040)
Lag 1	0.023	−0.017	−0.012	−0.042
	(0.021)	(0.028)	(0.014)	(0.049)
Lag 2	−0.001	0.040	0.003	0.004
	(0.013)	(0.028)	(0.019)	(0.051)
Lag 3	−0.023	−0.022	−0.050***	0.098**
	(0.017)	(0.031)	(0.019)	(0.042)
P-value (F): Lagged Income	0.49	0.44	0.06	0.14
P-value (F): Contemp. & Lagged Income	0.66	0.48	0.08	0.22
Mean: DV	320	269	80	792
Mean: Admin. Income	272	605	329	561
Months	34	25	43	26
Households	26	19	20	17
Observations	884	475	842	441
Min Month	2012m1	2010m10	2011m4	2011m4
Max Month	2014m10	2012m10	2014m10	2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Table 3.26: Formal Loan Repaid Regressed on Gender-wise NREGA Income

	DV: Formal Loans (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Imputed Male Income (in logs)				
Contemporaneous	−0.020	0.018	−0.010	0.029
	(0.030)	(0.039)	(0.007)	(0.039)
Lag 1	−0.046	0.031	−0.003	0.013
	(0.032)	(0.041)	(0.006)	(0.043)
Lag 2	0.054	0.037	−0.001	−0.001
	(0.044)	(0.051)	(0.006)	(0.044)
Lag 3	−0.021	−0.002	−0.002	0.016
	(0.032)	(0.045)	(0.005)	(0.045)
Imputed Female Income (in logs)				
Contemporaneous	−0.029	−0.012	−0.001	−0.037
	(0.030)	(0.029)	(0.005)	(0.038)
Lag 1	−0.005	0.015	0.008	−0.017
	(0.025)	(0.029)	(0.007)	(0.042)
Lag 2	0.026	−0.067	0.003	−0.041
	(0.029)	(0.047)	(0.008)	(0.048)
Lag 3	−0.006	0.034	0.005	−0.010
	(0.028)	(0.042)	(0.007)	(0.047)
P-value (F): Lagged Male Income	0.44	0.46	0.93	0.95
P-value (F): Contemp. & Lagged Male Income	0.57	0.40	0.67	0.88
P-value (F): Lagged Female Income	0.85	0.56	0.47	0.39
P-value (F): Contemp. & Lagged Female Income	0.85	0.61	0.63	0.20
P-value (F): Male & Female Income	0.88	0.62	0.81	0.58
Mean: DV	432	404	25	857
Mean: Male Income	44	195	181	226
Mean: Female Income	229	409	148	336
Months	34	25	43	26
Households	26	19	20	17
Observations	884	475	842	441
Min Month	2012*m*1	2010*m*10	2011*m*4	2011*m*4
Max Month	2014*m*10	2012*m*10	2014*m*10	2014*m*10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Table 3.27: Informal Loan Repaid Regressed on Gender-wise NREGA Income

	DV: Informal Loans (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Imputed Male Income (in logs)				
Contemporaneous	0.037	−0.008	0.053	0.008
	(0.026)	(0.011)	(0.036)	(0.008)
Lag 1	−0.025	0.018	−0.039	0.002
	(0.021)	(0.023)	(0.030)	(0.003)
Lag 2	−0.008	0.011	0.052**	0.004
	(0.013)	(0.030)	(0.023)	(0.004)
Lag 3	−0.029	0.011	−0.056	0.009
	(0.019)	(0.030)	(0.036)	(0.009)
Imputed Female Income (in logs)				
Contemporaneous	0.018	−0.007	−0.047	−0.006
	(0.012)	(0.013)	(0.038)	(0.006)
Lag 1	0.007	0.005	0.034	−0.007
	(0.014)	(0.019)	(0.035)	(0.007)
Lag 2	−0.023	−0.036	−0.014	−0.002
	(0.015)	(0.034)	(0.025)	(0.003)
Lag 3	−0.012	−0.030	−0.001	−0.001
	(0.019)	(0.029)	(0.034)	(0.002)
P-value (F): Lagged Male Income	0.42	0.68	0.12	0.77
P-value (F): Contemp. & Lagged Male Income	0.57	0.79	0.19	0.88
P-value (F): Lagged Female Income	0.39	0.20	0.78	0.78
P-value (F): Contemp. & Lagged Female Income	0.29	0.32	0.67	0.89
P-value (F): Male & Female Income	0.60	0.77	0.25	1.00
Mean: DV	295	245	388	6
Mean: Male Income	44	195	181	226
Mean: Female Income	229	409	148	336
Months	34	25	43	26
Households	26	19	20	17
Observations	884	475	842	441
Min Month	2012m1	2010m10	2011m4	2011m4
Max Month	2014m10	2012m10	2014m10	2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Table 3.28: Loan Repaid to Friends and Relatives Regressed on Gender-wise NREGA Income

	DV: Loan Repayments to Friends & Relatives (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Imputed Male Income (in logs)				
Contemporaneous	0.053	−0.002	−0.027	−0.017
	(0.055)	(0.035)	(0.030)	(0.051)
Lag 1	0.005	0.005	−0.051	−0.116**
	(0.049)	(0.041)	(0.034)	(0.058)
Lag 2	−0.036	0.004	−0.044	0.061
	(0.049)	(0.056)	(0.041)	(0.051)
Lag 3	−0.036	−0.047	0.001	−0.096
	(0.063)	(0.061)	(0.024)	(0.061)
Imputed Female Income (in logs)				
Contemporaneous	0.027	0.047	−0.002	0.073
	(0.023)	(0.039)	(0.027)	(0.052)
Lag 1	−0.014	0.025	0.052	0.159**
	(0.028)	(0.038)	(0.035)	(0.067)
Lag 2	0.022	−0.074	0.027	−0.066
	(0.031)	(0.064)	(0.042)	(0.056)
Lag 3	0.022	0.023	−0.003	−0.015
	(0.034)	(0.057)	(0.025)	(0.054)
P-value (F): Lagged Male Income	0.73	0.87	0.45	0.04
P-value (F): Contemp. & Lagged Male Income	0.52	0.95	0.32	0.06
P-value (F): Lagged Female Income	0.60	0.69	0.50	0.09
P-value (F): Contemp. & Lagged Female Income	0.41	0.62	0.67	0.05
P-value (F): Male & Female Income	0.48	0.82	0.55	0.08
Mean: DV	1511	494	318	751
Mean: Male Income	44	195	181	226
Mean: Female Income	229	409	148	336
Months	34	25	43	26
Households	26	19	20	17
Observations	884	475	842	441
Min Month	2012m1	2010m10	2011m4	2011m4
Max Month	2014m10	2012m10	2014m10	2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Table 3.29: Formal Loan Received Regressed on Gender-wise NREGA Income

	DV: Formal Loans Received (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Imputed Male Income (in logs)				
Contemporaneous	−0.037*	0.040	−0.005	0.054
	(0.022)	(0.025)	(0.004)	(0.048)
Lag 1	−0.005	−0.053	0.000	−0.015
	(0.047)	(0.039)	(0.003)	(0.049)
Lag 2	0.107*	−0.068*	−0.001	−0.013
	(0.059)	(0.037)	(0.003)	(0.059)
Lag 3	−0.087**	0.041	−0.001	0.022
	(0.037)	(0.038)	(0.002)	(0.048)
Imputed Female Income (in logs)				
Contemporaneous	−0.010	−0.097**	−0.000	0.018
	(0.027)	(0.044)	(0.004)	(0.048)
Lag 1	0.006	0.029	−0.003	0.015
	(0.022)	(0.047)	(0.003)	(0.055)
Lag 2	−0.011	0.046	0.004	0.030
	(0.030)	(0.043)	(0.008)	(0.059)
Lag 3	−0.005	−0.029	−0.003	−0.117*
	(0.028)	(0.037)	(0.003)	(0.068)
P-value (F): Lagged Income	0.09	0.08	0.97	0.95
P-value (F): Contemp. & Lagged Income	0.17	0.13	0.85	0.84
P-value (F): Lagged F. Share	0.97	0.59	0.76	0.36
P-value (F): Contemp. & Lagged F. Share	0.96	0.15	0.88	0.51
Mean: DV	432	404	25	857
Mean: Admin. Income	272	605	329	561
Months	34	25	43	26
Households	26	19	20	17
Observations	884	475	842	441
Min Month	2012m1	2010m10	2011m4	2011m4
Max Month	2014m10	2012m10	2014m10	2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Table 3.30: Informal Loan Received Regressed on Gender-wise NREGA Income

	DV: Informal Loans Received (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Imputed Male Income (in logs)				
Contemporaneous	−0.053*	−0.027	−0.068**	−0.035
	(0.028)	(0.023)	(0.031)	(0.031)
Lag 1	−0.023	−0.020	0.058	0.035
	(0.022)	(0.028)	(0.047)	(0.024)
Lag 2	−0.025	−0.020	−0.004	−0.017
	(0.020)	(0.038)	(0.044)	(0.029)
Lag 3	−0.028	−0.016	−0.000	0.024
	(0.021)	(0.025)	(0.022)	(0.036)
Imputed Female Income (in logs)				
Contemporaneous	−0.009	−0.044**	0.056*	0.011
	(0.023)	(0.022)	(0.034)	(0.018)
Lag 1	−0.024	−0.012	−0.032	−0.003
	(0.020)	(0.015)	(0.047)	(0.024)
Lag 2	−0.004	0.003	−0.031	−0.045
	(0.030)	(0.014)	(0.039)	(0.033)
Lag 3	0.000	−0.006	0.039	0.034
	(0.028)	(0.030)	(0.029)	(0.025)
P-value (F): Lagged Income	0.34	0.67	0.64	0.56
P-value (F): Contemp. & Lagged Income	0.24	0.52	0.23	0.61
P-value (F): Lagged F. Share	0.60	0.81	0.36	0.29
P-value (F): Contemp. & Lagged F. Share	0.73	0.22	0.36	0.42
Mean: DV	295	245	388	6
Mean: Admin. Income	272	605	329	561
Months	34	25	43	26
Households	26	19	20	17
Observations	884	475	842	441
Min Month	2012m1	2010m10	2011m4	2011m4
Max Month	2014m10	2012m10	2014m10	2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Table 3.31: Microfinance Loan Received Regressed on Gender-wise NREGA Income

	DV: SHG Loans Received (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Imputed Male Income (in logs)				
Contemporaneous	0.026	−0.043	−0.003	−0.029
	(0.047)	(0.029)	(0.023)	(0.046)
Lag 1	−0.008	0.071**	0.004	0.078
	(0.036)	(0.035)	(0.050)	(0.057)
Lag 2	0.025	0.070	−0.036	0.067
	(0.035)	(0.044)	(0.039)	(0.051)
Lag 3	−0.061**	−0.030	0.039	−0.030
	(0.025)	(0.043)	(0.045)	(0.052)
Imputed Female Income (in logs)				
Contemporaneous	−0.066**	0.028	−0.010	0.035
	(0.032)	(0.031)	(0.024)	(0.041)
Lag 1	0.054*	−0.039	0.003	0.013
	(0.031)	(0.038)	(0.056)	(0.056)
Lag 2	0.010	−0.039	0.047	0.005
	(0.020)	(0.039)	(0.040)	(0.058)
Lag 3	−0.008	−0.008	−0.059	−0.008
	(0.024)	(0.039)	(0.048)	(0.059)
P-value (F): Lagged Income	0.06	0.02	0.78	0.25
P-value (F): Contemp. & Lagged Income	0.11	0.05	0.89	0.39
P-value (F): Lagged F. Share	0.28	0.25	0.50	1.00
P-value (F): Contemp. & Lagged F. Share	0.32	0.40	0.63	0.94
Mean: DV	494	319	308	688
Mean: Admin. Income	272	605	329	561
Months	34	25	43	26
Households	26	19	20	17
Observations	884	475	842	441
Min Month	2012m1	2010m10	2011m4	2011m4
Max Month	2014m10	2012m10	2014m10	2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Table 3.32: Loan Received from Friends and Relatives Regressed on Gender-wise NREGA Income

	DV: Loan Received from Friends & Relatives (in logs)			
	Aurepalle	**Dokur**	**JC Agraharam**	**Pamidipadu**
Imputed Male Income (in logs)				
Contemporaneous	0.041	0.036	−0.040	0.047
	(0.081)	(0.068)	(0.079)	(0.039)
Lag 1	−0.135*	−0.039	0.036	0.020
	(0.077)	(0.090)	(0.072)	(0.053)
Lag 2	0.034	0.041	0.098	−0.003
	(0.074)	(0.066)	(0.072)	(0.058)
Lag 3	−0.029	0.037	0.018	0.047
	(0.071)	(0.070)	(0.076)	(0.059)
Imputed Female Income (in logs)				
Contemporaneous	−0.014	0.007	0.085	−0.013
	(0.043)	(0.073)	(0.084)	(0.042)
Lag 1	0.074	−0.001	−0.053	0.088
	(0.051)	(0.082)	(0.077)	(0.068)
Lag 2	0.001	−0.035	−0.062	−0.057
	(0.051)	(0.059)	(0.073)	(0.070)
Lag 3	−0.002	−0.048	−0.029	−0.075
	(0.043)	(0.059)	(0.074)	(0.067)
P-value (F): Lagged Income	0.28	0.89	0.39	0.74
P-value (F): Contemp. & Lagged Income	0.42	0.93	0.46	0.70
P-value (F): Lagged F. Share	0.50	0.76	0.57	0.40
P-value (F): Contemp. & Lagged F. Share	0.66	0.88	0.53	0.40
Mean: DV	1511	494	318	751
Mean: Admin. Income	272	605	329	561
Months	34	25	43	26
Households	26	19	20	17
Observations	884	475	842	441
Min Month	2012*m*1	2010*m*10	2011*m*4	2011*m*4
Max Month	2014*m*10	2012*m*10	2014*m*10	2014*m*10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * $p<0.1$, ** $p<0.05$, *** $p<0.01$
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Table 3.33: Formal Saving (Paid) Regressed on Gender-wise NREGA Income

	DV: Formal Saving (Paid) (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Imputed Male Income (in logs)				
Contemporaneous	0.074	0.027	−0.030	−0.059
	(0.052)	(0.036)	(0.042)	(0.061)
Lag 1	0.047	−0.050	0.002	0.077
	(0.045)	(0.033)	(0.043)	(0.066)
Lag 2	0.011	−0.010	0.045	0.123**
	(0.043)	(0.043)	(0.056)	(0.061)
Lag 3	−0.088**	0.057*	−0.035	0.060
	(0.045)	(0.031)	(0.042)	(0.067)
Imputed Female Income (in logs)				
Contemporaneous	0.020	−0.024	0.084*	−0.059
	(0.030)	(0.036)	(0.045)	(0.060)
Lag 1	−0.021	0.041	0.048	0.047
	(0.026)	(0.040)	(0.046)	(0.066)
Lag 2	0.003	0.021	0.019	−0.038
	(0.023)	(0.038)	(0.056)	(0.072)
Lag 3	0.001	−0.004	0.104**	−0.062
	(0.025)	(0.035)	(0.044)	(0.071)
P-value (F): Lagged Male Income	0.21	0.28	0.77	0.02
P-value (F): Contemp. & Lagged Male Income	0.30	0.42	0.83	0.03
P-value (F): Lagged Female Income	0.87	0.60	0.04	0.66
P-value (F): Contemp. & Lagged Female Income	0.93	0.73	0.02	0.71
P-value (F): Male & Female Income	0.66	0.63	0.01	0.06
Mean: DV	174	136	233	791
Mean: Male Income	44	195	181	226
Mean: Female Income	229	409	148	336
Months	34	25	43	26
Households	26	19	20	17
Observations	884	475	842	441
Min Month	2012m1	2010m10	2011m4	2011m4
Max Month	2014m10	2012m10	2014m10	2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Table 3.34: Microfinance Saving (Paid) Regressed on Gender-wise NREGA Income

	DV: Microfinance Saving (Paid) (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Imputed Male Income (in logs)				
Contemporaneous	0.022	0.008	−0.032	0.048
	(0.032)	(0.031)	(0.031)	(0.032)
Lag 1	0.052	0.038	−0.031	0.042
	(0.035)	(0.033)	(0.026)	(0.032)
Lag 2	−0.065*	0.013	−0.064**	0.031
	(0.034)	(0.033)	(0.032)	(0.033)
Lag 3	0.059*	−0.047	−0.037	0.004
	(0.033)	(0.032)	(0.027)	(0.040)
Imputed Female Income (in logs)				
Contemporaneous	−0.005	0.007	0.053	−0.064**
	(0.030)	(0.033)	(0.033)	(0.028)
Lag 1	−0.003	−0.029	0.033	0.026
	(0.031)	(0.032)	(0.028)	(0.033)
Lag 2	−0.028	0.054	0.047	0.046
	(0.031)	(0.033)	(0.034)	(0.035)
Lag 3	−0.041	0.055*	0.038	−0.046
	(0.031)	(0.032)	(0.028)	(0.035)
P-value (F): Lagged Male Income	0.07	0.39	0.05	0.17
P-value (F): Contemp. & Lagged Male Income	0.11	0.48	0.05	0.07
P-value (F): Lagged Female Income	0.24	0.10	0.14	0.30
P-value (F): Contemp. & Lagged Female Income	0.37	0.14	0.09	0.12
P-value (F): Male & Female Income	0.19	0.19	0.10	0.02
Mean: DV	1290	445	36	944
Mean: Male Income	44	195	181	226
Mean: Female Income	229	409	148	336
Months	34	25	43	26
Households	26	19	20	17
Observations	884	475	842	441
Min Month	2012m1	2010m10	2011m4	2011m4
Max Month	2014m10	2012m10	2014m10	2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Table 3.35: Loan to Other (Saving) Paid Regressed on Gender-wise NREGA Income

	DV: Loan to Other (Saving) Paid (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Imputed Male Income (in logs)				
Contemporaneous	−0.008	0.010	−0.002	0.046
	(0.012)	(0.029)	(0.012)	(0.041)
Lag 1	−0.005	−0.011	−0.013	−0.096**
	(0.012)	(0.025)	(0.015)	(0.045)
Lag 2	−0.001	−0.017	0.050	−0.032
	(0.014)	(0.030)	(0.044)	(0.037)
Lag 3	0.002	0.003	−0.034*	−0.009
	(0.013)	(0.025)	(0.018)	(0.048)
Imputed Female Income (in logs)				
Contemporaneous	0.009	−0.038	−0.011	−0.042
	(0.021)	(0.026)	(0.015)	(0.051)
Lag 1	0.023	−0.009	−0.001	0.016
	(0.022)	(0.025)	(0.013)	(0.046)
Lag 2	−0.001	0.048	−0.052	0.012
	(0.013)	(0.033)	(0.047)	(0.035)
Lag 3	−0.022	−0.013	−0.018	0.097**
	(0.017)	(0.031)	(0.017)	(0.038)
P-value (F): Lagged Male Income	0.98	0.90	0.30	0.15
P-value (F): Contemp. & Lagged Male Income	0.95	0.96	0.43	0.25
P-value (F): Lagged Female Income	0.52	0.51	0.35	0.08
P-value (F): Contemp. & Lagged Female Income	0.67	0.51	0.45	0.14
P-value (F): Male & Female Income	0.90	0.71	0.42	0.33
Mean: DV	320	269	80	792
Mean: Male Income	44	195	181	226
Mean: Female Income	229	409	148	336
Months	34	25	43	26
Households	26	19	20	17
Observations	884	475	842	441
Min Month	2012m1	2010m10	2011m4	2011m4
Max Month	2014m10	2012m10	2014m10	2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Table 3.36: Formal Saving (Received) Regressed on Gender-wise NREGA Income

	DV: Formal Saving (Received) (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Imputed Male Income (in logs)				
Contemporaneous	−0.003	0.036	0.005	0.024
	(0.009)	(0.026)	(0.015)	(0.032)
Lag 1	−0.002	−0.075**	0.042	0.028
	(0.008)	(0.036)	(0.032)	(0.034)
Lag 2	0.001	−0.005	−0.055	0.014
	(0.009)	(0.021)	(0.034)	(0.037)
Lag 3	−0.003	0.030	0.012	0.030
	(0.008)	(0.036)	(0.013)	(0.039)
Imputed Female Income (in logs)				
Contemporaneous	−0.017*	0.024	0.026	−0.067*
	(0.009)	(0.028)	(0.019)	(0.039)
Lag 1	−0.016*	0.020	−0.018	0.049
	(0.008)	(0.027)	(0.036)	(0.033)
Lag 2	−0.007	−0.030	0.034	0.034
	(0.007)	(0.031)	(0.036)	(0.031)
Lag 3	0.000	−0.038	0.002	−0.029
	(0.007)	(0.036)	(0.015)	(0.040)
P-value (F): Lagged Male Income	0.98	0.15	0.28	0.55
P-value (F): Contemp. & Lagged Male Income	0.99	0.15	0.39	0.65
P-value (F): Lagged Female Income	0.25	0.35	0.82	0.31
P-value (F): Contemp. & Lagged Female Income	0.32	0.45	0.73	0.34
P-value (F): Male & Female Income	0.68	0.45	0.65	0.65
Mean: DV	175	268	85	416
Mean: Male Income	44	195	181	226
Mean: Female Income	229	409	148	336
Months	34	25	43	26
Households	26	19	20	17
Observations	884	475	842	441
Min Month	2012m1	2010m10	2011m4	2011m4
Max Month	2014m10	2012m10	2014m10	2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Table 3.37: Microfinance Saving (Received) Regressed on Gender-wise NREGA Income

	DV: Microfinance Saving (Received) (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Imputed Male Income (in logs)				
Contemporaneous	0.021	−0.007		−0.028
	(0.029)	(0.006)		(0.028)
Lag 1	−0.023	−0.001		0.034
	(0.022)	(0.005)		(0.028)
Lag 2	−0.028	0.000		0.023
	(0.022)	(0.005)		(0.037)
Lag 3	0.015	0.001		−0.029
	(0.031)	(0.004)		(0.054)
Imputed Female Income (in logs)				
Contemporaneous	0.010	0.002		0.021
	(0.011)	(0.006)		(0.017)
Lag 1	0.021	0.001		−0.034
	(0.015)	(0.005)		(0.032)
Lag 2	0.007	−0.001		−0.039
	(0.011)	(0.005)		(0.028)
Lag 3	0.001	−0.001		0.015
	(0.012)	(0.007)		(0.042)
P-value (F): Lagged Male Income	0.44	0.99		0.55
P-value (F): Contemp. & Lagged Male Income	0.51	0.83		0.63
P-value (F): Lagged Female Income	0.21	0.99		0.23
P-value (F): Contemp. & Lagged Female Income	0.34	0.98		0.26
P-value (F): Male & Female Income	0.72	0.99		0.65
Mean: DV	404	72		452
Mean: Male Income	44	195		226
Mean: Female Income	229	409		336
Months	34	25		26
Households	26	19		17
Observations	884	475	4825	441
Min Month	2012m1	2010m10		2011m4
Max Month	2014m10	2012m10		2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Table 3.38: Loan to Other (Saving) Received Regressed on Gender-wise NREGA Income

	DV: Loan to Other (Savings)(Received) (in logs)			
	Aurepalle	Dokur	JC Agraharam	Pamidipadu
Imputed Male Income (in logs)				
Contemporaneous	0.008*	0.004	−0.018	0.006
	(0.005)	(0.019)	(0.012)	(0.011)
Lag 1	0.006	0.004	0.005	0.001
	(0.004)	(0.026)	(0.004)	(0.009)
Lag 2	0.009*	−0.012	−0.011	0.012
	(0.005)	(0.022)	(0.008)	(0.009)
Lag 3	0.006	−0.010	0.001	0.007
	(0.005)	(0.030)	(0.003)	(0.014)
Imputed Female Income (in logs)				
Contemporaneous	−0.006	0.016	−0.001	0.003
	(0.006)	(0.021)	(0.008)	(0.011)
Lag 1	−0.003	−0.010	−0.003	−0.004
	(0.005)	(0.027)	(0.004)	(0.008)
Lag 2	−0.001	−0.001	0.000	0.014
	(0.004)	(0.019)	(0.005)	(0.009)
Lag 3	−0.001	0.003	−0.004	−0.002
	(0.005)	(0.025)	(0.005)	(0.008)
P-value (F): Lagged Male Income	0.29	0.89	0.53	0.60
P-value (F): Contemp. & Lagged Male Income	0.43	0.93	0.61	0.56
P-value (F): Lagged Female Income	0.90	0.98	0.85	0.42
P-value (F): Contemp. & Lagged Female Income	0.84	0.93	0.93	0.46
P-value (F): Male & Female Income	0.85	0.98	0.93	0.78
Mean: DV	270	469	19	18
Mean: Male Income	44	195	181	226
Mean: Female Income	229	409	148	336
Months	34	25	43	26
Households	26	19	20	17
Observations	884	475	842	441
Min Month	2012m1	2010m10	2011m4	2011m4
Max Month	2014m10	2012m10	2014m10	2014m10

Notes:
Robust standard errors in parentheses, clustered at the group month level. * p<0.1, ** p<0.05, *** p<0.01
Sample: Only ICRISAT-NREGA households.
All regressions include household and month fixed effects.

Chapter 4

Measuring Malnutrition and Dietary Diversity: Theory and Evidence from India

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Adequate nutrition constitutes one of the most basic dimensions of human well-being. Ample evidence exists for the functional link between a diverse diet and health outcomes or economic performance. However, a concise measure to capture nutritional diversity that utilizes typical household level data, often the only data available in developing countries, is yet to be developed. I develop a theoretical framework for such a measure by extending the Alkire-Foster (AF) methodology. The new framework enables the calculation of both the incidence and intensity of nutritional deprivation. Applying this framework, I construct a Nutritional Deprivation Index (NDI) for Indian states using household survey data on food consumption. The NDI is unique, and compared to existing measures, it is more effective in identifying the inadequately nourished while also revealing the extent and kind of food inadequately nourished deprived face.

4.1 Introduction

"[H]ealth is among the most important conditions of human life and a critically significant constituent of human capabilities which we have reason to value" (Sen, 2002). Within the capability space of health, being well-nourished to enjoy a life free of hunger and starvation is certainly the most basic functioning.[1] In this context, while arguing for the right to food the United Nations (1999) states in Comment No. 12: *"The right to adequate food is realized when every man, woman and child, alone or in community with others, has the physical and economic access at all times to adequate food or means for its procurement*."

[1]For more on Amartya Sen's capability approach and the terminology, see for instance Sen (1981, 1992, 2002).

I want to discuss two key points of this Comment. One, the focus is on the *access* to food and not just the availability of food. Sen (1981) argues for such a distinction. "Starvation is the characteristic of some people not having enough food to eat. It is not the characteristic of there being not enough food to eat. While the latter can be a cause of the former, it is but one of many possible causes." Existing measures of food availability within a country fail to account for the question of adequate access and can be misleading due the inherent and "inevitable" inequality in terms of access to food (Barrett, 2010). Second, the Comment concerns the right to *adequate* food and not just some quantity of food. There is widespread consensus that merely meeting standardized calorie norms, as set for example by the Food and Agriculture Organization (FAO), does not translate into adequate food or nutrition. Instead, measuring adequate nutrition involves measuring access to dietary diversity (Deaton and Drèze, 2009). According to Gopalan (1992), there are two practical ways to measure undernutrition which, in combination, provide valuable information to combat undernutrition: either through anthropometric data collection or through surveys of diets. This paper focuses on utilizing the latter.

Both intrinsic as well as functional arguments make the case for the importance of dietary diversity. Studies on nutrition in India show that diets have become somewhat more diverse with increasing income levels over the last decades, though not much (Deaton and Drèze, 2009). Trends of the "nutrition transition" in industrialized countries across continents during the last century reveal preferences for diverse diets, even across income groups (Drewnowski and Popkin, 1997; Smith et al., 2016; Tilman and Clark, 2015). In this paper, the reason for measuring progress in dietary diversity in poor societies of low income countries (LICs) is to examine the extent and occurrence of a shift away from the traditional staple-based diets, which are based on just a few food groups and contain mostly just starchy roots and coarse grains (Drewnowski and Popkin, 1997). Therefore, problems arising with more diverse but more sugary or fat diets are not discussed here (Tilman and Clark, 2015). Besides the intrinsic value and pleasure in a diverse diet, there is ample evidence for the functional link between a diverse diet and health outcomes, and between a diverse diet and economic performance. Alderman et al. (2005), for instance, highlight the long chain between diverse childhood nutrition to cognitive development, physical stature, strength, earlier school enrollment, more regular school attendance, greater learning and eventually greater adult productivity. Similarly, various studies using cross-sectional data for sub-Saharan African and South Asian countries including India show a direct link between dietary diversity and the nutritional adequacy of a diet, per capita consumption, total per capita caloric availability, household per capita daily caloric availability from staples, and household per capita daily caloric availability from nonstaples (Hoddinott and Yohannes, 2002; Ogle, 2001; Bhargava, 2014; Hatloy et al., 1998). Further, Steyn et al. (2006) show that dietary diversity correlates with micronutrient intake. Arimond and Ruel (2004b) show that dietary diversity does predict height-for-weight z-scores (HAZ), weight-for-age (WAZ) z-scores and undernutrition.[2] For the Indian context, Menon

[2]Definition as given by Barrett (2010): "[...] hunger refers to the physical discomfort caused by a lack of food

et al. (2015) use nationally representative data (National Family Health Survey 3, 2005-06) to show that dietary diversity of children aged 6-23 months is "strongly and significantly associated with HAZ, WAZ, stunting and underweight". Their results are robust to the inclusion of controls for household wealth. Earlier studies, too, establish such a correlation and praise the usefulness of a dietary diversity index or child feeding index to predict anthropometric outcomes in settings ranging from Latin America to rural Kenya (Onyango et al., 1998; Ruel and Menon, 2002, for instance). Thus, one may infer a great deal from dietary diversity on anthrometrics even when data on the latter or not available.

The most widely used method to measure dietary diversity is to capture the simultaneous consumption of food groups via "a simple count of food groups over a given reference period" (Ruel, 2002).[3] This can be summarized in the dietary diversity index (*DDI*). For a diet to qualify as diverse it must include the minimum number of food groups defined as mandatory.[4] The ratio of those consuming less than the threshold to overall population yields the DDI. Some studies count the number of individuals whose number of diverse food groups is *at least as high or above* the threshold. In such cases, the DDI is the ratio of those obtaining a diverse diet to the overall population. In this paper, however, I consider the DDI as the incidence of those *not* obtaining a diverse diet. The DDI is considered a promising indicator of dietary quality in the field of development economics (Villa et al., 2011).

However, there are several drawbacks to this approach. For one, the *DDI* reflects merely the incidence of inadequate food consumption and neglects the extent of inadequacy. In doing so, the DDI treats the absence of a diverse diet in such a way that the extent of nutritional deprivation across different food groups is not accounted for. For instance, individuals consuming very few diverse food groups are considered as equally deprived as those consuming just below the required minimum of groups.[5] The second weakness relates to minimum requirements of a food group. By not considering the quantity consumed of a food group but merely counting incidences of consumption, the *DDI* may underestimate the number of inadequately nourished individuals. For example, an individual may consume a food group in a quantity that is insufficient for a healthy life, but sufficient to be counted within the framework of the DDI. The third weakness is related to the previous one. The *DDI* neglects idiosyncratic variations in food requirements. While every person is in need of a diverse diet, the extent of

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and can only be properly gathered at the individual level. Underweight summarizes individual anthropometric measures - such as weight-for-height, weight-for-age, or mid upper-arm circumference - at least two standard deviations below global reference values. Undernutrition reflects insufficient dietary energy (caloric) intake, according to internationally agreed standards. Malnutrition refers to undernutrition, obesity, and micronutrient (mineral and vitamin) deficiencies."

[3]See, for example, the U.S. Agency for International Development (USAID)'s Food and Nutrition Technical Assistance Project (FANTA) at http://www.fantaproject.org/monitoring-and-evaluation/household-dietary-diversity-score. The FAO has carried out much research using such a counting score, and provides guidelines to conduct dietary diversity surveys. See, for example, http://www.fao.org/publications/card/en/c/5aacbe39-068f-513b-b17d-1d92959654ea/.

[4]The mandatory number is arbitrary and context-dependent.

[5]This violates dimensional monotonicity.

minimum requirements varies greatly by age, gender, health status, and occupation (Gopalan, 1992; Kakwani, 1992), besides other individual factors and even varying intra-individual requirements (Srinivasan, 1992; Kakwani, 1992). Therefore, a dietary measure should ideally apply person-specific thresholds for each food group.[6]

In this paper, I develop a framework for a *Nutritional Deprivation Index (NDI)* to measure access to diverse diets using individual-level data. An alternative framework is also defined for when only household level data are available. I apply the household framework to compute an *NDI* using household-level data on food consumption from India's 2011-12 National Sample Survey (NSS). The *NDI* overcomes the above mentioned weaknesses of the *DDI* by adapting and extending the Alkire-Foster counting approach (Alkire and Foster, 2011), which is a technique widely used in multidimensional poverty measurement. The *NDI* addresses the first two weaknesses of the *DDI* by accounting for the actual amount consumed of each food group as well as the number of under-consumed food groups. By doing so, the framework yields both the incidence and intensity of nutritional deprivation. The absence of idiosyncratic thresholds in the *DDI* is also addressed by the *NDI*. It allows for minimum food group requirements which vary by food group as well as by individual characteristics such as age, gender, and occupation. Overall, the *NDI* is superior to the *DDI* in measuring dietary diversity for a variety of reasons. First, it overcomes the three weaknesses of the *DDI*. Second, it provides information about both the incidence and intensity of nutritional deprivation. Third, the *NDI* framework inherits several properties of the AF methodology which allow for useful decompositions of the *NDI* and its components (the incidence and the intensity of nutritional deprivation).

This is demonstrated in the paper by applying the *NDI* and *DDI* framework to the household-level data on food consumption amongst India's rural population. The analysis reveals that the *DDI* underestimates the extent of food inadequacies. According to the *DDI* approach 67 per cent is deprived in at least one food group. In contrast, applying the *NDI* framework yields that around 60 per cent is nutritionally deprived in at least five of eight food groups. Further, the *NDI* highlights that the nutritionally deprived are primarily deprived of leafy vegetables, fruits, and dairy products. Finally, the *NDI* reveals that the average intensity of nutritional deprivation amongst those experiencing the lack of diverse diets is nearly 70 per cent. Decomposing the *NDI* by state and social subgroups highlights considerable variation in the kinds of food deprivation. For example, in the northern state of Punjab, nutritional deprivation in cereals contributes to overall nutritional deprivation. In the most populous state of Uttar Pradesh, however, cereals are sufficiently consumed while the consumption of leafy vegetables and fruits is insufficient. Decompositions by social groups reveal that almost 50 per cent of the Scheduled Tribes are inadequately nourished in five of eight food groups, whereas it is just 22 per cent for the "Others". I also find that larger households are less adequately nourished according to the headcount ratio of the *NDI* than smaller ones. In this manner, the

[6] Kakwani (1992) and Osmani (1992) discuss possible errors when average requirements are used despite given inter-individual variation in dietary requirements.

NDI addresses the gaps in the existing measure (*DDI*) and proves to be a more accurate tool to quantify access to diverse diets, using data that are readily available in a significant number of surveys. It is a step forward in measuring the most basic functioning of human well-being in the capability space of health.

At the outset of this paper, a few caveats to using household data to measure dietary inadequacies have to be mentioned. Household level data on consumption, as NSS data for India, may not map onto nutritional adequacy for a number of reasons. One, intra-household inequalities in food consumption cannot be accounted for. There is a large literature on intra-household allocation of nutrients showing that individual consumption or nutrient intake responds differently to, say, changes in income, and that the response can be gender-specific (e.g. Behrmann, 1992). Second, person-specific differences in metabolism exist (Gopalan, 1992), and thus individual nutritional needs vary beyond age, gender, and occupation. Since such differences are not captured by the household data, the applied thresholds may serve as reasonable rule-of-thumb yardsticks but are certainly not sufficiently precise to capture individual needs. Third, the household level data on food consumption do not elicit on the individual ability to convert the consumed resources into functionings. Thus, we do not know after all whether a certain realized diet improves the functioning of, say, being well-nourished. Fourth, there is non-sampling measurement error in the NSS data as in any other household survey. In particular for purposes of measuring dietary diversity, it matters that rich households are less likely to be captured by the household survey. Also, despite a relatively short recall period of seven days, the quantity of food groups consumed are likely to suffer from measurement error, and "[q]uite likely, there is some underestimation of consumption in the NSS data, particularly among higher-income groups [...]"(Deaton and Drèze, 2009).

Ideally, I would employ nationally representative individual level data. These should include information on both daily individual consumption of all food groups (in grams) and individual metabolism. However, to my knowledge such data do not exist. Thus, while the method presented in this paper is unique and optimally suited for individual level data the application to household level data is second best.

The paper is structured as follows. First, Section 4.2 introduces the *NDI* framework. Section 4.3 presents an application using data on food consumption from India's National Sample Survey. It exemplifies how widely available household survey data can be applied to compute an *NDI* and its various decompositions. In Section 4.4, I compare the *NDI* with the traditional measure of a *DDI* in terms of accuracy in identifying inadequately nourished households. The final Section 4.5 concludes with a discussion on further research.

4.2 Towards a Nutritional Deprivation Index: The General Framework

In this section, I explain the counting approach to measure nutritional deprivation in a multidimensional manner following the Alkire-Foster (AF) methodology. The AF method, as presented in Alkire and Foster (2011) has been widely adopted to measure multidimensional poverty. In particular, for the global Multidimensional Poverty Index (MPI) the AF methodology is applied to monitor multidimensional poverty of ten indicators spanning health, education, and living standard across more than 100 countries (Alkire and Santos, 2014). Since 2010, the global MPI has been published by the United Nations Development Programme (UNDP) in its annual Human Development Reports (HDR)[7]. Numerous governments have applied the AF methodology to design and compute their own country-specific multidimensional poverty measures, for example Colombia, Mexico, and Bhutan. Besides for purposes of poverty measurement, the AF methodology has been applied in other fields of research as well, so for example to measure access to modern energy in sub-Saharan Africa (Bensch, 2013) or to measure women empowerment (Alkire et al., 2013), to name a few.[8]

In Subsection 4.2.1, the key features of the AF methodology are briefly presented, before I introduce an extension to AF methodology in Subsection 4.2.2 for individual-level data. In Subsection 4.2.3 I show that how the framework can be adjusted in such a way, that household-level data on food consumption, too, can be applied to compute an NDI.

4.2.1 The Alkire Foster Methodology

The methodology and terminology as presented in Alkire et al. (2015) are straightforward.[9] I follow both entirely. The aim of the AF methodology is to provide for a framework which allows to measure joint (simultaneous) deprivations in various dimensions using a counting approach. Collecting all realizations, or so called achievements, of each individual in each dimension a dual cut-off approach is used to first translate achievements into deprivations, and to then determine an individual as jointly deprived or not deprived in a given number of all dimensions. Ultimately, this yields the incidence (H) of the jointly deprived and the intensity (A) of experiencing joint deprivations. In the framework of poverty measurement, it yields the incidence and intensity of multidimensional poverty. The product of H and A yields an index score, $M0$. In the following, the dual cut-off approach of the AF methodology is shown. Based on this and an extension to the first cut-off, I build a Nutritional Deprivation Index.

According to the notation given by Alkire et al. (2015), think of an $n \times d$ dimensional achievement matrix X with n individuals and d dimensions, with achievements x_{ij} of indi-

[7] At http://hdr.undp.org/en/reports a list of all Human Development Reports can be found.
[8] More studies can be found at: http://www.ophi.org.uk/resources/
[9] Consult http://multidimensionalpoverty.org/contents/ for an online version of the book.

vidual i in dimension j. The dual cut-off approach is applied as follows. To apply the first cut-off entails using dimension-wise thresholds. These are collected in the d-dimensional vector z, such that

$$z = (z_1, ..., z_d). \tag{4.1}$$

Applying the thresholds to determine whether achievement x_{ij} lies above or below z_j, the so called deprivation matrix g^0 is constructed with its elements $g^0_{ij} = 1$ whenever individual i is deprived in dimension j, i.e. when $x_{ij} < z_j$, and $g^0_{ij} = 0$ whenever $x_{ij} \geq z_j$. Given a d-dimensional vector of weights, $w = (w_1, ..., w_d)$, each dimension is weighted accordingly. Adding up the number of weighted deprivations $w_j g^0_{ij}$ for each individual i yields individual i's deprivation score, $c_i = \sum_{j=1}^{d} w_j g^0_{ij} = \sum_{j=1}^{d} \overline{g}^0_{ij}$. Ultimately, n deprivation scores are collected in the vector of deprivation scores $c_i = (c_1, ..., c_n)$.

Applying the second cut-off of the AF method entails 'censoring' those individuals who inhibit less deprivations than the minimum threshold k, and by identifying those who are jointly deprived in at least k deprivations. Formally, an identification function ρ_k is applied such that $\rho_k(x_i; z) = 1$ if $c_i \geq k$, and $\rho_k(x_i; z) = 0$ otherwise. Applying the identification function to all entries, $w_j g^0_{ij}$, yields the censored matrix of deprivations, $g^0_{ij}(k)$, which is the product of g^0_{ij} and $\rho_k(x_i; z)$. Counting the censored deprivations yields the censored deprivation score vector $c(k)$, which includes n deprivation scores, denoted for individual i by $c_i(k) = \sum_{j=1}^{d} w_j g^0_{ij}(k)$.

In order to calculate the multidimensional headcount ratio H (or the incidence of the multidimensionally deprived), the number of individuals with non-zero entries in the censored deprivation score vector $c(k)$ sum up to q, so that $H = q/n$. In order to measure the intensity of deprivations, the average deprivation share of the multidimensionally deprived, A, is defined as $A = \sum_{i=1}^{q} c_i(k)/q$. Multiplying these two measures, $H \times A$ yields the adjusted headcount ratio M_0. It is also the mean of the censored deprivation score $c(k)$ or the mean of the censored deprivation matrix $g^0_{ij}(k)$. Thus, it can be formally notated as both:

$$M_0 = \mu(c(k)) = \frac{1}{n} \times \sum_{i=1}^{n} c_i(k) \tag{4.2}$$

and

$$M_0 = H \times A = \frac{q}{n} \times \frac{1}{q} \sum_{i=1}^{q} c_i(k) = \frac{1}{n} \sum_{i=1}^{n} c_i(k) = \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{d} w_j g^0_{ij}(k) \tag{4.3}$$

Properties of the AF Methodology

The AF methodology has several attractive properties. I show the most basic and useful ones here, as I will apply them in the empirical part. Broadly, one can think of components of the M_0, H, and A. For instance, instead of a headcount ratio for the entire country one may be interested in H for the country's regions. Likewise, one may be interested in the dimensions of M_0 and the question arises which dimension contributes most to M_0. What is the dimension with the highest deprivation rates? Thus, with the censored deprivation matrix in mind, one is interested in M_0, H, and A by columns (dimensions) and rows (sub-groups). The AF methodology allows to undertake such "decompositions" in a coherent manner as the $M0$ measure satisfies both the properties of population subgroup decomposibility and dimensional breakdown (Alkire et al., 2015; Foster et al., 1984).

To begin with dimensional decomposition, the censored headcount ratio of dimension j is defined as

$$h_j = \frac{1}{n} \sum_{i=1}^{n} g_{ij}^0(k), \tag{4.4}$$

which is the mean of the j^{th} column of the censored deprivation matrix $g^0(k)$. The dimensional contribution of each dimension $j = 1, ..., d$ to M_0 is defined as

$$\phi_j^0 = w_j \frac{h_j(k)}{M_0} \tag{4.5}$$

Importantly, the sum of all censored headcount ratios yields M_0. Decomposing the censored deprivation matrix by subgroups(rows) yields subgroup-specific values M_0, H, and A. Multiplied with respective population shares the sum of all subgroup-specific values yields the overall measures. Formally, given m subgroups and the population share of subgroup l given by $v^l = n^l/n$, the overall M_0 is

$$M_0 = \sum_{l=1}^{m} v^l M_0^l \tag{4.6}$$

Similarly, both overall incidence and overall intensity satisfy the property of subgroup decomposibility, so that

$$H = \sum_{l=1}^{m} v^l H^l \tag{4.7}$$

$$A = \sum_{l=1}^{m} v^l A^l \tag{4.8}$$

4.2.2 A Nutritional Deprivation Index: Extending the Alkire Foster Methodology

In order to construct a Nutritional Deprivation Index (NDI) which is sensitive to idiosyncratic food requirements, the AF method as presented above needs to be adjusted. In terms of notation and within the AF framework, one can think of the d dimensions as food groups of interest, for example those recommended by the FAO. The $n \times d$ dimensional achievement matrix X thus contains entries of x_{ij} which represent realizations of consumption for individual i in food group j (see matrix 4.9).

$$X = \begin{bmatrix} x_{11} & \dots & x_{1d} \\ \vdots & \ddots & \vdots \\ x_{n1} & \dots & x_{nd} \end{bmatrix} \tag{4.9}$$

In order to allow for idiosyncratic food requirements, I adjust the AF methodology by introducing idiosyncratic minimum requirements for each food group j. Recall, that for the first cut-off in the AF methodology a d-dimensional row vector z of thresholds is applied. If the dimensions are food groups, this would imply that all individuals are treated equally in terms of food requirements. However, it is widely known that food requirements vary from person to person and by age, gender, health status, and occupation (Gopalan, 1992; Kakwani, 1992; Deaton and Drèze, 2009). In fact, requirements may even vary intra-individually depending on health status or activity level (Srinivasan, 1992; Kakwani, 1992). Given, however, only dimension-wise cut-offs neglects idiosyncratic requirements. For example, dimension-wise cut-offs may be average thresholds for the entire population across age groups. This would results in two types of errors. Either, for example, the consumption of fruits by infants could be below the population-wise cut-off, while the infants' consumption might just be adequate. Or, for example, the relatively high consumption of cereals by laborers could be inadequate to cover nutritional requirements but would be above the population-wise threshold. Hence, in both cases dimension-wise cut-offs yield wrong estimates, which may be overestimates (infants) or underestimates (laborers) of the inadequately nourished. Therefore, I account for idiosyncratic differences in food requirements by including person-specific thresholds, i.e. n different cut-offs. I thus employ an $n \times d$-dimensional cut-off matrix Z (see matrix 4.10), instead of just the d-dimensional row vector z, shown in equation 4.13. This adjustment is crucial and presents the major adjustment to the classical AF method.

$$Z = \begin{bmatrix} z_{11} & \dots & z_{1d} \\ \vdots & \ddots & \vdots \\ z_{n1} & \dots & z_{nd} \end{bmatrix} \tag{4.10}$$

I use Z to determine whether individual i consumes less in dimension j than individual i's specific threshold z_{ij}. Applying the cut-off matrix Z, I compute a deprivation matrix g^{0_z}. This represents the first step of the dual cut-off approach. The elements of g^{0_z} are then: $g_{ij}^{0_z} = 1$ when $x_{ij} < z_{ij}$, and $g_{ij}^{0_z} = 0$ whenever $x_{ij} \geq z_{ij}$. All subsequent steps of the AF methodology (including the second step of the dual cut-off method) remain the same, such that I ultimately calculate a Nutritional Deprivation Index, NDI, as the product of the headcount ratio of the nutritionally deprived, H_N, and the average deprivation share of the nutritionally deprived, A_N.

It might seem that having a matrix of vectors would fundamentally alter the properties satisfied by the AF methodology, given that the original paper requires the cut-offs to be "fixed and given." However, in the case of nutrition, in fact, far from generating incomparabilities between individuals, a characteristic-specific cut-off creates comparability whereas a uniform vector of cut-offs would not do so. Thus the cut-offs create comparable deprivations in the space of nutritional functionings. For this reason they can be applied whilst maintaining the same properties of the AF methodology. In the following section, I show how the NDI can be computed when only household level data are available.

4.2.3 Adjustment to Allow for Household-level Data

Most national surveys collect data at the household level. That implies that information on, say food consumption is not available for each individual but is aggregated at the household-level. Thus it is not possible to apply individual food reference lines. However, if the survey provides information on the number of individuals in a household, their gender, age and occupation, as most household surveys do, then individual-level reference lines can be summed up at the household level. Doing so yields household-wise minimum requirements for each food group. The Z matrix can be written as a Z^h matrix with household-level thresholds for each food group as its entries.

The following example shall highlight the simple point. Typically, one observes for the entire household i a row vector of food consumption (achievements), capturing food intakes (in grams) for, say three food groups including cereals (C), vegetables (V), and pulses (P), so that hypothetically for household i:

$$x_i = \begin{pmatrix} 1360 & 300 & 450 \end{pmatrix}$$

Knowing the composition of the household yields the Z-matrix containing individual requirements, for example:

$$Z = \begin{pmatrix} 600 & 100 & 120 \\ 480 & 100 & 90 \\ 300 & 100 & 60 \end{pmatrix}$$

Adding up these requirements by food group yields the z^h vector for household i:

$$z_i^h = \begin{pmatrix} 1380 & 300 & 270 \end{pmatrix},$$

or more generally the d-dimensional z^h vector for household i:

$$z_i^h = (z_{i1}^h, \ldots, z_{id}^h). \tag{4.11}$$

Repeating this for every household and collecting all rows of household-wise z^h vectors yields matrix Z^h:

$$Z^h = \begin{bmatrix} z_{11}^h & \cdots & z_{1d}^h \\ \vdots & \ddots & \vdots \\ z_{n1}^h & \cdots & z_{nd}^h \end{bmatrix}, \tag{4.12}$$

the threshold matrix of household-wise food group requirements. Built on this first and adjusted step of the dual cut-off methodology for household-level data, a nutritional deprivation index is constructed. Applying the elements of Z^h as household-specific thresholds yields g^{0_z}, $g^{0_z}(k)$, H_N, A_N, and NDI, as before in the framework for individual-level data .

To comment briefly on the household-specific thresholds: First, the adjustment of using household specific cut-offs comes close to the idea of using equivalence scales in poverty measurement. Given only household consumption expenditure, per capita expenditures are often calculated using age and gender specific weights - equivalence scales. Second, the measure is sensitive to household composition and needs. As the individual thresholds are summed up at the household level, household-specific needs are captured, even though intra-household allocations and inequalities cannot be captured.

4.3 Application: An NDI for Rural India

In this section, I present results of applying the NDI to household-level data for India. Being one of the fastest growing countries during the last decades, it makes for an interesting example. In particular, a nutritional index for India is of great interest since despite considerable advances in poverty alleviation India still accounts for the highest number of malnourished children in the world.[10] In particular, compared to its South Asian neighbors, India is lagging behind in many indicators related to health and nutrition (Drèze and Sen, 2013). Multidimensional poverty in India as measured by Alkire and Seth (2015a) varies greatly by state and sub-population. Alkire and Seth show that the progress in poverty alleviation between 1999 and 2006 has not been even. Richer states were able to reduce multidimensional poverty at much higher rates than the relatively poorer ones. Likewise, poverty rates for Hindu families and upper caste families reduced relatively faster than for more disadvantaged groups of Muslim families and scheduled tribes. Building on the study by Alkire and Seth (2015), this paper contributes to existing research on state and subgroup-wise differences in India. I construct an NDI and decompose the index by states and sub-groups. This shall serve mainly illustrative purposes of the new measure while also providing evidence on nutritional deprivation in rural India.

[10] http://www.economist.com/blogs/graphicdetail/2015/07/daily-chart-0

4.3.1 Data

I use data from India's reputed National Sample Survey Organization (NSSO) for the year 2011-12. With more than 100,000 households interviewed the sample is representative at the national as well as at the state-level. In its 68th round, the NSSO collected consumption data on prices and quantities using a seven as well as a 30 day recall period. In the following, I make use of the seven day recall period assuming that it is the most accurate in terms of reflecting quantities of food products. Since the data are collected year-round, all agricultural seasons are equally covered. Thus, one may rule out seasonal artefacts in the data. I focus on rural India, only, for two reasons. First, given the high prevalence rate of undernutrition in rural India (Drèze and Sen, 2013), it is important to shed light on one of the major causes of undernutrition in the very same region. Second, given that a large share of India's rural population consumes home-cooked food and less frequently outside meal options (Deaton and Drèze, 2009), which is more difficult to measure and convert into food groups, I neglect urban areas in this paper. For all estimations of aggregates, I apply the standard NSS survey weights.

4.3.2 Indicators, Cut-offs, and Weights

In order to measure food inadequacies in several food groups simultaneously using the framework outlined above, it is necessary to make important judgment calls on four interchangeable and "flexible" parameters. First, what indicators do best capture a diverse diet in rural India? Second, what are the indicator and person-specific cut-offs? Third, what dimensional weights ought to be used? And fourth, what k-value is most appropriate?

Choice of Indicators

Most measures of dietary diversity, like the DDI, use broad food groups as indicators, instead of micro-nutrients, for example. I follow the Indian National Institute of Nutrition's (NIN) guidelines and focus on food groups. The NIN's argumentation is that, since "people consume food, it is essential to advocate nutrition in terms of foods, rather than nutrients. Emphasis has, therefore, been shifted from a nutrient orientation to the food based approach for attaining optimal nutrition" (National Institute of Nutrition, 2011). It has been common practice by the NIN since 1998 to report on dietary intake in India and provide for dietary guidelines in India. Based on that, the NIN publishes detailed statistics on food intakes for eight broadly categorized food groups. These are Cereals, Pulses & Meat, Dairy products, Leafy Vegetables, Other Vegetables, Fruits, Oils and Fats, Roots and Tubers. I utilize these eight categories to measure nutritional inadequacy via the NDI framework.

Choice of Cut-offs

In order to create a Z^h matrix - the threshold matrix containing household-wise food reference lines - I exploit two sources of information. First, I employ household-level information given in the survey data (NSS 2011-12) on the number of individuals within a household, each member's age, gender, and occupation. Second, I utilize information provided by the National Institute of Nutrition (2011) on "recommendations for a healthy diet". These recommended daily allowances (RDAs) are age, gender, and occupation-specific based on what the NIN considers as "nutrient-centred." The "guidelines promote the concept of nutritionally adequate diets and healthy lifestyles from the time of conception to old age." Since these RDAs are widely used, so for example by the FAO Nutrition and Consumer Protection Division (2008), I consider these guidelines as justifiable cut-offs. Therefore, to create the Z^h matrix I sum up the food reference lines, as given in Table 4.1, at the household-level and as per household composition.

However, since the RDAs are meant as guidelines for a "healthy diet" for the average Indian person, they are likely to be relatively high for households living in poverty. Thus, in order to measure (non)access to nutrition of an "acceptable" minimum which guarantees to avoid hunger and starvation, much lower RDAs may be considered. I do so in the subsequent analyses by applying the RDAs of only a quarter of their value (RDA 25 %) and one half (RDA 50 %).

Choice of Weights

In terms of choosing weights for each food groups, I apply equal weights of 1/8 for each food group. I do so, since the NIN and FAO consider these eight food groups as equally essential for a diverse diet. If, however, the focus is on measuring access to the most essential and vital food groups to, for example, avoid undernutrition one could easily change the weights. For instance, one may consider that cereals, vegetables, and proteins are the most vital food groups of the eight. Following this logic, one could set the food group-wise weights in such a way that the said three groups are weighted each with 1/4 and the remaining five with each 1/20. Since such a procedure requires as much justification as choosing equal weights, I restrict the analysis in this paper to an application of only equal weights. After all, this paper's application of NSS data shall mainly serve illustrative purposes of the new NDI framework and is at no means ideal.

Choice of k-values

In the subsequent analyses, I report the various parameters of the NDI for several k values. Recall that in this application of household-level data and eight food groups, a household is nutritionally deprived if it is deprived in more than k food categories. Counting those households which are deprived in more than k food groups and taking the mean of the sub-sample of interest yields the headcount ratio of nutritional deprivation, or H_{Nk}. Calculating the average deprivation count of the nutritionally deprived (in k food groups) yields A_{Nk}. The product of H_{Nk} and A_{Nk} yields NDI_k.

Table 4.1: Recommended Daily Allowances (RDAs)

	Activity and Gender				Age and Gender						Age only			
	Sedentary		Heavy		16-18		13-15		10-12		7-9	4-6	1-3	infant
Items	M	F	M	F	M	F	M	F	M	F				
Cereals	375	270	600	480	450	330	420	330	300	240	180	120	60	15
Pulses & Meat	75	60	120	90	90	75	75	60	60	60	60	30	30	7.5
Dairy Products	300	300	300	300	500	500	500	500	500	500	500	500	500	400
Leafy Vegetables	100	100	100	100	100	100	100	100	100	100	100	50	50	25
Other Vegetables	200	200	200	200	100	100	100	100	100	100	100	100	50	25
Fruits	100	100	100	100	100	100	100	100	100	100	100	100	100	100
Oils & Fat	25	20	40	30	50	35	45	40	35	35	30	25	25	20
Roots & Tubers	200	200	200	200	200	200	150	100	100	100	100	100	50	25

Notes: All figures are in grams and are recommendations per day.
Source: FAO Nutrition and Consumer Protection Division (2008), NIN, Hyderabad, India, 2008.

4.3.3 Findings for Rural India using 2011-12 NSS Data

The following trends emerge from the application of using Indian NSS data (2011-12) for rural areas. Table 4.2 depicts state-wise and so called raw headcount ratios for all food groups. These headcount ratios are 'raw' in the sense of showing the deprivations for the population, irrespective of how many deprivations a household may face. According to Table 4.2 in almost every food group I find considerable state-wise variation. For instance, the North Eastern states of Manipur, Meghalaya, Mizoram, Nagaland and Assam are hardly deprived at all in cereals, whereas states like Maharashtra and Karnataka account for incidences of about eight per cent. While such incidences are rather small in magnitude, they appear much higher for the food group of pulses. Here, the highest rate is above 80 per cent (Rajasthan) and the lowest as low as four per cent (Nagaland). Average deprivations in leafy vegetables are very high in comparison, and reach up to 100 per cent (Puducherry). Raw headcount ratios do not inform about the joint deprivations households face in several food groups simultaneously. They do, however, provide information on average intakes of each food group and provide a good starting point to think about and calculate joint deprivations. These are captured using the counting approach described above. I present the results for rural India in Table 4.3. I report all ratios of interest - H_N, A_N, NDI - for k-values ranging from one to eight. It is apparent, that H_N decreases with increasing k-values, while A_N increases. For low k-values H_N is almost 100 per cent, implying that the entire rural population is inadequately nourished in at least one food group. A_N for a k-value of one is at about 50 per cent, implying that those who are inadequately nourished in at least one food group are on average inadequately nourished in four of eight food groups. At a k-value of five H_N is around 30 per cent and A_N at 70 per cent, implying that a third of India's rural population is inadequately nourished in at least five food groups, and on average in 5.6 food groups.

Table 4.2: *NDI* **using Household Data: State-wise Raw Headcount Ratios**

	Cereals	Pulses	Dairy P.	Leafy Veg.	Other Veg.	Fruits	Oils	Roots
Andaman and Nicobar	4.46	5.12	89.42	63.3	10.95	51.97	6.45	98.44
Andhra Pradesh	5.57	22.1	73.03	95.25	11.33	55.83	15.12	99.33
Arunachal Pradesh	2.7	14.94	91.69	43.76	28.88	67.31	60.02	77.8
Assam	1.52	15.65	96.51	68.63	19.15	74.43	38.69	77.7
Bihar	0.59	41.86	74.28	80.75	9.71	76.85	34.89	29.18
Chandigarh	9.99	27.56	24.52	95.82	9.26	54.5	9.42	76.55
Chhattisgarh	2.54	47.14	94.97	72.27	8.37	82.96	29.73	88.14
Dadra and Nagar Haveli	14.97	29.67	74.37	99.93	26.88	77.52	19.97	96.88
Daman and Diu	16.43	11.38	68.94	100	21.07	71.39	9.57	87.22
Delhi	11.81	37.79	26.86	91.51	14.97	56.96	9.76	76.23
Goa	6.23	9.76	52.49	85.37	27.09	7.67	16.86	99.38
Gujarat	8.81	55.2	46.33	94.23	12.01	70.49	4.71	88.12
Haryana	4.7	63.53	16.6	85	7.38	51.26	29.74	75.69
Himachal Pradesh	3.01	19.25	29.85	85.76	15.34	64.92	12.94	87.31
Jammu and Kashmir	1.41	31.8	24.05	41.48	17.26	66.67	8.79	91.29
Jharkhand	3.48	46.93	83.44	81.3	17.72	86.65	40.83	32.3
Karnataka	8.31	34.5	71.71	88.19	22.94	39.37	20.32	99.9
Kerala	10.5	12.96	74.21	98.74	25.67	11.23	36.9	99.35
Lakshadweep	6.55	12.39	99.29	100	36.82	2.56	25.37	98.86
Madhya Pradesh	2.82	54.23	69.89	92.66	20.92	72.14	25.98	86.22
Maharashtra	8.29	33.57	69.25	86.5	22.78	56.76	9.41	97.82
Manipur	1.09	31.75	99.89	64.87	44.54	84.39	67.73	94.68
Meghalaya	2.25	21.44	96.88	71.88	31.46	81.69	53.42	86.18
Mizoram	0.1	12.9	92.22	30.36	26.17	81.56	20.8	84.11
Nagaland	0	3.61	98.42	31.37	19.75	77.23	82.64	87.01
Orissa	2.35	41.21	91.91	79.71	13.28	79.36	49.25	62.04
Puducherry	11.34	12.65	47.44	99.95	15.99	39.57	18.62	97.73
Punjab	6.78	58.04	18.37	88.8	6.53	67.03	9.86	75.59
Rajasthan	2.34	81.84	35.03	92.6	22.39	71.82	27.59	92.03
Sikkim	5.89	45.15	39.58	48.67	14.78	90.62	14.77	81.86
Tamil Nadu	9.46	22.73	65.56	95.96	20.55	42.61	27.06	99.78
Tripura	1.06	17.47	95.45	47.52	5.2	65.71	42.43	84.23
Uttar Pradesh	2.09	46.26	63.05	92.39	18.15	74.67	25.56	35.6
Uttaranchal	1.81	31.84	32.51	77.55	9.05	66.16	8.27	73.27
West Bengal	4.78	28.43	91.07	76.64	20.5	78.15	20.45	27.34

Calculated from NSS Round 68, Consumption Module 2011-12. 50 per cent of Food Reference Value applied.

Table 4.3: ***NDI*** **using Household Data:** H_N, A_N, $M0_N$, **and** H_D **over** k**-values**

k	H_N	A_N	$M0_N$	H_D
1	99.62	48.57	0.484	67.32
2	96.28	49.82	0.48	27.78
3	83.32	53.68	0.447	5.99
4	59.07	60.33	0.356	1.51
5	31.52	69.36	0.219	1.34
6	12.26	80.13	0.098	1.3
7	4.01	90.71	0.036	1.14
8	1.03	100	0.01	0.71

Calculated from NSS Round 68, Consumption Module 2011-12.

Decomposition by States

Figure 4.1 presents maps depicting state-wise headcount ratios, H_N, for k-values ranging from three to eight.[11] At higher k-values, one particular region appears to be particularly exposed to nutritional deprivation. The belt stretches from Rajasthan in the North West via Madhya Pradesh and Jharkhand to Orissa. These regions are known to be the most disadvantaged areas in other aspects, too, be it monetary or multidimensional poverty, health, education or living standards (Alkire and Seth, 2015a). In the following, I stick to presenting results for a k-value of five.

Breakdown and Contribution by Food Group

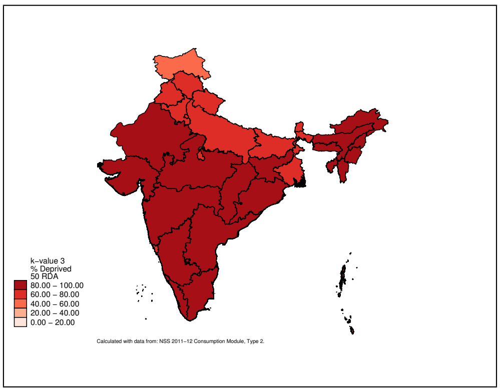
In Figure 4.2, I show Censored Headcount (CH) Ratios for every food group and for the k-value of five. Being nutritionally deprived and deprived in, say cereals yields the CH for cereals. The CH of cereals is the lowest in comparison to the other seven, which can reach values of more than 25 per cent. The highest ones are found for the groups of leafy vegetables and roots. Related to Figure 4.2 is Figure 4.3. It presents state-wise contributions of food groups to the overall NDI score, $M0$. The broad pattern reveals that food group contributions to food inadequacy are broadly similar but still vary by state. Similarly, but not the same as the raw headcount ratios, I find that the contribution of cereals to the overall measure is near zero, but is about five per cent in some states (Delhi, Kerala). The highest contributions to nutritional inadequacies can be found for pulses, leafy vegetables, and fruits.

Decomposition by Socioeconomic Subgroups

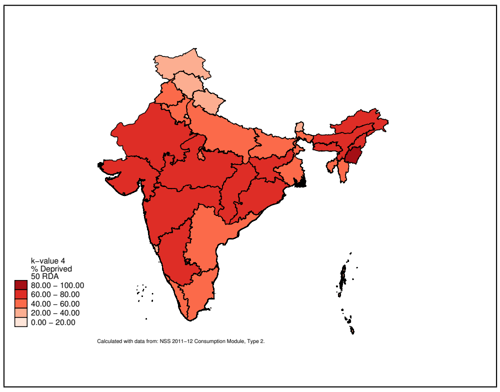
Besides large regional differences across rural India there exist large inequalities across socioeconomic subgroups such as caste, gender, and religion among others (Drèze and Khera, 2013; Alkire and Seth, 2015b). In Table 4.4, I present the three measures of the NDI (H_N, A_N, $M0_N$) along with the censored headcount ratios of each food group, given a k-value of five. It is

[11] I exclude maps for higher k-values here, as there is hardly any variation at such high levels of k.

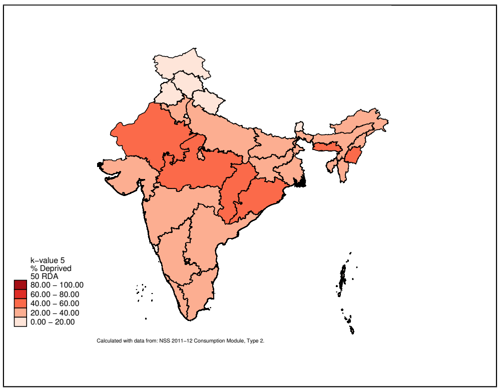
(a) $k = 3$



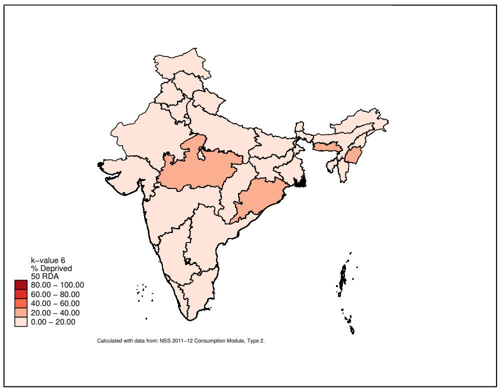
(b) $k = 4$



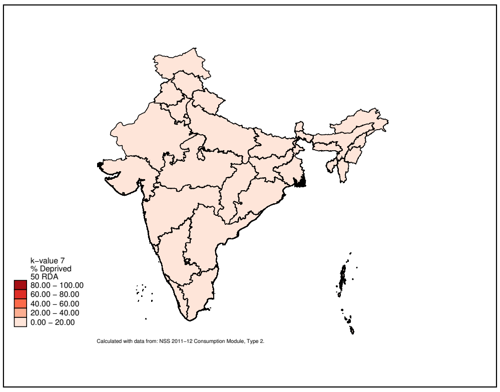
(c) $k = 5$



(d) $k = 6$



(e) $k = 7$



(f) $k = 8$

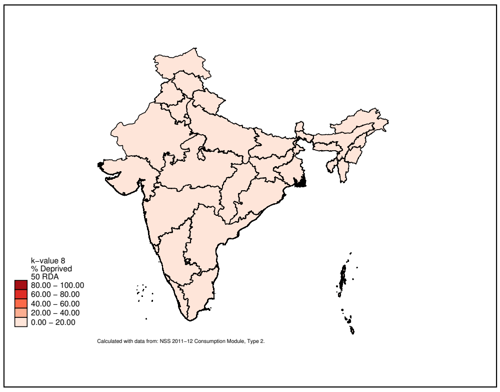


Figure 4.1: State-wise H_D by k-value

apparent that the traditionally most disadvantaged groups have also the least access to an adequate nutrition. Therefore, households belonging to Scheduled Tribes, the landless or very large household account for the highest H_N (above 40 per cent). While A_N does not vary much across subgroups, it is around 70 per cent, H_N varies substantially. For instance, among caste groups H_N for higher castes (other) (22 per cent) is less than half the value of H_N for Scheduled Tribes. Across landholding classes, the pattern is quite clear: the more landholding the less chances of being inadequately nourished. Also across censored headcount ratios, the large

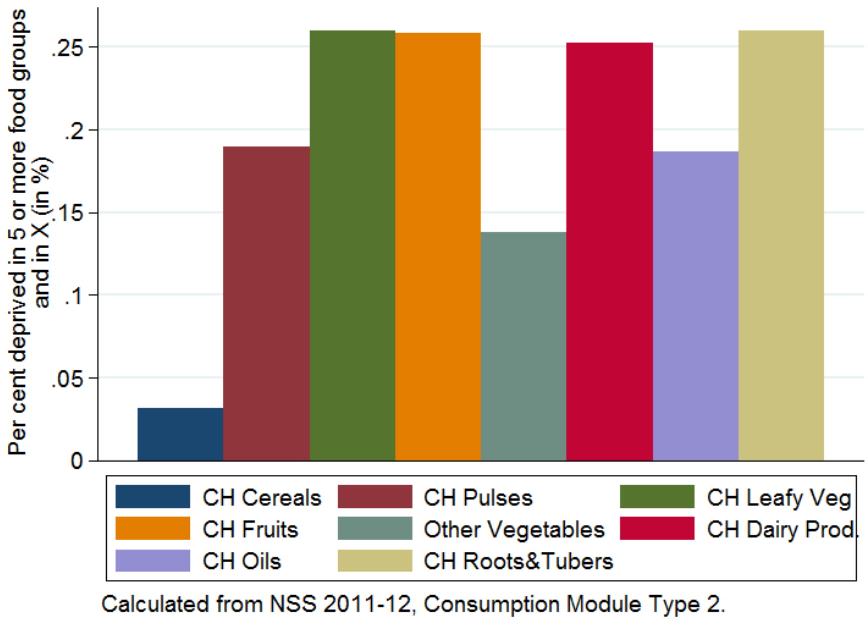


Figure 4.2: Censored Headcount Ratios for k=5

landowners are the least likely to be deprived in any of the eight food groups while being at the same time nutritionally deprived in at least five of them. A similar pattern is evident for the decomposition by household size. The larger the household the higher the chances of being inadequately nourished. With increasing household size censored headcount ratios increase, almost continuously.

4.4 Comparison between *NDI* and *DDI*

In this Section, I compare the *NDI* and the *DDI* in two ways. First, I compare the conceptional frameworks of the two approaches. For this purpose, I show how the *DDI* is constructed and how its weaknesses are overcome in the *NDI* framework. Second, I show empirically the differences in outcomes the two approaches yield.

4.4.1 The *DDI* Framework

In most studies, the *DDI* serves as a count of food groups and yields the ratio of those not consuming a diverse diet to the total sample population. Traditionally, neither food-specific nor person-specific thresholds are set. Only incidences of the joint non-consumption in several food groups are counted. For comparison with the *NDI* framework, I construct the *DDI* as close as possible to the *NDI* using the dual cut-off methodology. The latter has not been referred to as such in *DDI* studies; certainly so since the *DDI* normally does not include any

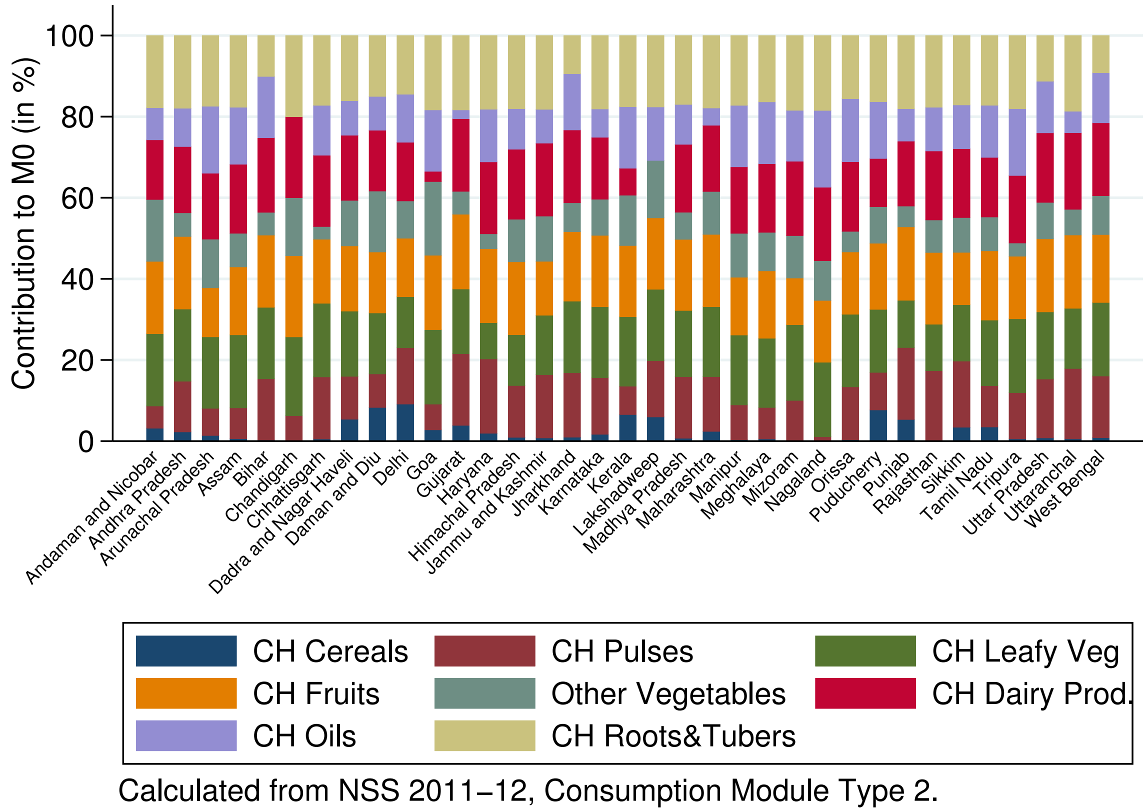


Figure 4.3: Percentage Contribution of Food Groups to $M0$ for $k = 5$

explicit dimensional thresholds one does not think of two cut-offs. The z-vector contains the dimensional cut-offs and can be thought of as only containing zeros for each dimension. The minimum threshold to determine dietary diversity in food groups is in effect a k-value, similar to the one of the NDI framework which builds on the AF methodology. Therefore, I present the DDI framework using the dual cut-off approach which will exemplify the differences between the NDI and DDI.

To begin with, in the DDI framework the threshold vector z_D for d food groups is

$$z_D = (z_1, ..., z_d), \tag{4.13}$$

with all entries being zero. As in the NDI framework, one can think of an achievement matrix, X, with x_{ij} entries reflecting realizations in food consumption for person i in food group j. Now, in order to count incidences of consumption and collect this information in a deprivation matrix, say g^{0_D}, the following holds: given that the threshold vector includes only zeros, elements $g_{ij}^{0_D} = 1$ if $x_{ij} = z_j$, and $g_{ij}^{0_D} = 0$ if $x_{ij} > z_j$. Building on this, a vector of deprivation counts, c^D, contains row-wise counts of deprivations. Ignoring dimensional weights, its entries c_i are $c_i = \sum_{j=1}^{d} g_{ij}^{0_D}$. Regarding the second cut-off, a person is considered as deprived

Table 4.4: Subgroup Decomposition for k-value = 5

Subgroup	H_N	A_N	$M0_N$	CH Cereals	CH Pulses	CH Dairy P.	CH Leafy V.	CH Other V.	CH Fruits	CH Oils	CH Roots &. T.
Caste											
Scheduled Tribes	46.8	72.0	0.337	4.5	36.9	44.5	43.3	21.8	44.2	30.8	43.5
Scheduled Castes	37.2	69.1	0.257	2.6	29.8	34.4	36.0	14.2	35.0	23.7	29.6
Backward Classes	29.7	68.5	0.203	2.2	22.9	27.0	29.1	11.8	27.1	17.5	25.2
Other	22.4	69.3	0.155	2.2	17.0	19.7	21.6	11.7	20.4	12.6	18.8
Religion											
Hinduism	32.5	69.5	0.226	2.7	26.0	29.7	31.4	13.6	30.1	19.5	27.8
Islam	25.5	68.1	0.173	1.3	16.5	24.0	24.7	12.0	23.8	17.5	18.8
Christianity	32.5	72.0	0.234	5.0	19.3	31.8	30.4	18.6	27.0	25.7	29.7
Other	23.6	67.3	0.159	2.4	18.9	18.7	22.8	8.1	22.2	11.0	23.0
Landholding Class											
Landless	46.1	68.3	0.314	6.8	39.8	42.7	45.0	12.9	43.6	21.8	39.0
Marginal	32.1	68.7	0.220	1.6	24.8	30.0	30.8	12.8	29.9	20.2	26.1
Small	27.5	68.1	0.188	0.3	20.7	23.5	27.0	11.9	26.5	13.9	26.3
Semi-Medium	24.2	66.3	0.161	0.3	18.0	18.3	23.4	11.2	23.1	10.6	23.5
Medium	25.0	68.3	0.171	0.0	21.0	18.5	24.8	16.1	22.0	10.5	23.5
Large	18.7	65.4	0.123	0.2	15.4	9.4	18.7	12.4	14.7	8.7	18.4
Household Size											
Less than 3 Members	22.4	76.9	0.172	9.7	20.9	20.3	21.6	12.8	18.3	13.2	20.9
3-4 Members	25.2	67.6	0.170	1.0	19.3	23.2	24.2	9.2	23.6	14.7	21.1
5-6 Members	38.0	68.6	0.260	1.5	28.5	34.7	36.3	15.7	35.4	24.4	31.8
More than 6 Members	42.7	69.1	0.295	1.0	33.0	38.8	41.9	19.5	40.7	25.4	35.5

Calculated from NSS Round 68, Consumption Module 2011-12. Applied RDA: 50 per cent of RDA.
Landholding classes in hectares: $0.002 < \text{land} \leq 1$ (Marginal), $1 < \text{land} \leq 2$ (Small), $2 < \text{land} \leq 4$ (Semi-Medium), $4 < \text{land} \leq 10$ (Medium), land >10 (Large)

in dietary diversity (not consuming a diverse diet) if she is deprived in at least k food groups. Applying k to the c^D-vector thus yields the $c^D(k)$-vector with entries $c_i(k) = 1$ if $c_i \geq k$ and $c_i(k) = 0$ if $c_i < k$. Now, traditionally the DDI framework has been used only to report the incidence of those not consuming a diverse diet, which is H_D. The latter can be written as: $H_D = \frac{\sum_{i=1}^{n} c_i(k)}{n}$.

Viewing the DDI in such an Alkire-Foster-type framework the DDI resembles the NDI in two ways. One, the joint deprivations in food groups are considered. Thus, both the NDI and the DDI account for simultaneous deprivations in food inadequacies at the individual level. Second, both the NDI and the DDI framework yield a headcount ratio of the inadequately nourished, H_N and H_D, respectively.

However, the DDI framework has three major shortfalls, which the NDI framework overcomes. First, the DDI does not elicit beyond the incidence of food inadequacy. While H_D is certainly very informative as such, it does not inform about the intensity of food inadequacy. Therefore, inequalities in food diversity among those not consuming a diverse diet may be stark but overlooked by focusing only on H_D. In fact, H_D identifies everyone as equally deprived in dietary diversity as long as they consume less than k different food groups, even though some may consume much less than the minimum k while others consume just below k. Formally, H_D violates the monotonicity principle, according to which, in the context of the DDI, additional deprivations should increase food inadequacy and thus the value of H_D. The violation of the monotonicity principle is a well known problem in poverty measurement. To overcome it, other poverty measures go beyond the headcount ratio and allow to estimate the intensity of poverty (Foster et al., 1984; Ray, 1998; Alkire et al., 2015). The NDI framework, too, overcomes this problem by accounting for the average intensity of food deprivation, A_N. The headcount ratio H_N, similar to H_D, still violates the dimensional monotonicity. But since both the incidence as well as the intensity of food inadequacy are calculated the NDI framework provides for much richer information. Further, the ultimate NDI-figure, $M0$, which is the product of H_N and A_N, does not violate dimensional monotonicity.

Second, the DDI framework does usually not include dimensional thresholds. Recall, the z_{DDI}-vector contains only zeros. Doing so, the DDI does not control for heterogeneous food requirements and thus ignores the extent of food deprivations within food groups. The DDI framework could easily allow for the inclusion of food-group specific thresholds as these could be collected in the z_D-vector. However, this is rarely done. The NDI framework, on the other hand, does account for dimensional thresholds.

Third, the DDI framework does not include any individual specific thresholds for the various food groups. Similar to not including dimensional thresholds, not accounting for idiosyncratic differences in food requirements underestimates the incidence of food inadequacies and neglects the extent of food inadequacy entirely. For instance, food requirements vary immensely by age, gender, occupation and other factors (Gopalan, 1992; Kakwani, 1992), but the DDI ignores all of these by just counting incidences of consumption irrespective of any thresholds. The NDI overcomes this weakness by accounting for idiosyncratic thresholds. The $n \times d$-dimensional Z-matrix combines both idiosyncratic and dimensional thresholds.

4.4.2 Empirical Differences in NDI and DDI Applications

Given the fundamental differences in the two conceptual frameworks described above, empirical outcomes can be expected to be different. To show this, I utilize the NSS household-level data for rural India (2011-12), as before.

Headcount ratios for any given k-value will always be higher for H_N than for H_D, or at least as high. This is due to the z-cut-offs which are always zero in the DDI framework and are always greater than zero in the NDI framework. Therefore, under the DDI framework, by counting tiny amounts of food consumption one would identify these as "no deprivation", whereas under the NDI one would identify these tiny amounts as a food shortfall and a deprivation, given that they are below the household-specific threshold of z_h.

Table 4.3 presents both H_N and H_D. Clearly, H_N is always higher than H_D across all k-values. In terms of levels, the two headcount ratios are very different, especially so for lower k-values. For a k-value of 1, the H_D figure is 67 per cent, implying that 67 per cent of India's rural population do not at all consume at least one of the eight food groups. H_D then drops sharply to 28 per cent given a k-value of 2. In contrast, for the same k-values H_N is much higher at about 100 per cent and 96 per cent, respectively. This means that almost all rural households are inadequately nourished in at least two food groups given the z_h-cut-offs. The H_D figures drop much further and faster than the H_N figures, so that already at a k-value of 4 the incidence figure is close to 1 per cent, which the H_N reaches only at a k-value of 8. These differences are also visible and even more pronounced in the state-wise decomposition of H_N and H_D

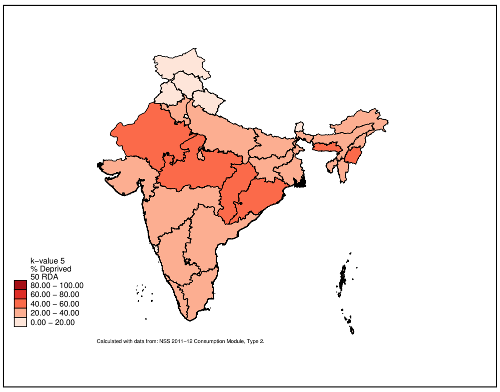
Table 4.5: State-wise Headcount Ratios H_N and H_D for k-value = 5

	$k=1$		$k=2$		$k=3$		$k=4$		$k=5$		$k=6$		$k=7$		$k=8$	
State	H_N	H_D	H_N	H_D	H_N	H_D	H_N	H_D	H_N	H_D	H_N	H_D	H_N	H_D	H_N	H_D
Andaman & N.	100.00	56.22	97.19	22.62	79.39	5.35	38.96	1.76	9.74	1.76	3.60	1.76	1.76	1.76	0.60	0.60
Andhra P.	99.97	59.40	98.58	23.87	87.08	7.25	58.84	3.42	24.30	2.85	7.36	2.70	4.32	2.67	2.36	1.98
Arunachal P.	99.27	80.39	92.12	50.42	82.01	28.51	62.99	15.12	38.37	5.53	16.60	1.99	7.04	1.61	1.65	1.59
Assam	99.76	58.69	96.29	23.20	84.04	4.98	63.09	1.06	33.42	0.94	13.57	0.94	4.01	0.89	0.95	0.89
Bihar	98.68	77.19	92.20	30.40	75.15	4.19	49.07	0.11	25.70	0.08	7.89	0.08	1.70	0.08	0.08	0.07
Chandigarh	99.92	97.72	90.78	32.49	69.90	0.00	26.36	0.00	11.17	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Chhattisgarh	99.89	81.69	98.22	44.53	93.41	7.39	77.29	1.25	44.13	0.93	17.80	0.93	3.47	0.93	1.24	0.92
Dadra & N.	100.00	91.68	100.00	76.13	96.18	37.78	93.58	16.60	49.23	16.60	25.39	16.60	17.98	16.60	16.53	16.53
Daman & Diu	100.00	79.67	99.76	44.00	82.96	14.64	57.73	9.02	16.37	9.02	9.02	9.02	9.02	9.02	9.02	9.02
Delhi	97.78	69.24	97.78	12.12	61.48	6.31	28.19	6.31	9.98	6.31	7.28	6.31	6.31	5.53	5.53	5.53
Goa	100.00	54.63	94.35	13.95	68.29	0.08	35.13	0.00	14.66	0.00	6.53	0.00	0.08	0.00	0.00	0.00
Gujarat	99.95	73.78	98.72	22.02	90.36	4.43	68.63	1.43	34.09	1.43	9.97	1.43	3.05	1.42	1.42	1.11
Haryana	99.51	75.00	95.58	28.29	78.13	3.42	53.82	0.53	23.46	0.42	6.09	0.34	1.03	0.34	0.46	0.34
Himachal P.	98.25	69.20	91.42	16.08	68.06	1.72	38.46	0.75	15.73	0.75	5.36	0.75	1.85	0.71	0.43	0.43
Jammu & K.	99.06	48.67	87.70	8.87	56.06	0.63	28.74	0.48	11.42	0.48	3.16	0.37	1.42	0.36	0.24	0.22
Jharkhand	99.70	89.32	96.71	57.35	87.95	18.53	64.38	2.19	39.73	1.63	14.98	1.63	4.80	1.63	1.32	1.31
Karnataka	99.96	42.33	98.29	8.69	86.90	2.82	60.68	2.16	32.47	2.07	11.18	2.00	4.39	2.00	1.35	0.51
Kerala	100.00	61.50	99.43	20.14	84.24	5.23	49.12	3.02	22.21	2.53	9.20	2.47	4.12	2.10	2.03	1.33
Lakshadweep	100.00	83.93	100.00	23.22	98.83	11.57	44.34	6.45	19.05	6.45	6.45	6.45	6.45	0.00	0.00	0.00
Madhya P.	99.67	74.60	98.01	30.47	90.34	7.02	73.74	0.94	49.84	0.85	24.16	0.85	6.70	0.72	0.98	0.66
Maharashtra	99.56	44.01	96.69	17.22	88.04	7.55	67.31	3.97	36.55	3.84	13.79	3.83	4.87	2.71	1.79	1.73
Manipur	100.00	76.27	98.85	47.83	94.27	9.61	80.84	1.50	57.05	1.38	33.28	1.24	11.58	1.24	1.13	1.13

Meghalaya	99.92	51.13	98.93	24.21	90.76	2.14	70.69	1.50	49.00	1.50	28.71	1.50	11.43	1.50	1.50	1.50
Mizoram	99.83	67.53	96.67	25.35	86.14	7.73	57.53	2.87	28.90	1.22	8.82	0.35	1.41	0.00	0.00	0.00
Nagaland	99.78	62.02	98.71	15.99	94.08	3.77	72.16	0.51	28.35	0.00	7.47	0.00	0.28	0.00	0.00	0.00
Orissa	99.86	66.23	97.78	34.56	88.62	6.37	70.07	0.79	43.40	0.62	20.22	0.55	4.33	0.40	0.64	0.16
Puducherry	100.00	59.46	94.57	20.19	78.67	8.76	36.04	5.91	13.61	5.91	6.84	5.91	5.91	5.91	2.52	2.12
Punjab	99.79	83.28	93.88	31.85	76.67	2.50	45.84	1.98	16.77	1.98	5.50	1.98	2.04	1.51	0.17	0.17
Rajasthan	99.89	74.94	98.17	33.62	93.05	5.04	76.57	0.30	45.12	0.18	19.32	0.09	6.62	0.03	0.02	0.02
Sikkim	99.24	67.30	95.89	12.52	71.11	3.60	35.62	2.77	13.71	2.74	5.46	2.74	3.36	2.74	2.62	2.62
Tamil Nadu	99.91	45.98	98.54	14.05	82.49	3.73	57.83	1.90	33.14	1.85	16.99	1.85	7.48	1.78	2.42	0.58
Tripura	99.98	62.29	95.97	25.27	81.56	5.42	55.96	1.05	25.94	0.78	9.40	0.78	1.47	0.40	0.40	0.11
Uttar P.	99.57	80.25	94.09	34.97	78.98	7.66	54.33	0.75	29.26	0.65	10.81	0.65	3.45	0.54	0.39	0.29
Uttaranchal	98.42	64.14	87.21	17.69	64.04	1.29	35.50	0.54	11.89	0.34	2.13	0.34	0.47	0.34	0.30	0.30
West Bengal	99.59	70.28	95.94	33.20	77.66	5.04	47.52	0.67	22.08	0.62	8.20	0.59	2.11	0.46	0.64	0.38

Calculated from NSS Round 68, Consumption Module 2011-12. Applied RDA: 50 per cent of RDA.

(a) H_N for $k = 5$



(b) H_D for $k = 2$

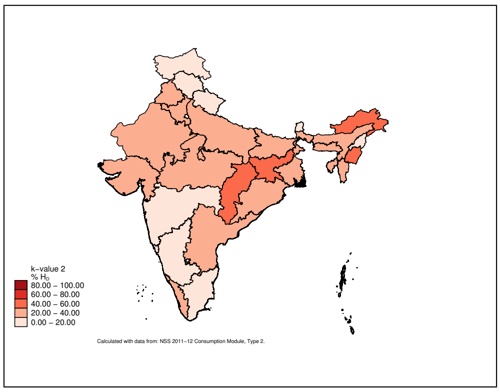


Figure 4.4: State-wise H_N for $k = 5$ and H_D for $k = 2$

(Table 4.5). For example, at a k-value of one, H_N is as high as 100 per cent in almost every state, whereas H_D can be as low as 42 per cent (Karnataka).[12] Similar to the national figures, state-wise H_D reduces much faster than H_N with increasing k. In Karnataka, for instance, H_D decreases to 9 per cent at a k-value of two and declines further to two per cent at a k-value of four. In contrast, H_N reduces at a much smaller rates with higher k-values, so that only at a k-value of eight it is at level of two per cent.

H_N and H_D are similar in magnitude at the national and state level at two specific k-values. At a k-value of two for H_D and at a k-value of five for H_N, the national incidence rates are not too far apart: H_N is just above 30 per cent and H_D is just below 30 per cent. While the two ratios at the national level are not far apart given, maps for state-wise variation in H_N and H_D, given the two specific k-values, reveal a different scenario (Figure 4.4). H_N for a k-value of five is particularly high in the Northern Hindi speaking belt (Rajasthan, Madhya Pradesh, Chhattisgarh, and Orissa). H_D, on the other hand, does not replicate such a pattern entirely as there is more variation across Indian states. For example, Chhattisgarh and Jharkhand are among the most deprived states, the remaining four states identified under H_N as part of the "belt" are not in this group, however. Further, while there does not appear to be much variation across states in Central and Southern India under the H_N, there is a stretch identified as much less food deprived under the H_D. This stretch reaches from Maharashtra via Karnataka to Tamil Nadu. To sum up, the two frameworks yield highly divergent results. It is apparent that a DDI underestimates food inadequacies to a great extent by just focusing on non-zero food intakes, which by particularly pronounced in regional estimations.

One may conjecture that household-level data are not ideal for either of the two measures. Both measures are ideally applied to individual-level data to account for intra-household allocations. I show, however, that even household-level data can be applied using the NDI framework when "tweaked" for household-level data by summing up individual thresholds at the

[12] For completeness, Appendix Figure ?? includes maps showing the state-wise variation in levels of H_D for all k-values up to six.

household level. Such a scenario is not feasible in the traditional DDI framework when all thresholds are set at zero. Therefore, the NDI has some advantage in this regard. Both the DDI and NDI are ideally suited to capture food groups for a short recall period, for example, two days. For longer periods its values, especially those of the DDI, are certain to drop drastically, as evident from Table 4.3.

Both frameworks depend to a great deal on the data collected. If these are based on national household consumption surveys both frameworks will suffer from sampling error. Any measure is bound to suffer from such drawbacks if no census data can be collected. In addition, for the ideal NDI, individual level-data on consumption (in quantity) would be necessary. Given the long list of food items as for example in the latest NSS round, the collection of such data at the individual level is likely to be very time consuming, and might stretch resources of national statistics offices beyond capacities. Certainly, in favor of the DDI speaks that individual-level data on just the incidence of eight food groups can be collected in much less time. If, however, the data collection is focused on just the eight food groups of interest, resources of national statistics offices may also suffice to collect quantity-wise information on consumption at the individual level. The latter are then ideally suited for an NDI.

4.5 Concluding Remarks

This paper presents a new tool to measure dietary diversity: the Nutritional Deprivation Index (NDI). Being a counting method, the NDI extends the widely used Dietary Diversity Index (DDI) and builds on the Alkire-Foster methodology. I show that the NDI can be applied to both individual as well as household-level data from ordinary national sample surveys. The NDI overcomes three major weaknesses of the DDI. First, while the DDI only considers the incidence of the inadequately nourished, the NDI provides both the incidence and the intensity of nutritional deprivation. Doing so, the NDI framework yields the headcount ratio of the inadequately nourished and the average deprivation share of the inadequately nourished. Second, the NDI provides for food group-specific thresholds, which are overlooked in common applications of the DDI. Third, in combination with food group-specific thresholds, the NDI allows for individual-specific thresholds. Since consumption is shown to vary substantially by age, occupation, activity level, and gender among many other factors (Gopalan, 1992; Osmani, 1992; Behrmann, 1992; Deaton and Drèze, 2009; Tilman and Clark, 2015), the NDI feature of allowing for both idiosyncratic and food group-specific thresholds is certainly advantageous and makes the NDI superior to the DDI framework.

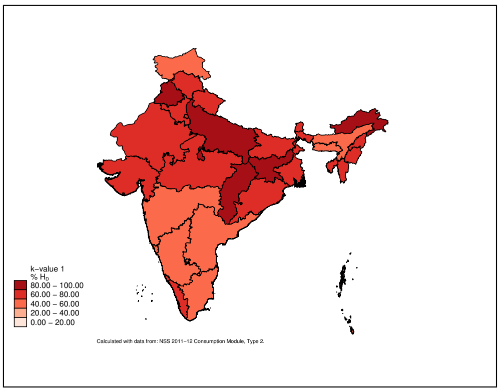
In this paper, I demonstrate how the NDI can be applied to ordinary household-level data for rural India. I implement several advantages of the NDI framework, such as regional decomposition and dimensional breakdowns, which provide for interesting information. My analyses reveal that the highest incidences of inadequately nourished households are in the Northern states of Rajasthan, Madhya Pradesh, Chhattisgarh, and Orissa. Going beyond an analysis of headcount ratios, these households are deprived in at least five of eight food groups, and primarily so in the food groups of pulses, leafy vegetables, and fruits. Further, the traditionally most disadvantaged socioeconomic subgroups are the most exposed to inadequate nutrition. These include Scheduled Tribes and Scheduled Castes, the landless, and households with many household members. The results exemplify that the manifold decompositions of the NDI are ideal for targeting purposes. Using this framework, policy makers can, on the one hand, identify inadequately nourished regions and subgroups, while on the other hand identify the most needed food groups. Such a measure can be of great use in low income countries or regions of crises. The rich information gained from an application of the NDI could also inform awareness campaigns designed for wealthier societies, where despite available resources to afford a healthy and diverse diet, many households in higher income countries chose not to do so (Tilman and Clark, 2015).

The outlined technique of an adjusted Alkire-Foster methodology has the potential of being used in other fields of research related to health, nutrition, and health economics. For example, the technique can be easily adopted to measure child nutrition and deficiencies in micro-nutrients in a multidimensional setting. The outlined technique can be adapted to allow for child nutrition-specific weighting schemes, so that nutrients or food groups important during child feeding, e.g. milk, calcium, receive higher weights. Going beyond food groups, one can think of converting food groups into micro-nutrients to measure a more finely tuned measure of nutrition. This may overcome the limitation of food groups being substitutes in the NDI framework. While research has established a link between dietary diversity - as based on the DDI - and anthropometric outcomes (e.g. Menon et al., 2015), such a correlation still needs to be established for the likely link between parameters of the NDI and anthropometric outcomes.

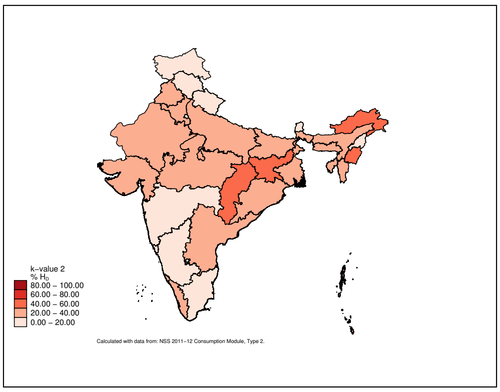
Appendix

4.A Figures

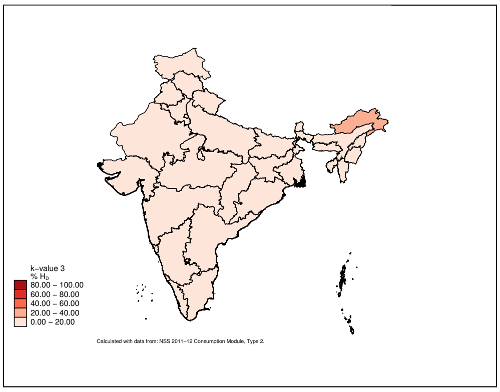
(a) $k = 1$



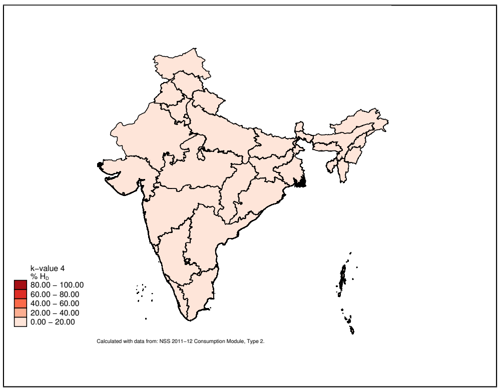
(b) $k = 2$



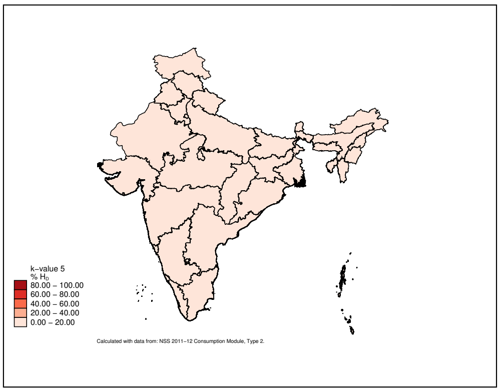
(c) $k = 3$



(d) $k = 4$



(e) $k = 5$



(f) $k = 6$

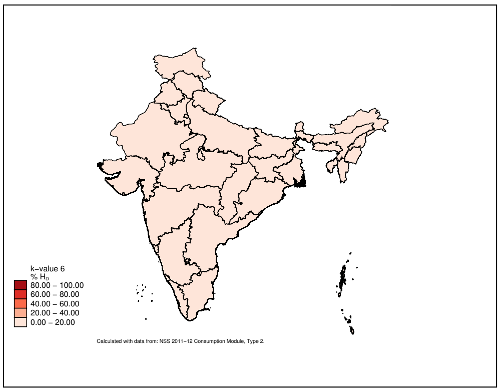


Figure 4.5: State-wise H_D by k-value

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