How do credit constraints affect households? Evidence from a natural experiment

Renuka Sane*
Susan Thomas
Indira Gandhi Institute of Development Research

December 15, 2012

Abstract

Micro-finance in a state in India ground to a halt in October 2010, when the state government passed an Ordinance that effectively prohibited any new loans and stopped collection of repayments. This paper evaluates the impact of such a large-scale withdrawal of credit on the average household expenditures in regions affected by the Ordinance, comparing it to matched regions in the country which did not suffer such a withdrawal. It finds that average household expenditures fell sharply in the effected regions, and more sharply for those households that had a greater exposure to micro-credit.

*PRELIMINARY DRAFT. PLEASE DO NOT CIRCULATE. We thank Ajay Shah for useful discussions. Email: renuka@saner.org.in, URL: http://www.saner.org.in

Contents

1 Introduction

Long before the recent regulatory focus on the problems of financial exclusion, the importance of access to credit has been a focus of research on finance. However, a disproportionate fraction of this literature has focussed on the impact of credit constraints on the financing patterns of firms, most probably driven by the lack of access to publicly available household level data on financing patterns. The last decade has seen an emergence of a literature on credit constraints faced by households, on the back of the emergence of rapidly growing micro-credit industries. The form of these industries have been different in different regions: payday lending in developed countries and micro-finance in emerging economies. In 2009, more than 10 million households had used payday loans (in the US), and there were 90 million micro-credit borrowers in 102 countries (Skiba and Tobacman, 2009).

The relevant literature has focussed on understanding the harm that lending can impose on the welfare of a household when credit is mis-sold. For instance, there is little consensus on whether pay-day loans or micro-credit improve the lives of their borrowers. While rationale would indicate that such access is welfare improving, since customers reveal-preferred to borrow, other research suggests that people are not financially sentient and overlook the costs of such borrowing, are naive about time-inconsistent preferences and end up in financial distress (Armendáriz and Morduch, 2010; Skiba and Tobacman, 2009; Lusardi and Tufano, 2009; Thaler, 1990).

In the case of micro-credit there is an added tension between the goals of poverty-alleviation of the original micro-finance movement and profit maximisation of commercial micro-finance today (Arun and Hulme, 2008). These tensions are reflected in the on-going debate on how to regulate these sectors (Davis, 2009; Shankar and Asher, 2010; Skiba, 2012). In practice, governments have often taken measures such as capping of interest rates and sometimes outright ban of the micro-credit products.

In India, one of the state governments (Andhra Pradesh) passed an Ordinance that effectively prohibited any new micro-finance loans and stopped collection of repayments in October 2010 (State government of Andhra Pradesh, 2010). The micro-finance industry in the state has not restarted any significant lending operations since that time. This paper investigates the impact of the Ordinance on household expenditures in the region. Since the objective of this (and similar) bans is driven by the desire for consumer protection and consequently improvements in consumer welfare, a test of it's impact is whether household welfare in this state has improved after the ban on micro-credit. Specifically, this paper focusses on consumption expenditure as one of the critical measures of household welfare.

In order to do this, the paper uses data from a national level panel household survey, run quarterly since 2008. The data includes the average expenditure of households at the level of geographically similar districts, both as aggregate expenditure for the average household in the previous quarter, as well as across different expenditure heads. While this does not permit an evaluation of the impact on individual households, it does help to evaluate the aggregate impact on average household expenditure in a region. The data also permits the identification of similar regions in the country which did not simultaneously suffer the exogenous shock to restrict access to credit, which is matched to the affected regions by various control variables parameters such as income and access to finance. A difference-in-difference methodology is used to estimate the impact on average household expenditure of the affected regions relative to the unaffected regions. The evidence shows a fall of average expenditure of households in regions in Andhra Pradesh across the board. Moreever, the fall is greater for groups that are more exposed to micro-credit.

The paper presents evidence on the adverse impact of policies that restrict access to credit. These results echo that of Morgan and Strain (2008) who find that households welfare saw a decrease when payday credit was banned in states of Georgia and North Carolina, and Morse (2011) who points out that access to payday credit in the event of a natural disaster is welfare-improving, even when the credit is extended at 400 percent APR.

The paper contributes to the fledgling evidence on the general impact of micro-credit. Most studies on the impact of micro-finance are in the form of randomized control trials (RCTs), where some households (or areas) are provided with access to credit, and are then compared to those who did not have this access (Banerjee et. al., 2009; Karlan and Zinman, 2010; Crépon, Devoto, Duflo, and Parienté, 2011; Karlan and Zinman, 2011; Augsburg et. al., 2012). Research on examining the general equilibrium (GE) effects has been relatively scant (Kaboski and Townsend, 2011; Buera, Kaboski, and Shin, 2012). While RCTs suffer from the problem of external validity, the

GE approach typically provides results out of a simulated model. The ideal approach would involve the application of the micro-credit treatment on the scale of a country. This paper is able to utilize precisely such a natural experiment.[1]

The paper is structured as follows. Section 2 describes the literature on impact of credit access on household welfare. Section 2.1 describes the setting of the natural experiment of credit withdrawal at the national level in India which forms the basis of the analysis. The identification strategy in section 3. Section 4 contains a description of the data, and Section 5 describes tests of the reliability of the approach. Section 6 presents the results, and Section 8 concludes.

2 How do credit constraints matter

Research on credit constraints has mostly focused on the impact of alleviating constraints on various outcomes such as consumption and entrepreneurship. Central to these empirical exercises is the observation that consumption displays excessive sensitivity to income, and people with access to credit are better able to smooth their consumption (Jappelli, Pischke, and Souleles, 1998). In models with liquidity constraints, households build up precautionary savings, and thus lower consumption (Zeldes, 1997).

In recent empirical work, Kaboski and Townsend (2012) claim that credit constraints are particularly binding in consumption decisions. They find that two kinds of households increase consumption upon credit receipt: those that are consumption constrained with short-term liquidity needs and those with buffer stocks larger than necessary after the credit constraint has been relaxed. Increases in consumption through the micro-credit channel are also validated by (Banerjee et. al., 2009) in India and (Crépon, Devoto, Duflo, and Parienté, 2011) in Morocco.[2] Research on unexpected credit withdrawals is scant. Whatever little evidence there is on restricting access to credit,

[1] The total population of Andhra Pradesh is about 84 million making it the fourth largest state in India, as large as Germany and larger than all other European countries.

[2] In Morocco, the effects on consumption are pronounced only for those that did not have an existing business.

shows that it hinders productive investment and/or consumption smoothing, at least over the short-term (Morgan and Strain, 2008; Zinman, 2010).

When credit is withdrawn, it is expected that borrowers could substitute towards other potentially more expensive, sources of credit. This depends on the ability of borrowers to tap into other sources which may have been limited before micro-finance, and become even less accessible after, since removal of any source of credit may lead to lower repayment capacity. Another hypothesis is that there are disruptions in consumption smoothing, especially for those households with limited access to other lenders. Liquidity constraints can have large effects on the level of consumption even when they do not currently bind, as long as it is possible that they bind in the future (Zeldes, 1997; Gross and Souleles, 2002). For example, households may accrue buffer stocks of liquid assets in response to uncertainty about the ability to borrow. This, in turn, could lead to reduced consumption.

In the case of low-income households, consumption credit also serves the role of insurance. In situations involving uncertain income streams, it enables risk-pooling across time (Eswaran and Kotwal, 1989). In an experiment on micro-credit borrowers in the Philippines, Karlan and Zinman (2011) find that micro-credit is used to buffer fluctuations in income and expenses. Morse (2011) shows that access to payday lending allows households to cope through natural disasters and thus mitigate financial distress. Sudden micro-credit withdrawal may make households more vulnerable to income shocks, and drive down consumption further.

Credit access, and by analogy credit withdrawal, can also have general equilibrium (GE) effects. Buera, Kaboski, and Shin (2012) study the GE effects of micro-credit and show that ultimately, the impact is a complex function of the interaction between interest rates, wages and capital accumulation and often leads to redistribution away from high-savers to low-savers. This may imply that households that were not directly micro-finance borrowers, may also get affected as lack of credit may disrupt the functioning of the micro-credit dependent households, and have a cascading effect on the income-generation opportunities of other households.

The link between consumption and credit points to potential declines in expenditures in the absence of the latter. If micro-credit did matter, then we expect that the the average household expenditure would decline in regions affected by the credit withdrawal. We would also expect that these declines are strongest for those households that were most dependent on the channel of credit which are withdrawn.

2.1 The institutional setting of the natural experiment

Micro-finance institutions (MFI) are part of a large but fragmented credit industry that provides loans to borrower households in India. The industry consists of four kinds of providers:

- Rural-lending arms of the formal banking sector. These are of two types: a) Regional Rural Banks (RRBs) which were established specifically with the objective of providing credit access to the poor and b) Co-operative societies.
- Bank linked Self-Help Group (SHG) programs. These are programs run by commercial banks to lend to groups of 10 to 20 women.
- Micro-Finance Institutions (MFIs). These are private sector entities in the business of extending credit to small groups similar to that of the SHGs. These include not-for profit non-governmental organisations (NGOs), and for-profit non-banking finance companies (NBFCs).
- Traditional money lenders.

While loans outstanding of MFIs have been traditionally smaller compared to that of the SHGs, the growth rate of the MFIs had been larger than that of SHGs in recent years (Srinivasan, 2009). By 2010, the annual rate of growth was supposed to be around 80 percent and MFI clients stood at 27 million (Srinivasan, 2010).

The MFI presence is extremely skewed in India, with Southern India (particularly the states of Andhra Pradesh, Tamil Nadu and Karnataka) accounting for most of the loan portfolio. The state of Andhra Pradesh (AP) has been the locus of the industry in India.[3] Andhra Pradesh has been at the forefront of promoting the bank-led self-help group (SHG) program (Datta and Mahajan, 2003), as well as the state where the largest micro-finance institutions (MFIs) are headquartered, consituting the largest share of micro-credit

[3] Chakrabarti and Ravi (2011) provide an overview of the micro-finance industry in India. Srinivasan (2010) provides an overview of the state of the sector.

borrowers and loans outstanding in the country (Srinivasan, 2010).

In response to several mis-selling allegations made against the MFIs in 2010[4] the state government intervened by passing an ordinance that made it extremely difficult for MFIs to function in the state (State government of Andhra Pradesh, 2010). This had a series of consequences on the micro-finance industry.

1. As part of the Ordinance, MFIs have been unable to collect repayments from their customers which resulted in a large scale increase in the default on their loan portfolios.

2. The scale of the defaults in their loan portfolio resulted inthe MFIs themselves defaulting to their funding channels. Liquidity providers to this industry, such as the banks, stopped their access to future funds. The lack of funds to lend set in motion an increased incentive on the part of the borrower household to default on their loans to the MFIs, further exacerbating the worsening financial health of the MFI.

3. A larger consequence was that the banks, fearing that other state governments in India would follow the Andhra Pradesh example and implement similar ordinances in their states, stopped lending to all MFIs irrespective of whether their loan portfolio had a large exposure to Andhra Pradesh credit or not.

Thus, the Ordinance on micro-lending that was passed by the Andhra Pradesh government resulted in the the entire micro-finance industry facing a freeze in liquidity during the period from December 2010 to nearly a year after. While money has started to flow to MFIs in other states micro-finance in AP continues to remain in statis. MFIN (2012) points out that the portfolio of MFIs in AP decreased by over 35 percent, while that of MFIs outside of AP grew by 25 percent over 2011-12. Loan disbursements by the MFIs have also decreased in 2011-12, largely driven by the decrease in disbursements in AP. This captures a sense of the void in the micro-acredit channels for borrower households in the state, relative to other states in India.

This setting that we have access to test the impact of a decrease in micro-credit is unique from a couple of perspectives: (1) The change has taken place for a large sample of people. The population of Andhra Pradesh is about

[4] Arunachalam (2010) is a good reference to details of both the crisis.

84 million making it the fourth largest state in India, as large as Germany and larger than all other European countries. (2) The regulatory change is restricted to only one state. This enables the comparison of the effect of the change in credit access across different states within India.

3 Methodology

The aim of the paper is to evaluate the impact of unexpected credit withdrawal on household expenditures. The empirical modeling problem is the evaluation of a causal impact of the AP Ordinance on the expenditures of households.

Let R_{it} be an indicator if region i was affected by the AP crisis i.e. was a region in the state of Andhra Pradesh at the time of the Ordinance t. Let y^1_{it+s} be the average expenditure in region i at time $t+s, s>0$. Let y^0_{it+s} be the average expenditure in region i had the Ordinance not been implemented. The causal effect of the Ordinance for region i at time period $t+s$ is:

$$y^1_{it+s} - y^0_{it+s}$$

The problem however is that y^0_{it+s} is unobservable.

We follow the micro-econometric evaluation literature (Rosenbaum and Rubin, 1985; Heckman et. al., 1997; Dehejia, 2005) and define the average effect of the Ordinance on regions in AP as

$$E(y^1_{t+s} - y^0_{t+s}|R_{it}=1) = E(y^1_{t+s}|R_{it}=1) - E(y^0_{t+s}|R_{it}=1)$$

where causal inference relies on the construction of the counter-factual for the last term in the above equation, which is the outcome the affected regions would have experienced, on average, had they not been been covered by the Ordinance. This is estimated by the expenditure of regions that were unaffected by the Ordinance i.e. $E(y^0_{it+s}|R_{it}=0)$.

An important feature in the construction of the counter-factual is the selection of a valid control group such that contemporaneous effects correlated with the region are controlled for. We use the Andhra Pradesh Ordinance as a natural experiment to create the counter-factual. The Ordinance was sudden, and its impact was lethal - from a state with the highest penetration of micro-credit, Andhra Pradesh is now amongst the lowest in terms of new disbursements. This natural experiment therefore allows us to compare outcomes with regions that did not suffer from such a crisis, thus serving as a counter-factual. This is the crux of the identification strategy of this paper.

3.1 Matching

The approach is to apply matching techniques to identify pairs as follows: each region in Andhra Pradesh to similar regions in states that are matched in relevant covariates. This would enable an identification of the counterfactuals. This type of matching procedure is preferable to randomly selecting regions outside of AP as it is less likely to lead to estimation bias by picking regions with completely different characteristics. As the Ordinance was completely exogenous, the method used is the nearest neighbour matching with the Mahalonobis distance measure. In its simplest form, 1:1 nearest neighbor matching selects for each treated unit i the control unit with the smallest distance from individual i. The Mahalanobis distance measure is calculated as follows:

$$D_{ij} = (X_i - X_j)'\Sigma^{-1}(X_i - X_j)$$

where D_{ij} is the distance between unit i and j and X_i and X_j are the characteristics of the control and treatment units.

The choice of these covariates is driven by the influence of the variables on the overall economy of the region, that in turn is likely to influence borrowing and expenditure. The first two variables we consider are average income of households, and the number of households. These variables provide an estimate of the prosperity in the region, as well as size. As our focus is the impact of an Ordinance related to micro-credit, it is important to control for a) similarities in the clientele of micro-finance, and b) similarities in access to formal finance. We therefore consider two variables: first we consider the proportion of the population that is between the age of 20 and 60 i.e. working age in a particular region as it is this segment which is the client of the micro-credit institutions. Second, we consider the proportion of the population that is classified as financially excluded i.e. does not have a bank account, or a credit card, life insurance policy or any formal-sector financial product. Considering the centrality of micro-credit in providing access to those outside the purview of formal finance, this variable is critical to finding regions comparable to those affected by the Ordinance. We then consider the proportion of farmers in the region. Finally, we consider the proportion of households who have studied upto class ten to serve as a proxy for the human capital in the region. The estimation procedure thus uses six covariates for the matching exercise, which is consistent with the requirements of the Mahalanobis distance procedure (Zhao, 2004).

We do not use the penetration of micro-credit as a variable because it is likely to be affected by the treatment. We also do not use the observed outcome variables in the matching procedure to avoid the problem of variable selection based on estimated effects (Stuart, 2010).

3.2 Difference-in-difference

The matching estimator described above makes a strong ignorability assumption that there are no unobserved differences between treatment and control, conditional on observed covariates. In the context of a region, this may be a difficult assumption to justify. Since we observe expenditure pre and post the Ordinance, we use a difference-in-differences (DID) matching estimator on the matched regions instead, as they are a considerable improvement on standard matching estimators (Blundell and Dias, 2000). This estimator allows the elimination of unobserved time-invariant differences in expenditures between affected and non-affected regions that standard matching estimators fail to eliminate (Smith and Todd, 2005).

We estimate a difference-in-difference model of the following form

$$y_i = \beta_0 + \beta_1 ap + \beta_2(postcrisis) + \beta_3(ap * postcrisis) + \epsilon_i$$

where y_i is: the outcome of interest. ap is a dummy for whether the region is in the state of Andhra Pradesh. Post crisis refers to the quarters after the credit-crisis and includes the four quarters of March, June, September and December 2011. Pre-crisis quarters include the four quarters of March, June, September and December 2010.[5] β_3 is the difference-in-difference estimator. It is identified through variation in average expenditure between regions in

[5]The survey data in December 2010 reflects variables as of June to September 2010. This is why the December 2010 quarter is considered as a pre-crisis quarter. More details on the survey data are presented in Section 4.

AP and regions outside AP before the crisis, and comparison of this difference with variation in average expenditure between the same two groups after the crisis. If after the credit crisis regions in AP saw greater falls in expenditure compared to regions outside of AP, then the interaction term, ap * post crisis should be negative and statistically significant.

3.3 Multiple inference

Studies which evaluate a large number of outcomes suffer from the problem of *multiple inference*. The reported p-values are typically correct for tests conducted in isolation. In the case of multiple outcomes, however, it is possible that some outcomes display significance even if no effect exists. Small samples ensure that the results are of a high magnitude as well (Anderson, 2008). We deal with this by adjusting the p-values of each test upwards to reduce the probability of a false rejection using the False Discovery Rate method.[6]

4 Data

The dataset used for the analysis is a household survey across all the states of India, carried out on a quarterly basis since June 2009 by the Centre for Monitoring Indian Economy. This is called the Consumer Pyramids data.

4.1 The Consumer Pyramids household survey

The survey provides data on income, expenditures and savings of households aggregated at the level of a region. A household includes persons who share a "common kitchen". Households are selected through multiple stages of stratification and then are randomly selected from the ultimate strata. Multiple

[6] The False Discovery Rate method of Benjamini, Hochberg, and Yekutieli control the false discovery rate, the expected proportion of false discoveries amongst the rejected hypotheses. FDR procedures are considered less stringent compared to familywise error rate (FWER) procedures (such as the Bonferroni correction). This however leads to an increase in power at the cost of increasing the rate of type I errors, which is a reasonable trade-off considering the small sample size of this study

Table 1 Expenditure heads

This table presents the items for which CMIE collects data on household expenditures. It also describes the sub-components of each expenditure head, and the percentage share of each item in total expenditure in Andhra Pradesh in September 2010.

Heading	Description	% share in total expenditure (AP, Sep 2010)
Food	Various food items	48.74
Power and Fuel	Cooking fuel, petrol, diesel, electricity	9.58
Cosmetics	Includes toiletries	7.08
Education	Books and various fees	5.53
Miscellaneous	Includes tourism, social obligations	4.76
Communication	Telephone, Newspaper, TV, Internet	4.63
Clothing	Garments, footwear and accessories	4.54
Transport	Daily bus/train/autorickshaw fare	3.80
Intoxicants	Cigarettes and alcohol	2.73
Bills	House rent and other charges	2.25
EMIs	Installments on cars, durable goods, home	1.95
Restaurants		1.78
Health	Medicines, Doctor fees, Hospitalisations	1.58
Recreation	CDs, movies, toys	1.05
Total		100.0

levels of geographical stratification are followed by the random selection of villages and Census Enumeration Blocks (CEBs)[7] from cities. Out of this, a set of regions, called the Homogeneous Regions (HRs), are defined which is a collection of districts with relatively consistent internal features. The HRs are distinct from the districts of the neighbouring regions with boundaries that are contained within the state boundaries i.e. each state is made up of its own HRs. The database consists of 200 HRs in total across rural and urban India. Andhra Pradesh accounts for 14 HRs, 7 in urban areas and 7 in rural.[8]

The primary variables considered in this analysis are the expenditures on various items of households. Table 1 reports the expenditure heads for which data is collected.

CMIE administers the surveys during January to March, April to June, July to September and October to December. These seek information as of the end of the immediately preceding December, March, June or September,

[7]A CEB usually consists of 120-150 households or 600-800 persons.

[8]Details on the sampling methodology and the Andhra sample are presented in the appendix.

Table 2 Income groups

The survey captures monthly income of all members of the household for the six-month period ending the reference month of the survey. This is annualised and aggregated to derive the annual income of the household.
The households are not selected in the sampling process by these income groups. The classification is done after the sampling and the execution of the survey. The household income groups are formed by studying the distribution of the annual income of households during the trial surveys. Income groups are formed at various percentiles. The corresponding income values by groups are rounded to the nearest thousand rupees to reflect how respondents report their incomes.

	Annual household income (Rs.)		% share in
	Lower limit	Upper limit	total population (Sep 2010)
I-1	1,000,000	–	0.97
I-2	720,000	1,000,000	1.39
I-3	360,000	720,000	8.76
I-4	240,000	360,000	11.69
I-5	180,000	240,000	10.88
I-6	120,000	180,000	16.60
I-7	96,000	120,000	9.97
I-8	60,000	96,000	19.34
I-9	36,000	60,000	15.23
I-10	24,000	36,000	3.52
I-11	0	24,000	1.66

respectively or the periods ending in these months. Thus, the survey results as of December 2010 reflect data for the months of July to September 2010.

CMIE further categorizes households based on total annual income of all members in the household. Surveying was not stratified by income levels; the income levels were created after the survey was completed. The classification is done after the sampling and execution of the survey. A detailed breakdown of the households by income classes is provided in the Table 2. At this point in time, CMIE has only released expenditure data at the household type level in each HR, and data on indivudual household are not available for the analysis.

The broad approach in making the estimations is to use the weighted sample averages to estimate the population averages. Aggregate estimations (such as total income of all households in a city) are made by taking sample means and multiplying these by the projected number of households. Census data is extrapolated to obtain the projected number of households at the time of the survey.

The disaggregated estimates by groups of households (i.e. rich, or poor) are estimated using the sample averages and the proportion of households that fall into the group as per the results of the survey. Thus, if say, 30 per cent of the households in a city are found to be in the I-3 category, then CP uses the average income of the households in the relevant group to estimate the total income of the I-3 group.

In addition to this, CP also provides estimates of total and average household income, and proportion of borrower households at the level of each HR. The questions on sources of borrowing club together SHGs and MFIs under one category. As the focus of our study is the impact on consumption, it does not matter that SHG and MFIs are clubbed together.

4.2 Descriptions: Micro-finance in Andhra Pradesh

We next present the prevalence of micro-credit in Andhra and outline the various groups that would be the most vulnerable to any policy that curtails access to this form of finance.

In Table 3, we present the proportion of total households and the proportion of borrower households who had debt outstanding from a SHG/MFI in September 2010, two quarters before the crisis. We also segregate the households by various income classes. We do not present borrowings for the first two income classes (the rich) as they constitute a very small sample.

Households in rural AP are more indebted to SHG/MFIs across all income groups. The SHG/MFI presence increases as one moves down the income spectrum and peaks for those in the income groups in the middle income level. For example, 45 percent of the I-9 borrower households in rural AP had credit outstanding from a SHG/MFI in September 2010. Across all income groups, there are about 854 households in our AP sample that were utilising SHG/MFIs to meet part or all of their credit needs. This is about 11 percent of all households in AP.

Table 4 presents the purpose for which households across the various income groups borrow. Consumption expenditure is the most important reason for which households take loans. More than 60 percent of borrowers in the I-6 and I-7 categories and 70 percent of all borrower households between the I-8 to I-10 categories borrow for consumption purposes. The higher income

Table 3 SHG/MFI borrowing by income group in Andhra Pradesh

This table represents the proportion of total households and proportion of borrower households that have borrowed from a SHG/MFI categorized by income groups. The data is as of September 2010. A total of 11% of households had borrowed from SHG/MFI in the September 2010 quarter.

	% of borrower hh		% of total hh		
	Urban	Rural	Urban	Rural	N
I-3	2.23		0.24		0
I-4	5.62	30.7	0.6	7.8	8
I-5	20.4	24.1	2.6	7.1	30
I-6	17.2	33.9	2.9	9.5	88
I-7	20.2	39.8	4.7	12.5	103
I-8	24.6	39.8	8.1	13.5	319
I-9	31.9	45.0	11.4	16.3	239
I-10	23.8	40.1	9.9	15.3	30
I-11	16.8	25.2	7.2	13.1	38
Total	23.33	37.47	5.80	12.75	854

Table 4 Purpose of borrowing in Andhra Pradesh

This table presents the proportion of borrower households in Andhra Pradesh that have borrowed for various purposes. Consumption includes reasons of general consumption, health, marriage and education. Investment includes borrowing for business purposes as well as investments in other instruments. A household may borrow for more than two reasons, and hence the totals may not equal 100. The data is as of September 2010, the quarter before the credit crisis in AP. U stands for urban and R for rural.

	Housing		Consumption		Durables		Investment		Repay debt	
	U	R	U	R	U	R	U	R	U	R
I-3	61.1	72.5	72.7	34.1	43.2	38.4	35.6	100	58.9	72.5
I-4	35.3	19.1	55.3	41.1	32.3	9.5	49.7	59.5	35.7	17.3
I-5	41	12.9	47.5	47.0	27.8	8.9	36.5	44.7	34.0	6.0
I-6	21.1	18.6	63.3	55.7	18.6	18.6	27.0	28.1	22.7	14.5
I-7	18.7	13.8	67.3	58.8	18.2	16.9	13.8	25.9	19.1	9.7
I-8	12.7	16.3	73.8	69.9	16.8	7.6	9.8	12.7	16.7	10
I-9	11.5	12.2	74.1	70.7	7.1	6.4	5.5	12.8	13.8	14.0
I-10	15.8	28.1	97.7	43.9	4.8	10.3	0.9	23.6	8.6	27.1
I-11	9.7	17.5	79.8	39.9	12.1	3.5	8.02	47.7	17.8	11.6
Total	17.1	16.4	70.5	61.0	16.1	9.9	14.6	23.4	19.1	12.6

categories (I-3 to I-5) borrow to make investments, and also to purchase consumer durables. A far lower proportion of lower income categories purchase to purchase consumer durables. This is in contrast to Karlan and Zinman (2010) who find a sharp rise in the purchase of consumer durables upon credit receipt.

The prevalence of consumption as one of the primary uses of credit should impact expenditure in the absence of credit. Ballem et.al. (2011) also find that post the crisis, respondents claimed to have scaled back their business plans, or cut-down on expenditure on school fees, marriage other *non-productive* activities. Figure 1 presents the time-series of the sum of the average expenditure across all HRs in AP for four categories: food, power and fuel, cosmetics and toiletries, and intoxicants. There have been drops in expenditure across all products (except for power and fuel) after the December 2010 quarter.[9] In some cases, the fall had started before 2010, but declined further after the Ordinance. Food expenditure has recovered, but is slightly lower than what it was in the December 2009 quarter.

There is a lot of anecdotal evidence about multiple borrowing by households, and there might be some truth to those stories. Between 13 to 19 percent of borrower households claim to use credit to repay debts. This is also consistent with field work by Ballem et.al. (2011) who find that in their data 61 percent of respondents said that they had borrowed from MFIs to redeem high cost loans from moneylenders, or to pay to other MFIs. If the rollover of debt is factored by other lenders in their pricing of loans, then the suspension of micro-credit may also adversely influence the readiness of other borrowers to lend, and further shrink credit access.

5 Testing the reliability of the model

This section describes the matched sample, how well the match is achieved and whether the size of the sample is adequate to validate our hypothesis about the effect of the credit withdrawal.

[9]Power and fuel expenditure may have risen owing to rising fuel prices at the time, and this rise would be felt across the country.

Figure 1 Average expenditure in Andhra Pradesh

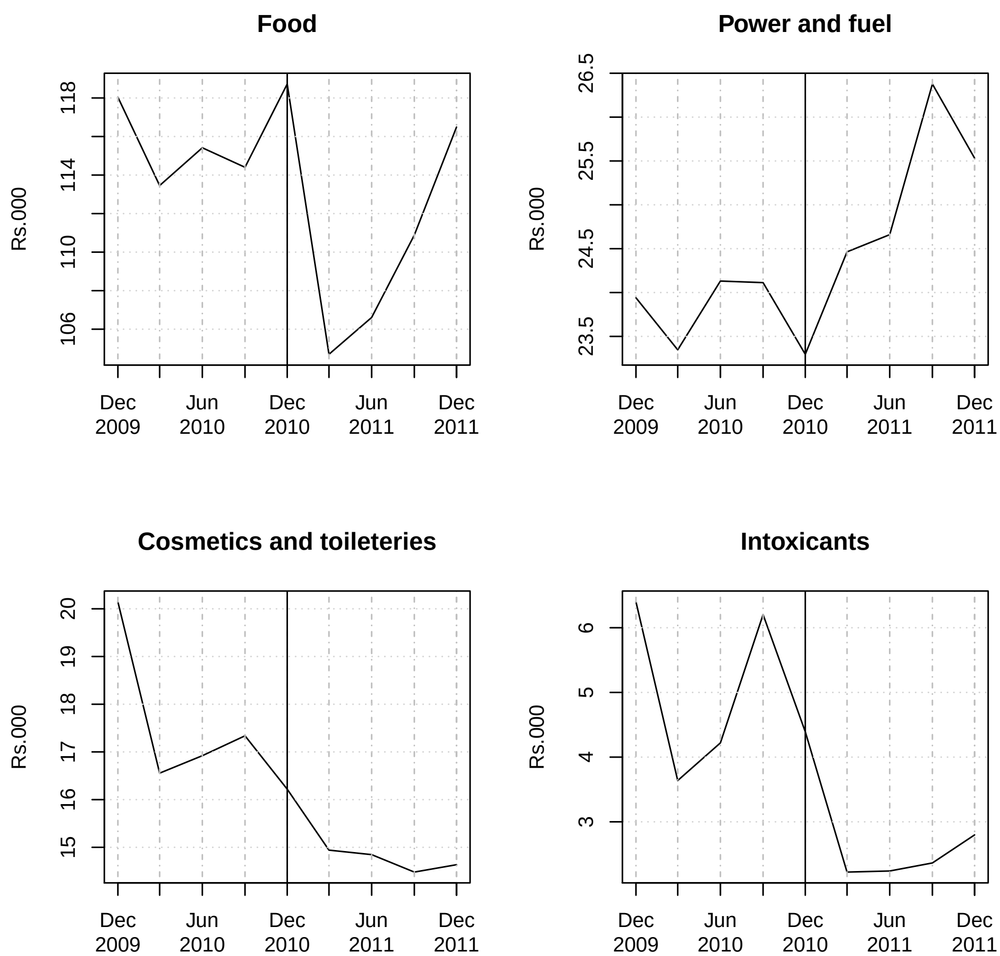


Table 5 Matched Homogenous Regions

This table shows the HRs and the states that constitute the control group, arising out of the matching procedure. The number selected column reflects the number of HRs selected from each state. For example, the value 2 indicates that there were two HRs selected from Rajkot - Bhavnagar in Gujarat i.e. both the rural and urban HRs in Rajkot - Bhavnagar were selected.

HR	State	number selected
Bhabua - Patna	Bihar	1
Champaran - Madhubani	Bihar	1
Rajkot - Bhavnagar	Gujarat	2
Banaskantha - Dohad	Gujarat	2
Vadodara - Valsad	Gujarat	2
Kutch - Jamnagar	Gujarat	1
Chhindwara - Jabalpur	Madhya Pradesh	1
Jhabua - Nimar	Madhya Pradesh	1
Hingoli - Gadchiroli	Maharashtra	1
Sundargarh - Anugul	Orissa	1
Darjiling - Koch Bihar	West Bengal	1

5.1 Matched sample

The matching methodology described earlier in the paper provides us with 14 control HRs outside of Andhra that were not subject to the same Ordinance, and consequent shut-down of the micro-finance industry after October 2010. To ensure that we have a matched sample that is truly not contaminated by the AP Ordinance, we excluded the states of Tamil Nadu, Kerala and Karnataka as these border AP and also suffered from the spillovers of the crisis in AP. Table B.2 lists out the matched HRs.

Of the 14 HRs, 7 are from the state of Gujarat in Western India. The rest are from states neighboring AP: Maharashtra, Orissa, and Madhya Pradesh and two states further north of AP such as Bihar and West Bengal. Even though Madhya Pradesh, Maharashtra, Orissa share a border with AP, they did not witness the political reaction against MFIs that the states bordering AP in the south did. The HRs are, by design, similar to the HRs in AP in terms of income and population, as well as the extent of financial inclusion, the prevalence of farmers, and overall population structure, and literacy levels.

Table 6 Match balance: t-stat and standardized difference

This table presents the match balance statistics between the treatment and control group. t-stat and p-val are generated from the t-test, SDIFF reflects the standardized difference. % balance improvement refers to the improvement in balance after matching for all the covariates.

	(1) Means Treated	(2) Means Control	(3) SD Control	(4) Mean Diff	(5) t-stat	(6) p-val	(7) SDIFF	(8) % Bal. Impr.
Class ten pass	2.59	2.51	0.33	0.08	-0.52	0.60	-12.21	84.65
Working	3.65	3.47	0.13	0.17	0.29	0.77	7.16	49.08
Farmer	0.36	0.24	2.88	0.12	-0.84	0.41	-19.69	80.01
Financially excluded	4.35	4.27	0.21	0.08	1.24	0.23	28.49	91.71
Average hh. income	10.25	10.33	0.52	-0.09	-0.80	0.43	-24.78	58.30
No. of households	7.08	6.71	0.92	0.37	1.58	0.13	40.66	52.99

5.2 Is there match balance?

A fundamental assumption of the matching approach is that conditional on the covariates, the potential outcomes y^1 and y^0 are independent of the treatment. The pre-treatment variables should be balanced between the Andhra HRs and the control HRs. Lack of balance points to a possible mis-specification of the matching estimation (Rosenbaum and Rubin, 1983). We therefore need to verify that this balancing condition is satisfied by the data.

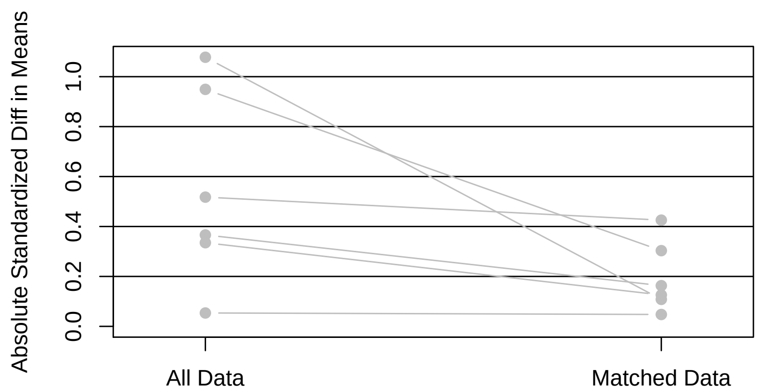
We first present results from parametric tests for matching in Table 6. These include the coefficients out of a paired t-test and standardized bias for each variable entering the matching model. The standardised bias for the income variable, for example is defined as the difference in means between regions in AP and the appropriately matched comparison group of regions outside of AP scaled by the average variances of the income variable in the two groups.

Column (5) in Table 6 shows the t-statistic and column (7) reports the standardized difference. The t-stats confirm that there is no significant difference between the two groups. The lower the standardized difference, the more balanced the treatment and control groups are for the variable in question. While there is no formal criterion for appropriate value of standardized difference, a value of upto 20 is considered acceptable (Rosenbaum and Rubin, 1985). In our data-set, except for the number of households variable, the standardized difference is less than or close to 20.

We also present the change in the standardized bias for all the covariates

Figure 2 Difference in the Standardized bias

This figure shows the change in standardized bias after matching. The left hand dots show the standardized bias for the entire data-set, while the right hand shows that for the matched data-set.



after matching in Figure 2. The standardized bias has fallen dramatically after matching, and we take this as evidence for the existence of a reasonable matched control sample. The t-test also does not show a significant difference for all variables, including those for whom the standardized bias is above 20, leading us to believe that the balancing conditions are satisfied for each variable.

Column (8) reports the percent improvement in balance for each of the co-variates, defined as $100((\mid a \mid - \mid b \mid)/\mid a \mid)$, where a is the balance before and b is the balance after matching. It shows that there has been a substantial improvement in balance as a result of the matching method.

We then estimate the Hotelling's T-square test which considers whether the differences between the variables can be taken as jointly significant. The chi statistic is 10.44 with a p-value of 0.12, the F-statistic is 1.35 with a p-value of 0.27, both indicating that the differences between the variables are not jointly significant.

Stuart (2010) points out that the parametric tests such as the t-test are often not accurate measures of balance as they compare only the averages, while the interest in a matching exercise is the entire distribution. We therefore also present quantile-quantile (QQ) plots for each covariate used in the matching exercise in Figure 3. If the empirical distributions are the same in the treated and control groups, the points in the Q-Q plots would all lie on the 45 degree line. Deviations from the 45 degree line indicate differences in the empirical distribution. As reflected in the figure, our matched sample lies on the 45 degree line, and indicates that our sample has match balance.

5.3 Is the sample size adequate?

A potential criticism of this estimation framework is the small sample size. The treatment and control groups have 14 observations each, bringing into question the power of the study, i.e. the probability of rejecting H_0 when H_0 is in fact true. To evaluate the power of the study, we conduct the entire estimation for a random set of 14 treatment HRs, for various effect sizes. The experiment for each variable is conducted 10,000 times.

Table 7 presents the power at various effect sizes. The empirical model presents very high power for effect size of more than Rs.300. This is reassuring as it shows that the model is robust and can accurately estimate the differential impact in expenditure between HRs in AP and outside.

6 Results

This section presents the results of the analysis done to answer the following questions about the effect of the micro-credit ban due to the Andhra Pradesh Ordinance:

- Is there a fall in consumption expenditure?
- Is the fall greater in areas with high exposure?
- Is the fall more significant in rural areas?
- How do the low-income groups compare to the high-income ones?
- What is the impact on borrowings, income and savings?

Figure 3 QQ plots

This figure shows the QQ-plots of the covariates used in matching, before after the matching exercise. The y-axis in each box reflects the treated units and the x-axis the control units. Deviations from the 45 degree line indicate differences in the empirical distribution and low match balance.

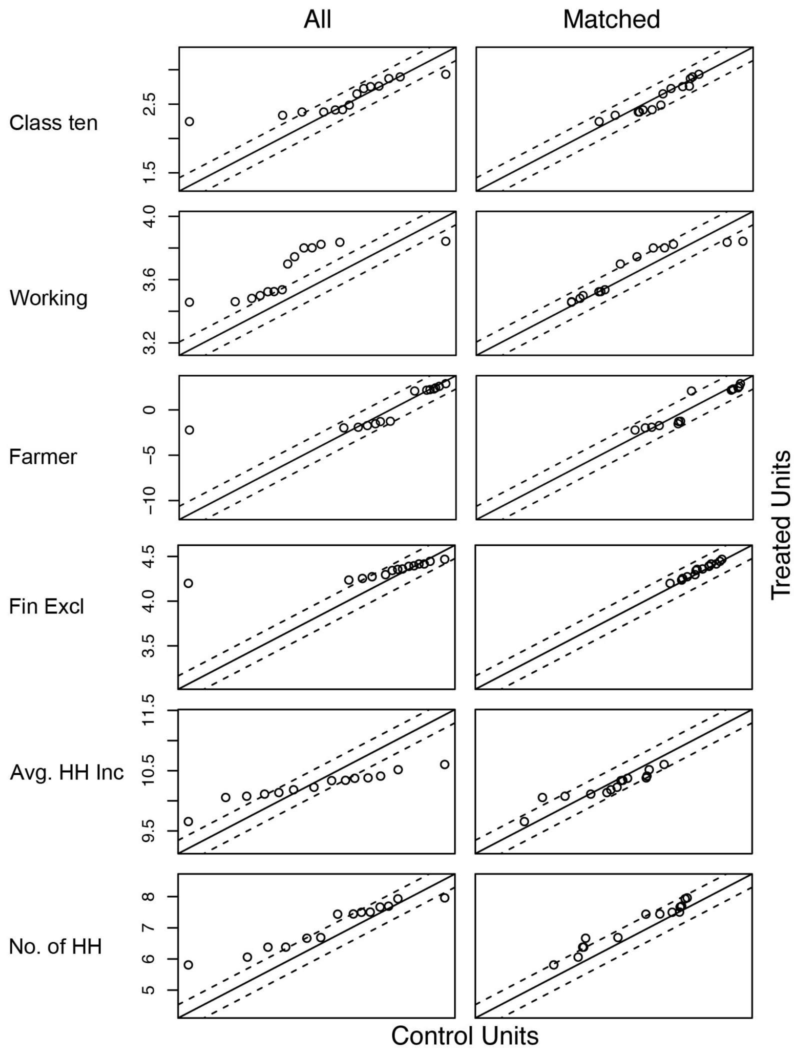


Table 7 Is the sample size adequate?: Power calculations

This table presents results from a simulation exercise that captures the effect size that can be captured with a probability of at least 0.7. For example, in the case of food, an effect size of more than Rs.400 has sufficient power i.e. the probability of rejecting H_0 when H_0 is in fact true is greater than or equal to 0.7.

	Effect size (Rs.)
Food	1000
Power and fuel	400
Cosmetics	200
Education	300
Miscellaneous	200
Communication	200
Clothing	300
Transport	200
Intoxicants	100
Bills	200
EMIs	300
Restaurants	200
Health	200
Recreation	100

6.1 Is there a fall in consumption expenditure?

Table 8 presents the estimates on various components of consumption expenditure. The table reports estimates of β_3, the difference-in-difference estimator, along with robust standard errors, and the p-values (and adjusted p-values).

The results suggest that average household expenditure in the crisis-affected regions has fallen by Rs.3375 over the four quarters post the crisis, significant at the 5 percent level. This fall is particularly significant for items that have a large share in the total expenditure of households such as food, power and fuel, cosmetics, education, clothing, and intoxicants.

Among all the broad categories, expenditure on items such as cosmetics, clothing and intoxicants comes under the category of discretionary spending. In times of crisis, these are the items one may expect to cut-down on. What is of greater concern is that the expenditure on food, education and power and fuel. The expenditures on these goods may not be as discretionary, and may be construed as greater evidence of welfare loss owing to the credit constraints imposed by the Andhra Ordinance. We also find that expenses such as intoxicants, often associated with waste, shows a relatively small

Table 8 Average expenditure of households

This table presents estimates of β_3, the difference-in-difference estimator, along with robust standard errors, and the p-values (and adjusted p-values) on various components of household expenditure.

	coeff	std.error	p.val	adj.p.val
Total	-3375.1	1450.5	0.02	0.05**
Food	-1302.6	419.1	0.00	0.01***
Fuel	-504.8	199.3	0.01	0.05**
Cosmetics	-165.1	68.32	0.02	0.05**
Education	-350.3	151.77	0.02	0.05**
Miscellaneous	-341.5	733.30	0.64	0.80
Communication	12.3	98.35	0.90	0.91
Clothing	-431.4	126.93	0.00	0.01***
Transport	-25.9	44.60	0.56	0.80
Intoxicants	-222.7	49.15	0.00	0.00***
Bills	-14.2	127.2	0.91	0.91
EMIs	31.5	63.9	0.62	0.80
Restaurant	-82.3	71.08	0.25	0.46
Health	17.8	58.6	0.76	0.88
Recreation	-24.6	24.68	0.32	0.53

*** indicates 1%; ** indicates 5%; indicates 10% level of significance

decrease, relative to more important items such as food. If the contention is that inhibiting access to micro-credit only curtail "wasteful" expenditure, then that contention is not borne out by the data.

The results so far have indicated a fall in average household expenditure on various items in AP relative to regions outside of AP. Average expenditure, however, could be driven by changes in expenditures of households completely unaffected by micro-credit and the Ordinance. In the following sections we examine expenditures of various groups of households that had greater exposure to micro-credit, and were more likely to have had their access to finance choked off because of the Ordinance.

6.2 Is the fall greater in areas with high exposure?

We turn to a comparison between the expenditures of households in HRs with the highest borrowing from SHG/MFI with that of expenditures in HR with the lowest borrowing from SHG/MFI.

We conduct the difference-in-difference estimation with one additional variable. This variable, ap-highmfi-postcrisis takes the value 1 for HRs that

Table 9 Average expenditure: high income households

This table presents the results from a difference-in-difference estimation. The variable of interest is ap-highmfi-postcrisis which takes the value 1 for HRs that have more than 35 percent of borrower households indebted to SHG/MFIs in September 2010.

	coeff	std.error	pval	adj.p.val
Total	-1753.4	1514.5	0.25	0.32
Food	-876.8	344.1	0.01	0.02**
Fuel	-472.8	145.9	0.00	0.01***
Cosmetics	-298.3	45.5	0.00	0.00***
Education	110.6	133.4	0.41	0.44
Miscellaneous	204.6	1015.9	0.84	0.84
Communication	-214.3	81.5	0.01	0.02**
Clothing	-122.7	107.3	0.25	0.32
Transport	-101.5	37.1	0.01	0.02**
Intoxicants	200.9	54.3	0.00	0.00***
Bills	-500.6	133.6	0.00	0.00***
EMIs	221.6	120.0	0.07	0.11
Restaurant	132.6	55.1	0.02	0.03**
Health	38.4	40.2	0.34	0.39
Recreation	-30.4	22.2	0.17	0.26

*** indicates 1%; ** indicates 5%; indicates 10% level of significance

have more than 35 percent of borrower households indebted to SHG/MFIs in September 2010 and for data that is in the post-crisis period. The coefficient on this variable identifies if the expenditure of high income groups has fallen in those HRs where there was a higher presence of SHG/MFIs relative to those where there was a lower presence of SHG/MFIs pre-crisis. The results are presented in Table 9.

Average expenditure of high income households in HRs with high exposure to SHG/MFIs has fallen sharply in the case of bills, communication, cosmetics, food, fuel and transport. The expenditure on intoxicants and restaurants in these HRs has actually gone up, though by a very small amount.[10] This reaffirms the proposition that lack of access to credit has hurt expenditures in regions that were most reliant on micro-finance.

[10]The effect size simulations in Table 7 indicate that an effect of more than Rs.200 can be picked up by the model. The value of Rs.132 in the case of restaurants is lower than Rs.200, and one cannot be confident about the power of the regression.

Table 10 Average expenditure: Rural areas

This table presents the results from a difference-in-difference estimation. The variable of interest is ap-rural-postcrisis which takes the value 1 for HRs in rural AP.

	coeff	std.error	p.val	adj.p.val
Total	-5349.4	1175.8	0.00	0.00***
Food	-1469.1	228.2	0.00	0.00***
Fuel	-944.7	71.6	0.00	0.00***
Cosmetics	-269.9	49.8	0.00	0.00***
Education	-215.2	91.9	0.02	0.03**
Miscellaneous	-531.0	934.7	0.57	0.66
Communication	-510.5	37.7	0.00	0.00***
Clothing	-242.4	85.9	0.01	0.01***
Transport	-106.1	38.1	0.01	0.01***
Intoxicants	17.7	45.1	0.70	0.75
Bills	-1089.1	70.8	0.00	0.00***
EMIs	241.5	82.4	0.00	0.01***
Restaurant	-107.9	52.3	0.04	0.05**
Health	-7.6	42.9	0.86	0.86
Recreation	-71.8	19.5	0.00	0.00***

*** indicates 1%; ** indicates 5%; indicates 10% level of significance

6.3 Is the fall more significant in rural areas?

Micro-finance had a larger customer base in rural areas. Any fall in consumption owing to micro-credit withdrawal should therefore affect rural areas more than urban areas. We conduct a difference-in-difference estimation with a variable that denotes where the HR was in rural Andhra Pradesh. The variable, ap-rural-postcrisis takes the value 1, if it was a rural HR in the postcrisis period and zero otherwise. The results are presented in Table 10.

The results indicate that the expenditure on most items fell in rural Andhra, significant at the 1 percent level. Rural areas also witnessed a fall in average expenditures on items that had not shown a decline in the overall regression. These include transport, bills, restaurants, and recreation. The coefficient on bills, at Rs.1089.11 is large and significant. It includes expenditures on house rent and other charges.

Restaurants and recreation occupy a very small share in the total expenditure of households and their co-efficients are of small magnitude as well. What is more interesting is the decline in expenditure on communication and transport. The latter especially may also hinder productive capacity of households if they find themselves unable to travel to the place of work. This interpretation, however, is at best a conjecture, as there is no way to identify whether this is indeed so.

6.4 How do the low-income groups compare to the high-income ones?

Table 3 in Section 4.2 showed that income group 9 (with annual income between Rs.36,000 and Rs.60,000) had the highest number of households with debt outstanding from a MFI/SHG, while income group 3 (with annual income between Rs.360,000 and Rs.720,000) had the lowest. We therefore examine if there is a difference in the expenditure between the two income groups, compared to the equivalent group in the control group. The results are presented in Table 11.

The first three columns reflect the estimates of the regression for the highest income group in the sample, while the last three columns reflect the estimates for the group with the highest proportion of households with micro-credit borrowings. We find that there have been declines in expenditures of low income households on food, clothing and intoxicants, significant at the 10 percent level. No such declines were found for the high income group, which had the lowest exposure to micro-credit, and which also traditionally has had access to formal sources of credit.

6.5 What is the impact on borrowings, income and savings?

The declines in consumption can be attributed to credit constraints if there has not been a corresponding rise in borrowings from other sources or a fall in income. We evaluate if there has been a change in the proportion of borrower households in AP relative to other HRs, and if there has been a decline in average household income after the Andhra Ordinance. We are constrained by the data to evaluate if there has indeed been a fall in average borrowings of households as the data only reports the proportion of households with debt outstanding, and does not tell us anything about the amount outstanding. Proportion of borrower households does not show

Table 11 Average expenditure of high and low income households

This table presents the results from a difference-in-difference estimation on two groups: the group with lowest access of SHG/MFIs and the group with the highest access of SGH/MFIs.

	I-3 (Lowest MFI access)			I-9 (Highest MFI access)		
	coeff	std.error	adj.p.val	coeff	std.error	adj.p.val
Total	-8024.6	3793.9	0.18	-1417.1	842.4	0.26
Food	-2111.7	930.1	0.18	-747.9	274.0	0.05**
Fuel	-1446.2	560.7	0.16	-49.2	77.6	0.72
Cosmetics	-396.5	224.3	0.20	-68.1	42.1	0.26
Education	-937.4	654.9	0.33	-124.9	63.9	0.20
Miscellaneous	-224.6	1414.5	0.94	-111.8	591.4	0.85
Communication	63.2	263.3	0.94	54.7	47.3	0.41
Clothing	-656.0	336.1	0.20	-213.9	82.3	0.05**
Transport	-252.6	136.7	0.20	53.4	35.9	0.26
Intoxicants	-121.8	123.4	0.61	-151.8	47.2	0.02**
Bills	25.5	339.2	0.9	-69.8	95.9	0.70
EMIs	410.8	774.6	0.8	102.2	66.5	0.26
Restaurant	-164.6	231.9	0.80	-13.2	49.6	0.85
Health	76.3	189.6	0.9	11.2	42.1	0.85
Recreation	-61.8	102.4	0.81	-5.4	15.5	0.85

*** indicates 1%; ** indicates 5%; indicates 10% level of significance

a change after the Ordinance. This however, does not tell us if the actual amount available to households has declined.

Average household income is lower in AP relative to regions outside of AP post the Ordinance. The fall is however not significantly different from zero. We therefore conclude that consumption declines described earlier cannot be explained by a fall in the average income of households.

If the Ordinance did increase uncertainty regarding future availability of credit, it may lead to a rise in savigs, as households build up liquid assets for precautionary purposes. We therefore examine average savings of households in AP. Average savings which are derived as the difference between the income and the expenses of households. We also evaluate changes in the saving rate which is savings as a per cent of the income of the household. Results in Table 12 show no change in average savings in absolute terms, but an increase in the saving rate, significant at the 10 percent level.

Table 12 Borrower households, income and savings

This table reflects results from a difference-in-difference estimation on borrowings, average income and savings.

	coeff	std.error	p.val	adj.p.val
Proportion of borrower households	2.3	4.3	0.59	0.59
Average household income	-2119.8	2456.2	0.39	0.61
Average household savings	-449.5	1709.7	0.79	0.79
Saving rate	7.0	3.5	0.05	0.10*

*** indicates 1%; ** indicates 5%; indicates 10% level of significance

7 Robustness checks

The results so far provide evidence that there has been a fall in average expenditure of households in regions affected by the microfinance crisis of 2010. These results are however subject to criticism that there may be other factors driving the particular outcome. We conduct two robustness checks

- We examine if there were other events that could have affected the consumption of Andhra households
- We conduct a simulation with placebo treatment HRs, i.e. where the Ordinance did not apply

7.1 Other events

The other big event to hit Andhra Pradesh was the drought in June to September 2011, for which the state government extended a relief package to the drought-affected districts.[11] This is after the credit crisis of October 2010, and the effect of this will show up in the quarters of December 2011 and January 2012 (as the December 2011 quarter reflects the expenditures of July to September 2010). As this is the last quarter in our data-set, it should not affect the expenditures in the preceding three quarters that were unaffected by the drought.[12]

[11]Business Line (2011).

[12]In the raw data, there was actually an increase in reported average expenditures in the December 2011 quarter. See Figure 1.

7.2 Placebo treatment

We also conducted a simulation exercise whereby we randomly selected 14 HRs (excluding those in Andhra Pradesh) and termed them treatment HRs. We then used the same matching methodology and found 14 control HRs. We then carried out the same difference-in-difference estimation on the treatment and control HRs. We conducted 10,000 simulation runs of this procedure.

If our results are a result of chance, or if other things are driving these results, we should see falls in average expenditures in the psuedo-treatment HRs (outside of AP). Table 13 presents the results of the simulation exercise. It shows the percent of times the null of no change in average expenditure was rejected.

Table 13 Average expenditure: high income households

This table presents the results of a simulation exercise on 14 random treatment HRs which were matched with 14 control HRs. The numbers reflect the percent of times the null of no change in average expenditure was rejected.

	Null rejected (%)
Food	1.03
Fuel	1.22
Cosmetics	1.18
Education	1.14
Miscellaneous	1.11
Communication	0.9
Clothing	1.18
Transport	1.14
Intoxicants	1.18
Bills	1.14
EMIs	1.07
Restaurant	1.06
Health	1.15
Recreation	0.95

In none of the estimation was the null of no change in expenditure rejected more than 2 percent of the time (in the 10,000 runs). This suggests that our results of a fall in average expenditure are driven by events specific to AP.

8 Conclusion

Micro-finance institutions in the south Indian state of Andhra Pradesh were accused of lending practices that adversely affected the lives of poor borrowers, to the extent that some were driven to suicide. The State Government of AP passed an Ordinance that effectively stopped collection of micro-debt and prohibited any new micro-loans in the state bringing the entire micro-finance industry to a stand-still. The sector continues to be in a deep-freeze in the state.

We use data from Consumer Pyramids, a national level quarterly panel household survey conducted by the Centre for Monitoring Indian Economy, to evaluate the response to the AP crisis. Our focus is the aggregate impact on average household expenditure in a region, and not the expenditure of individual households. We match the regions in Andhra Pradesh to regions across the country, and use the difference-in-difference methodology to estimate the impact on average household expenditure of the affected regions.

We find that the average expenditure especially on food, clothing, power and fuel, cosmetics and intoxicants fell sharply in Andhra Pradesh relative to the control group. The fall was especially pronounced for regions which had a larger presence of micro-credit, rural areas as well as lower income groups, all of whom were more reliant on micro-finance.

This study also contributes to the fledgling evidence on the impact of micro-credit. It points out that micro-credit matters, and large scale withdrawal of credit has detrimental impacts on consumption smoothing. Liquidity constraints in the context of micro-finance have always been studied by evaluating the response of credit-constrained households to increases in supply of credit. Household responses to withdrawal of credit are another way of studying this important topic. This study is one of the few to conduct such an analysis.

Finally, the paper provides evidence that financial policy that is put in place to ostensibly protect customers may end up reducing welfare by denying access to credit. The potential harm of such ad-hoc policies on the lives of people should be evaluated before large-scale implementation.

References

Anderson, Michael L. (2008): “Multiple Inference and Gender Differences in the Effects of Early Intervention: A Reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects,” *Journal of the American Statistical Association*, 103(484), 1481–1495.

Armendáriz, Beatrice, and James Morduch (2010): *The economics of microfinance*. Cambridge, MA.: MIT Press, second edn.

Arun, Thankom, and David Hulme (2008): “Microfinance A Way Forward,” Working Paper 54, Brooks World Poverty Institute, The University of Manchester.

Arunachalam, Ramesh S. (2010): “The 2010 Andhra Pradesh Micro-Finance Crisis Revisited...,” Blog: ”Candid Unheard Voice of Indian Micro-finance”, http://microfinance-in-india.blogspot.com/2010/12/2010-andhra-pradesh-micro-finance.html.

Augsburg et. al. (2012): “Microfinance, poverty and education,” Working Papers 18538, NBER.

Ballem et.al. (2011): “What are Clients doing Post the Andhra Pradesh MFI Crisis?,” Discussion paper, MicroSave.

Banerjee et. al. (2009): “The Miracle of Microfinance? Evidence from a randomized evaluation,” Working Paper 31, Centre for Microfinance, IFMR.

Blundell, Richard, and Monica Costa Dias (2000): “Evaluation methods for non-experimental data,” *Fiscal Studies*, 21(4), 427–468.

Buera, Francisco J., Joseph P. Kaboski, and Yongseok Shin (2012): “The Macroeconomics of Microfinance,” Working Paper 17905, NBER.

Business Line (2011): “AP to extend Rs 1,500-cr relief package for drought-hit districts,” http://www.thehindubusinessline.com/industry-and-economy/government-and-policy/article2675219.ece.

Chakrabarti, Rajesh, and Shamika Ravi (2011): “At the Crossroads: Microfinance in India,” *ICRA Bulletin: Money and Finance*, pp. 125–148.

Crépon, Bruno, Florencia Devoto, Esther Duflo, and William Parienté

(2011): "Impact of microcredit in rural areas of Morocco: Evidence from a Randomized Evaluation," .

Datta, Sankar, and Vijay Mahajan (2003): "Savings and Credit Movement of Andhra Pradesh," Discussion paper, BASIX.

Davis, Ian (2009): "Rural Banking: Designing an Effective Legal Framework for Microfinance," *The Journal of Business, Entrepreneurship & the Law*, 2(2).

Dehejia, Rajeev (2005): "Program evaluation as a decision problem," *Journal of Econometrics*, 125(1-2), 141–173.

Eswaran, Mukesh, and Ashok Kotwal (1989): "Credit as insurance in agrarian economies," *Journal of Development Economics*, 31, 37–53.

Gross, David B., and Nicholas S. Souleles (2002): "Do Liquidity Constraints and Interest Rates Matter for Consumer Behavior? Evidence From Credit Card Data," *The Quarterly Journal of Economics*.

Heckman et. al. (1997): "Matching as an econometric evaluation estimator: evidence from evaluating a job training programme," *Review of Economic Studies*, 64, 605–654.

Jappelli, Tullio, Stephen Pischke, and Nicholas Souleles (1998): "Testing for liquidity constraints in Euler equations with complementary data sources," *Review of Economics and Statistics*, LXXX, 251–262.

Kaboski, Joseph P., and Robert M. Townsend (2011): "A Structural Evaluation of a Large-Scale Quasi-Experimental Microfinance Initiative," *Econometrica*, 79(5), 1357–1406.

——— (2012): "The Impacts of Credit on Village Economies," *American Economic Journal: Applied Economics*, 4(2), 98–133.

Karlan, Dean, and Jonathan Zinman (2010): "Expanding Credit Access: Using Randomized Supply Decisions to Estimate the Impacts," *Review of Financial Studies*, 23(1), 433–464.

——— (2011): "Microcredit in Theory and Practice: Using Randomized Credit Scoring for Impact Evaluation," *Science*, 332, 1278–1284.

Lusardi, Annamaria, and Peter Tufano (2009): "Debt Literacy, Financial Experiences, and Overindebtedness," Working Paper 2009-08, CFS, http://hdl.handle.net/10419/43242.

MFIN (2012): "The MicroScape," Discussion paper, Microfinance Institutions Network.

Morgan, Donald P., and Michael Strain (2008): "Payday Holiday: How Households Fare After Payday Credit Bans," Staff Report 309, Federal Reserve Bank of New York.

Morse, Adair (2011): "Payday lenders: Heroes or villains?," *Journal of Financial Economics*, 102(1), 28–44.

Rangarajan, C. (2008): "Report of the Committee on Financial Inclusion," Discussion paper, RBI.

RBI (2004): "Master circular on Priority Sector Lending," Discussion Paper RBI/2004/12, BPD(PCB)MC. No. 1, /09.09.01/2004-05, Reserve Bank of India.

Rosenbaum, Paul R., and Donald R. Rubin (1983): "The central role of the propensity score in observational studies for causal effects," *Biometrika*, 70, 41–55.

——— (1985): "Constructing a control group using a multivariate matched sampling method that incorporates The Propensity Score.," *American Statistician*, 39, 33–38.

Sa-dhan (2007): "Core Values and Voluntary Mutual Code of Conduct For Microfinance Institutions," Discussion paper, Sa-Dhan : The Association of Community Development Finance Institutions.

Shankar, Savita, and Mukul G. Asher (2010): "Regulating Microfinance: A Suggested Framework," *Economic and Political Weekly*, 45(1).

Shylendra, H. S. (2006): "Microfinance Institutions in Andhra Pradesh," *Economic and Political Weekly*, pp. 1959–1963.

Skiba, Paige Marta (2012): "Regulation of Payday Loans: Misguided?," *69 Wash. & Lee L. Rev.*, 1023.

Skiba, Paige Marta, and Jeremy Tobacman (2009): "Do payday loans cause bankruptcy?," Research Paper 11-13, Vanderbilt Law and Economics.

Smith, Jeffrey A., and Petra E. Todd (2005): “Does matching overcome LaLonde’s critque of nonexperimental estimators,” *Journal of Econometrics*, 125, 305–353.

Srinivasan, N. (2009): “Microfinance India: State of the sector report 2008,” Report, Access Development Services, Sage Publications.

——— (2010): “Microfinance: State of the Sector Report 2010,” Discussion paper, Access Development Services, Sage Publications.

State government of Andhra Pradesh (2010): “An Ordinance to protect the women Self Help Groups from exploitation by the Micro Finance Institutions in the State of Andhra Pradesh and for the matters connected therewith or incidental thereto,” State government of Andhra Pradesh.

Stuart, Elizabeth A. (2010): “Matching methods for causal inference: A review and a look,” *Stat Sci*, 25(1), 1–21.

Thaler, Richard H. (1990): “Anomalies: Saving, Fungibility, and Mental Accounts,” *The Journal of Economic Perspectives*, 4(1), 193–205.

Thorat, Usha (2007): “Financial Inclusion – The Indian Experience,” Monthly bulletin, Reserve Bank of India.

Zeldes, Stephen P. (1997): “Consumption and Liquidity Constraints: An Empirical Investigation,” *Journal of Political Economy*, 97(2), 305–346.

Zhao, Z. (2004): “Using matching to estimate treatment effects: Data requirements, matching metrics, and monte carlo evidence,” *Review of Economics and Statistics*, 86(1), 91–107.

Zinman, Jonathan (2010): “Restricting consumer credit access: Household survey evidence on effects around the Oregon rate cap,” *Journal of Banking and Finance*, 34(3), 546556.

Appendix

A Sampling methodology

The factors used for the Urban sample are:

- Geographic stratification in terms of HRs
- Minimum of two cities within each HR
- Stratification of the municipal wards on the basis of asset ownership
- 21 random Census enumeration blocks per city
- Random selection of households within a CEB

The factors used for the Rural sample are:

- Village stratification within a rural HR
- Village stratification in terms of the population that was classified SC/ST
- Three groups: Top 25 percent, Bottom 25 percent and the middle.
- Random sampling of villages in each group
- Random sampling of households within the selected villages

B The Andhra Pradesh sample

Table B.1 Locations in Andhra Pradesh covered by the sample

The sample in Andhra Pradesh has:

- 14 HRs, 7 urban, 7 rural
- HRs and cities

The table shows the specific locations covered.

Srikakularm - Visakhapatnam	Gajuwaka, Visakhapatnam, Vizianagaram
Krishna - Godavari	Eluru, Kakinada, Rajahmundry, Vijayawada
Guntur - Nellore	Guntur, Nellore, Ongole
Kurnool - Chittor	Anantapur, Kurnool, Tirupati
Mahbubnagar - Khammam	Khammam, Mahbubnagar
Rangareddi - Warangal	Hyderabad, Kukatpally, Lal Bahadur Nagar, Qutubullapur, Secunderabad Cantonment Board, Warangal
Adilabad - Karimnagar	Adilabad, Karimnagar, Nizamabad, Ramagundam

Table B.2 Homogenous regions in Andhra Pradesh matched with other regions

	HR	State
1	Surguja - Mahasamund	Chattisgarh
2	Rajkot - Bhavnagar	Gujarat
3	Banaskantha - Dohad	Gujarat
4	Vadodara - Valsad	Gujarat
5	Jhabua - Nimar	Madhya Pradesh
6	Hingoli - Gadchiroli	Maharashtra
7	Bhabua - Patna	Bihar
8	Champaran - Madhubani	Bihar
9	Rajkot - Bhavnagar	Gujarat
10	Kutch - Jamnagar	Gujarat
11	Banaskantha - Dohad	Gujarat
12	Vadodara - Valsad	Gujarat
13	Damoh - Sidhi	Rajasthan
14	Darjiling - Koch Bihar	West Bengal