MEASURING THE AVERAGE IMPACTS OF CREDIT: EVIDENCE FROM THE INDIAN MICROFINANCE CRISIS

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ABSTRACT. In October 2010, the state government of Andhra Pradesh, India issued an emergency ordinance, bringing microfinance activities in the state to a complete halt and causing a nation-wide shock to the liquidity of lenders, especially those lenders with loans in the affected state. We use this massive dislocation in the microfinance market to identify the causal impacts of a reduction in credit supply on consumption, entrepreneurship, and employment. Using a proprietary, hand-collected district-level data set from 27 microlenders matched with household data from the National Sample Survey, we find that district-level reductions in credit supply are associated with significant decreases in casual daily wages, household wage earnings and consumption. In contrast to many experimental studies of microfinance, our estimates capture the average impacts on households, inclusive of general equilibrium effects. Moreover, we find significant heterogeneity by household landholdings, consistent with a model in which medium-wealth households scale back their businesses and landless households are hit by a fall in the wage.

1. INTRODUCTION

Microfinance is an important tool for financial inclusion across the developing world. According to the IFC, over the past 15 years, approximately 130 million individuals have borrowed from microfinance institutions (MFIs). In 2006, Muhammed Yunus and the Grameen Bank were awarded the Nobel Peace Prize.

While microfinance was initially heralded as a silver bullet in fighting poverty, a recent and impressive wave of experimental research has brought discipline to the debate about microfinance's impacts. Angelucci et al. (2015), Augsburg et al. (2015), Attanasio et al. (2015), Banerjee et al. (2015a), Crépon et al. (2015), and Tarozzi et al. (2015) all find strikingly similar results in a diverse set of countries and settings. This body of short to medium-run evidence paints a consistent picture of moderate impacts. Access to microfinance is generally found to cause modest business creation and business expansion, but the evidence on growth in revenues and profits is more mixed. There is some evidence that borrowers do purchase more household durables and business assets, but almost no evidence of an impact

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on non-durable consumption or on other indicators of welfare such as health, education, or most measures of women's empowerment.

While randomized controlled trials (RCTs) provide consistent estimates of the treatment effects with minimal assumptions, they are not without limitations. First, RCTs are only able to measure impacts for the group of individuals that was induced to take a loan because of the experiment. In many (though not all) research designs, these "complier" individuals are the marginal rather than the average borrowers. Further, RCTs are extremely well suited to measure partial equilibrium effects but often have a much more difficult time achieving the scale required to affect general equilibrium outcomes. Buera et al. (2012) were the first to simulate a model to highlight that when scaled economy-wide, the general equilibrium effects of microfinance may look quite different from the partial equilibrium effects measured in RCTs.

In this paper, we use variation from a natural experiment to estimate the general equilibrium impacts of a withdrawal of microfinance on the average rural household. In October 2010, the state government of Andhra Pradesh, India issued an emergency ordinance, bringing microfinance activities in the state to a complete halt and causing a nation-wide shock to the liquidity of lenders. According to data from the Microfinance Information Exchange (MIX), the aggregated gross loan portfolio of Indian microlenders fell by approximately 20% between fiscal year 2010 and fiscal year 2011. Panel A of Figure 1 plots the India-wide levels of microcredit from 2008 to 2013. The drop in lending post 2010 is visible in the figure. We use this massive dislocation in the microfinance market as a source of quasi-exogenous variation to study the effects of district-level reductions in credit supply on consumption, entrepreneurship, wages, and employment. Our empirical strategy only considers districts outside of Andhra Pradesh, which were not directly affected by the ordinance. Thus, this natural experiment is a unique opportunity to study a large supply shock to the microfinance sector in a setting where there was no concurrent demand shock.

With the help of the largest for-profit microfinance trade association in India, Microfinance Network (MFIN), we have hand-collected proprietary district-level data from 27 microlenders covering 2008 through 2013. We combine this data with household-level data from the National Sample Survey (NSS) rounds 64, 66, and 68 (2008, 2010, and 2012, respectively) to create a district-level panel. The NSS data gives detailed information about employment, wages, earnings, consumption, and self-employment activities.

We identify the causal impacts of microfinance by using variation in the balance sheet exposure of each lender to loans in the affected state, Andhra Pradesh, before the crisis. We also use pre-crisis variation in the geographical footprint of each lender. We show in our first stage regressions that districts that borrowed more from lenders with portfolio exposure to Andhra Pradesh witnessed much larger declines in lending between 2010 and 2012 than similar districts with the same amount of overall pre-crisis lending whose lenders did not have balance sheet exposure to Andhra Pradesh. Panel B of Figure 1 plots the trends in district-level GLP separately for districts with high and low indirect exposure to Andhra

Pradesh. Note that low exposure districts experience no absolute decrease in credit, while high exposure districts experience a large contraction following the crisis of 2010.[1]

Given that the credit supply shocks during the crisis operate at the district level, it is important to consider the potential general equilibrium consequences in addition to the standard set of partial equilibrium outcomes. In order to develop empirical predictions for this setting, we present a simple model of households, wage employment, self-employment and credit constraints in general equilibrium. We consider an environment where households have access to a self-employment opportunity that requires capital and labor and can also supply their labor to the casual labor market. Importantly, we assume that there exist credit market frictions that limit households from reaching the optimal business scale. Namely, households can borrow up to a fixed fraction of their wealth to finance production. Thus, households borrow to operate a business and decide how much net labor to supply or demand from the outside market. We assume that households vary in their wealth endowments so that some households choose to be net labor suppliers, while other are net demanders. The market wage is set such that net labor supply is equated to net labor demand.

We explore the comparative statics in this model when credit constraints tighten at the village level. One key prediction of the model is that district-level wages fall when credit contracts. This is a product of two forces. First, households with low to intermediate levels of wealth scale back their businesses and decrease their net demand for market labor. For some of these businesses, the effect is exacerbated by households switching from being net demanders to net suppliers of labor.

The model also predicts heterogeneous and sometimes non-monotonic effects of the crisis on household earnings and consumption. In this model, net market labor supply is monotonically decreasing in wealth. Therefore, the impacts of the decrease in wages on labor market earnings is felt most acutely by the poorest households. In contrast, households with intermediate levels of wealth experience the largest declines in earnings from self-employment income. Those richest households that remain unconstrained even after the reduction in credit can actually benefit from the decrease in the wage. These heterogeneous patterns suggest U-shaped relationships between wealth and treatment effects on both durable and non-durable consumption.

We find that the reduced form impacts of the reduction in microcredit largely match the predictions of our simple general equilibrium model. First, we do indeed find a decrease in the average casual daily wage for the most exposed districts between 2010 and 2012 relative to districts with the same amount of lending, but from less-exposed MFIs. We also find that the average household experiences statistically significant reductions in both non-durable and durable consumption. However, this reduction in expenditures has no effect on poverty headcounts in the affected districts (unlike the impacts of bank branch expansions found in

[1]Given that the crisis happened at the end of 2010, one might wonder why the effects of the crisis are most visible in 2012 rather than 2011. This is explained by the fact that most microloans have a maturity of one year. The bulk of the drop in credit came from MFIs delaying the issuance of new loans upon the repayment of old loans. This means that we only observe changes in district microfinance levels with a 6-12 month delay.

Burgess and Pande (2005)). We also find that at least part of this decrease in consumption can be attributed to decreases in household labor market earnings.

To test the heterogeneous predictions of the model, we explore heterogeneity in these impacts by land holdings. We indeed find that the effects on labor market earnings are most pronounced for the least landed quintile of the district land distribution and decline as land holdings increase. Moreover, we find U-shaped patterns in both non-durable and durable consumption. Further, we examine effects on household businesses heterogeneously by the number of employees and find that the largest consumption impacts accrue to the households with businesses employing fewer than six workers, while there are no detectable effects for the businesses with a larger payroll.

Our findings are robust to alternative specifications. First, we find that our exposure measure is not simply proxying for distance to Andhra Pradesh. Results are unchanged dropping border districts or including time varying controls for distance to the affected state. Second, we conduct a placebo test comparing high vs. low exposure districts between 2008 and 2010, *before* the crisis. This exercise does not replicate our findings, offering further support for the identifying assumptions behind our research design.

Our paper is related to two distinct literatures in economics and finance. First, we contribute to the active debate on the impacts of microfinance and provide novel estimates of impacts on the average borrower in general equilibrium. These impacts are arguably more important for policy-makers when deciding how much to subsidize or regulate the microfinance sector and when designing financial inclusion strategies. The results paint a different picture of microfinance than the RCT literature. Namely, changes to the availability of credit at the district level have important distributional consequences for non-borrowers through the equilibrium wage in the rural labor market. The paper is also related to the literature on financial access for the poor, especially Burgess and Pande (2005), who, as described above, show evidence that bank expansions increase welfare for rural districts. While we do not find effects on poverty headcounts, we do believe that our findings are broadly consistent with those of Burgess and Pande (2005).

Second, this paper is related to the large literature in macroeconomics and finance studying the effects of credit supply shocks and bank balance sheet effects in developed countries. Many papers have shown that in many diverse settings, shocks to bank liquidity are often passed on to borrowers through reductions in lending (Paravisini (2008), Khwaja and Mian (2008), Iyer et al. (2013), and Schnabl (2012)). More often then not, decreases in lending activity are not fully offset by the credit market. A smaller literature including Chodorow-Reich (2014), Jiménez et al. (2014), Greenstone et al. (2014), and Peek and Rosengren (2000) traces out effects (or lack thereof) of such credit supply shocks on real activity.

Our paper proceeds, in section 2 with a model exploring the effects of a credit shock on the investment of SMEs and the effects on labor demand and supply. Section 3 discusses the setting and data. We describe our empirical strategy in Section 4. Section 5 presents our results, and Section 6 concludes.

2. Model

Before turning to the empirical strategy and results, we first present a simple static general equilibrium model of the rural economy. We model the AP crisis as a tightening of credit constraints faced by households and generate empirical predictions by exploring the comparative statics resulting from the solution of each household's problem and the equilibration of labor demand and labor supply.

2.1. Model Environment.

Our goal is to capture the equilibrium effects of changes to aggregate credit supply on rural household outcomes including wages, labor hours, total labor market earnings, and business profits. We start by assuming that households each have access to a decreasing returns production technology $y_i = AK_i^{\alpha} L_i^{\beta}$, $\alpha + \beta < 1$. Output (y) is the numeraire good, and the two factors of production, capital (K_i) and labor (L_i), can be purchased for unit prices r and w, respectively. Households may hire labor from both their households L_i^H and from the outside labor market L_i^D for their businesses, such that $L_i = L_i^H + L_i^D$.

We next assume that households are endowed with a time endowment $\bar{T}$ that can be used toward outside labor supply L_i^S, home business labor supply L_i^H, or leisure l_i. In the basic version of the model, we assume that all agents supply their total labor inelastically, $L_i^S + L_i^H = T \leq \bar{T}$.[2]

We introduce heterogeneity in a household's land endowment D_i. In what follows, we assume $D_i \sim U\left[0, \bar{D}\right]$. We assume that land is an illiquid asset that cannot be used directly as a factor of production. However, land can be converted into capital through the financial markets. By posting land as collateral, households can borrow $b_i \leq \lambda D_i$. We assume that the market for loans is a nationwide market, thus households are price-takers in the interest rate r. The borrowing constraint λ is determined by the supply of funds to the microfinance market. We also assume that households must borrow to finance both capital and labor for production.

We feel that this form of borrowing constraints captures several of the salient features of the Indian microfinance market in an extremely simple way. First, low-wealth individuals are typically screened out from access to microfinance by the MFIs.[3] Microlenders also tend to screen out potential borrowers who are "too rich."[4] Our model gives rise to some households being unconstrained, that is their optimal choice of investments are below λD_i, which is consistent with microfinance serving clientele with intermediate levels of wealth.

[2] The results are similar if we allow labor supply to be endogenously determined. We solve such an extension in the Supplemental Appendix.

[3] The fact that individuals can be "too poor" for microfinance gives rise to the types of ultrapoor programs tested in Banerjee et al. (2015b). These programs aim to increase a household's wealth, captured by D_i in our model, so that they can become eligible for microfinance.

[4] The idea expressed by MFIs in conversations is that wealthy people have low value of future credit (and more disutility from weekly meetings) and are more prone to strategic default.

In equilibrium, the labor market must clear. The land endowments D_i will determine each household's total demand for labor. Wealthier households will thus be net demanders of labor, and poorer households will be net suppliers of labor to the market.

2.2. **Household Maximization.** Holding factor prices w and r fixed, households choose total labor, capital and borrowing to maximize business profits:

$$\max_{L_i,K_i} AK_i^{\alpha}L_i^{\beta} - wL_i - rK_i$$

s.t.

$$rK_i + wL_i \leq \lambda D_i$$

Turning to labor supply, if $L_i > T$, then $L_i^D = L_i - T$, $L_i^H = T$, and $L_i^S = 0$. If $L_i \leq T$, then $L_i^D = 0$, $L_i^H = L_i$, and $L_i^S = T - L_i$.

Let $\left(\tilde{L}\left(w,r\right), \tilde{K}\left(w,r\right)\right)$ be the labor and capital demand under perfect capital markets (i.e., $\lambda = \infty$), for fixed w, r. To make this interesting we assume the parameters are such that $\tilde{L}\left(w,r\right) > T$ for reasonable values of (w,r).

Proposition 1. *Households will fall into one of three types, depending on their land holdings, D_i: a) Households with sufficiently high landholdings will be unconstrained (i.e., able to invest $\tilde{L}$), net demanders of labor; b) households with intermediate landholdings will be constrained, net demanders of labor; and c) households with low landholdings will be constrained, net suppliers of labor.*

2.3. **Equilibrium.** Given that the labor market clears at the local level, in equilibrium, labor supply must equal labor demand.

$$\int L_i^S dF_i = \int L_i^D dF_i$$

This equilibrium condition will pin down the wage.

2.4. **Comparative Statics and Empirical Predictions.** We now explore what happens to the labor market equilibrium when credit supply is contracted, that is when λ decreases.

Proposition 2. *The equilibrium wage $w\left(\lambda\right)$ is strictly increasing in credit supply, $\frac{\partial w(\lambda)}{\partial \lambda} > 0$.*

We can now interpret how a decrease in credit supply should affect each type of household. To facilitate this discussion, we solve the model under two different borrowing regimes. Figure 3 plots household earnings against land endowments in the case of $\lambda = 1.7$ and $\lambda = 1$. The bottom panel shows the change in earnings from a decrease in credit supply for individuals of varying levels of land.

The unconstrained, net labor demanders face two different effects. First, the decline in the equilibrium wage increases business profits holding labor and capital fixed. Thus, households with high wealth that remain unconstrained after the policy change benefit from the decline in credit supply. Note that for the parameters used in Figure 3, this increase in earnings is very small.[5] Second, some households that were previously unconstrained, can no longer borrow enough after the credit contraction to reach the optimal scale of their business. This negative effect more than offsets the benefits from the lower wage for a substantial set of households in Figure 3.

The constrained, net labor demanders are hit hardest by the decrease in credit supply. These households become more constrained and are forced to operate their businesses at a smaller scale. For those households that continue to be net demanders of labor, the loss is partially offset by the decrease in wage. However, some households may be forced to switch from net demanders to net suppliers of labor. These households are made even worse off by the decrease in wages earned on the labor market.[6]

Finally, the constrained net labor suppliers also experience a negative effect of the credit contraction. However, the negative effect is smaller for individuals with extremely low levels of wealth. This pattern is clear in Figure 3. Individuals with the lowest levels of land experience a moderate decrease in earnings, which is mostly attributed to a decrease in labor market earnings. However, as wages increase, the reduction in earnings from the reduction in credit supply increases. This increase is due to the reduction in credit that limits the scale of the households business. However, these negative effects start to eventually decrease with wealth.

Therefore the model predicts monotonically decreasing treatment effects with wealth for labor market earnings and U-shaped treatment effects on business profits, total household earnings, business investment, and both durable and non-durable consumption.

3. Setting and Data

3.1. **Setting.**

The Andhra Pradesh Ordinance of 2010. On October 15, 2010, the AP government unexpectedly issued an emergency ordinance (The Andhra Pradesh Micro Finance Institutions Ordinance, 2010) to regulate the activities of MFIs operating in the state. The government was worried about widespread over-borrowing by its citizens and alleged abuses by microfinance collection agents. The provisions of the Ordinance (promulgated as a law in December 2010) brought the activities of MFIs in the state to a complete halt. Under the law (which still stands), MFIs are not permitted to approach clients to seek repayment and are further barred from disbursing any new loans.[7] In the months following the ordinance, almost 100% of borrowers in AP defaulted on their loans.[8] Furthermore, Indian banks pulled back tremendously on their willingness to lend to any MFI across the country.

[5]The model is solved for a uniform distribution of wealth on $[0, 30]$. We truncate the wealth levels shown in Figure 3. Note that due to the decreasing returns assumption, all households with high levels of wealth make the same production and labor supply decisions.
[6]This scenario is similar to (Jayachandran, 2006).
[7]However, it is not illegal for borrowers to seek out their lenders to make payments.
[8]We investigate the effects of this "windfall" in a companion paper (Banerjee et al., 2014).

What is important for this paper is that even MFIs even outside of Andhra Pradesh were affected. Lenders were forced to contract their lending activities in healthy districts in other states. Surprisingly, the defaults in Andhra Pradesh did not spread across the country. Furthermore, individuals continued to make their regular loan repayments even when they knew that their lender would not be able to give them more credit immediately upon full repayment.

3.2. **Data.** We use data from two sources in our empirical analysis. First, we hand collected proprietary administrative data from 27 microfinance institutions. This data is essential for constructing each district's pre-crisis balance sheet exposure to Andhra Pradesh. We next explain how we construct this exposure variable.

Measuring exposure to the AP Crisis. First, for each lender l, we calculate the share of the MFI's overall portfolio that was invested in Andhra Pradesh on the eve of the AP Crisis (the beginning of October, 2010):

$$fracAP_l = \frac{GLP_{l,AP,Oct2010}}{GLP_{l,Total,Oct2010}}.$$

Then, for each district d, we construct an aggregate exposure measure by taking the weighted average of $fracAP_l$ over all lenders who had outstanding loans in the district on the eve of the crisis, where the weights are that lender's total loan portfolio in the state, $GLP_{dl,Oct2010}$:

$$ExpAP_d^{Total} = \frac{\sum_l fracAP_l \times GLP_{dl,Oct2010}}{\sum_l GLP_{dl,Oct2010}}. \tag{3.1}$$

Thus, $ExpAP_d$ is a measure of the extent to which the district's loan portfolio on the eve of the crisis was exposed to the crisis. For instance, consider a district served by two lenders, each of whom makes 50% of the loans in the district. One lender operates solely in Northern India and has 0% of its portfolio in AP. The other is based in Southern India and has 40% of its portfolio in AP. Then $ExpAP_d^{Total} = \frac{.4+0}{2} = 0.20$.

Finally, we scale the exposure ratio (defined by equation 3.1) by the amount of credit outstanding per rural household. We calculate the rural population using the 2010 round of the NSS (discussed below). This scaling captures the idea that the same amount of outstanding credit will have a greater per-household impact in a less populous district vs a more populous one:

$$ExpAP_d = ExpAP_d^{Total} \times \frac{\sum_l GLP_{dl,Oct2010}}{RuralPop_{2010}} \tag{3.2}$$

NSS Data. Second, we use household data from three rounds of the Indian National Sample Survey (NSS). We use waves 64, 66, and 68 which correspond to years 2007-2008, 2009-2010, and 2011-2012, respectively. We focus on the schedules containing household composition, consumption and employment. Key variables are summarized in Table 1. (We summarize the 2012 values in low exposure districts for ease of comparison to the reduced form results, below.) Average GLP per rural household is INR 272. Household size is 4.7, and the average household has 1.55 income earners. Nondurable household consumption INR 6946 per month. Durable consumption per household is reported on an annual basis: it is INR 7902 per year. Household total weekly earnings average INR 1086. Members of the average household work approximately 11 person-days per week, of which 8.11 are in self-employment and 2.92 in non self-employment. The average daily wage in casual non-agricultural labor is INR 215.

4. Empirical Strategy

We estimate ITT impacts of reduced access to microfinance on a range of outcomes. The main estimating equation takes the difference-in-difference form

$$y_{idt} = \alpha + \delta_t + \delta_d + \beta \times Exposure_d \times Post_t + X_{idt}^{'}\gamma + \varepsilon_{idt} \tag{4.1}$$

where y_{id} are outcome variables for individual i in district d at time t; δ_t and δ_d are fixed effects for survey round (time) and district, respectively; $Exposure_d$ is a measure of the exposure of district d to the AP crisis; and β is the coefficient of interest. $X_{idt}^{'}$ includes controls for the calendar month when the survey was conducted; household size; the rural population of the district at t and its square; a dummy for the presence of microfinance in the district in 2008 interacted with round; and dummies for quartiles of 2008 gross loan portfolio, interacted with round. Note that we do not observe a panel of households, but rather repeated cross-sections. Standard errors are clustered at the district level.

We use two measures of exposure to the AP crisis, both based on $ExpAP_d$. First is the log of the exposure ratio (defined by equation 3.2) plus one. Second is a dummy for a positive exposure ratio, that is, for the presence of a lender that had any exposure to the AP crisis.

Our identification comes from the differential change in outcomes of household cohorts in otherwise-similar districts with differing degrees of exposure to the crisis. Given the time-varying controls we include, our identifying assumption is that households in districts with the same rural population and the same level of total MFI lending in 2008 are on similar trends regardless of whether the MFIs lending in the district were highly exposed to the AP crisis or not.

One piece of evidence supporting this assumption is the fact that microlenders before the crisis tended to offer a very homogeneous product. Most lenders used all of the following features: interest rates of approximately 25-30%, weekly or monthly meetings, meetings held in groups, similar loan sizes, and similar dynamic incentives. Moreover, most MFIs had borrowers recite a joint oath at the beginning of each repayment meeting. Given this standardization, this assumption appears *a priori* reasonable. Moreover, we present robustness and placebo checks below that lend direct support to this assumption.

5. Results

5.1. **First Stage.** Table 2 presents the first stage, estimated by equation 4.1 with a measure of credit outstanding in 2012 on the left-hand side. Row 1 of column 2 shows that a 1 log point increase in exposure to the crisis (as measured by the pre-crisis portfolio weighted exposure of the district's lenders to the AP crisis) is associated with INR 66 less credit outstanding per rural household in 2012 (significant at 1%). The second row of column 2 indicates that those districts with an AP-exposed lender have INR 223 less credit outstanding per rural household in 2012 (significant at 1%), compared to other similar districts whose lenders were not exposed to the crisis. The average of the dependent variable in 2012 for households in non-exposed districts is INR 324, so this is a large effect, implying that AP-exposed lenders cut back significantly on lending and this shortfall was not fully made up by other, non-exposed microlenders.

It is not surprising that other microlenders were unable to target the borrowers of exposed MFIs. First, expanding to new villages requires fixed investments in branch infrastructure and in staff. Second, even non-exposed MFIs report having trouble obtaining credit from the Indian banking sector, which traditionally provided most of the funding to the MFIs. Third, borrowers often were allowed to take larger loans only after establishing a successful repayment record with their lenders. Given that there was no microfinance credit registry, even if households were able to secure new loans from new lenders, those loans would likely have been smaller in size.

5.2. **Reduced Form: Main Results.**

Labor Outcomes. We begin by measuring district level impacts of the reduction in credit observed in Table 2 on the labor market. Table 3 reports treatment effects on total labor earnings, casual daily wages, household total labor supply and whether any household member reports involuntary unemployment. We begin by noting that the reduction in credit did have economically and statistically significant effects on both the agricultural and the non-agricultural daily wage. High exposure districts experienced a fall in the non-agricultural wage of INR 16, which is displayed in row 2 of column 3. We next ask if this decrease in wage affected total household labor supply and total labor earnings. In column 4, we find that there are no detectable effects on total days worked. Given that wages fell, but labor supply did not, this leads to an overall decline in household weekly labor market earnings of INR 78 in highly exposed districts relative to unexposed districts after the AP crisis (column 1). We also observe that households do not change their assessment of whether they are involuntarily unemployed differentially in high versus low exposure districts after the crisis (column 5). The principal margin of adjustment does appear to be the wage rather than the extensive margin of labor supply; consistent with the inelastic labor supply assumption in the model.

Our strong wage and labor earnings results correspond with the predictions of Buera et al. (2012) and highlight the importance of incorporating general equilibrium effects into the analysis.

Consumption and Self-Employment. Table 3 reports the effects of reduced credit access on expenditure, divided into nondurables, which are measured on monthly basis; and durables, measured on an annual basis. Column 1, row 1 shows that a 1 log point increase in exposure to the crisis is associated with a reduction of INR 86.2 in per capita monthly nondurable expenditures in 2012 (significant at 1%). Column 1, row 2 indicates that those districts with a highly AP-exposed lender have INR 345 lower per capita monthly nondurable expenditure (significant at 1%), compared to other similar districts whose lenders were not exposed to the crisis. Column 2 repeats the analysis for per capita annual durable expenditures in 2012. Row 1 shows that a 1 log point increase in exposure to the crisis is associated with a reduction of INR 197 (significant at 1%), and row 2 shows that those districts with a highly AP-exposed lender have INR 982 lower per capita annual durable expenditure (significant at 1%).

Column 3 examines effects on the likelihood that a household has any non-agricultural self employment. For both the continuous and binary measures of exposure, there is no evidence of a significant average effect; however, we will show below that there is evidence for an effect for households with intermediate landholdings.

5.3. **Heterogeneous Effects.** So far we have reported average effects, but another question of interest–both from a policy perspective and in terms of testing the implications of our model–is how the effects of the credit contraction are felt among those who are differentially affected by but the direct (lending) effect and the general equilibrium wage effect. Recall that the model predicts monotonically decreasing treatment effects with wealth for labor market earnings and U-shaped treatment effects on business profits, total household earnings, business investment, and both durable and non-durable consumption.

While we do not have panel data at the household level and so cannot follow households over time, we can examine effects separately for different parts of the distribution, defined by contemporaneous but "sticky" measures of household wealth. One such measure is land holdings; another is the size (measured as employment) of the household's business. For these analyses we focus on the binary measure of exposure to the crisis.

Heterogeneity by landholdings. Table 5 reports effects on key outcomes separately for each quintile of the within-district land distribution. Column 1 shows the effects on household weekly labor earnings associated with a high exposure to the crisis. As predicted, there is a fall for the earnings of households in quintile 1 (landless and near-landless) of INR 25 (significant at 5%). For higher land/wealth households, the effects are insignificant, with a pattern of point estimates that are generally shrinking in magnitude as land holdings increase. Thus, the low wealth households who are the largest suppliers of outside labor see the largest effect via the labor earnings channel.

Column 2 shows effects on monthly nondurable consumption. The largest magnitude effects are seen in the fourth quintile of the distribution, where monthly nondurable consumption falls by INR 141 (significant at 1%). Households in the 1st (poorest) quintile see a fall of INR 55 (significant at 5%); those in the third quintile see a fall of INR 76 (significant at 1%). The effect for the largest landholders is insignificant. Thus the effects are broadly consistent with the U-shaped pattern of results predicted by the model.

Column 3 examines annual durable consumption, and finds a similar pattern: large and highly significant effects for the fourth quintile of the distribution, where annual durable consumption falls by INR 358 (significant at 1%). The effects at both lower and higher quintiles are smaller in magnitude, again suggesting a U-shaped pattern.

Finally, column 4 shows effects for the likelihood that a household has any non-agricultural self employment. Again, effects are seen for the fourth quintile of the distribution, where the likelihood of any non-agricultural self employment falls by 0.9 percentage points (significant at 5%). The effects at other quintiles are close to zero.

This pattern suggests that medium landholders, who may be most likely to borrow directly from microfinance, respond to reduced credit access by reducing consumption and investment in household businesses (proxied by durable spending). The landless and near-landless experience falls in earnings, due to a combination of a reduced daily wage arising from reduced labor demand from local businesses. We do not find evidence of rationing in the market for casual labor, suggesting that the market equilibrates via the wage. Finally, the largest landholders, whose businesses may be able to reach the optimal scale even after the credit contraction, appear relatively unaffected by the reduction in credit access.

Heterogeneity by business scale. Table 6 reports effects on key outcomes separately for owners of "small" and "large" businesses: those with fewer than 6 employees and 6 or more, respectively.[9] Consistent with the model's predictions, the effects are entirely experienced by owners of small businesses, those whose scale is most likely to fall in response to the credit contraction. For these households, the effect of a 1 log point increase in exposure to the crisis that household weekly labor earnings fall by INR 17, monthly nondurable consumption falls by INR 84, and annual durable consumption falls by INR 214 (all significant at 5% or better). There are no significant effects for owners of larger businesses. Using the binary measure of exposure to the crisis, household weekly labor earnings fall by INR 77, monthly nondurable consumption falls by INR 309, and annual durable consumption falls by INR 1101 (all significant at 5% or better); again there are no significant effects for owners of larger businesses.

5.4. **Robustness checks.** Our results are robust to a variety of possible confounds. Table B.1 reports key outcomes for two alternate specifications that test the idea that exposure to the AP crisis may be proxying for distance to AP, and hence may be picking up effects that

[9]We show in Appendix Table B.4 that owning a large business is not differentially more common in high exposure versus low exposure districts following the AP crisis.

do not work through firms' balance sheets, but through other "spillover" effects of the crisis (economic uncertainty, etc.). The top panel drops districts which border AP. The second panel controls for distance from the district capital to Hyderabad (AP's capital), interacted with round. In both cases the effects on expenditure, earnings, labor supply and wages remain significant and quantitatively similar.

Table B.2 tests for the concern that states with greater exposure to the crisis may have been on differential trends even in the absence of the crisis. The top panel adds controls for state dummies interacted with round. The bottom panel adds controls for state dummies interacted with month of survey, in case more-exposed areas were surveyed by the NSS at times of the year when outcomes looked worse. In both case, our conclusions remain robust.

Finally, as a check of the identifying assumption, Table B.3 conducts a placebo test, dropping the round 68 data and assigning the round 66 observations the status of Post. If districts that were more exposed to AP were on differential trends prior to the crisis, we should see significant effects in round 66. None of the main outcomes is significant at standard levels.

6. Discussion

We use the Andhra Pradesh microfinance ordinance as a natural experiment to measure the real impacts of the loss of microfinance on rural households. Given the scale and maturity of the microfinance sector in India before the ordinance, the crisis presents a unique opportunity to study the impacts of microfinance on the average borrower in general equilibrium in contrast to experimental work which often measures impacts for marginal borrowers in partial equilibrium. We find that districts outside Andhra Pradesh that were nonetheless exposed to the crisis through the balance sheet of their lenders experience decreases in lending, consumption, earnings, and wages. Further, these impacts are borne heterogeneously across the wealth distribution within each district. The effects on the poorest households are largely mediated through the fall in equilibrium wage, while households with intermediate levels of wealth experience the largest declines in consumption of both durables and non-durables. No impacts are detectable for the richest households.

Our results show that the actions of politicians in Andhra Pradesh had large negative externalities on microcredit supply to the rest of the country. Microfinance institutions were no longer able to finance otherwise good borrowers in other states, which in turn led to decreased wages, consumption and earnings. Further, our results are not consistent with the narrative that overborrowing led to the AP crisis: the withdrawal of credit appears to have left many households worse off.

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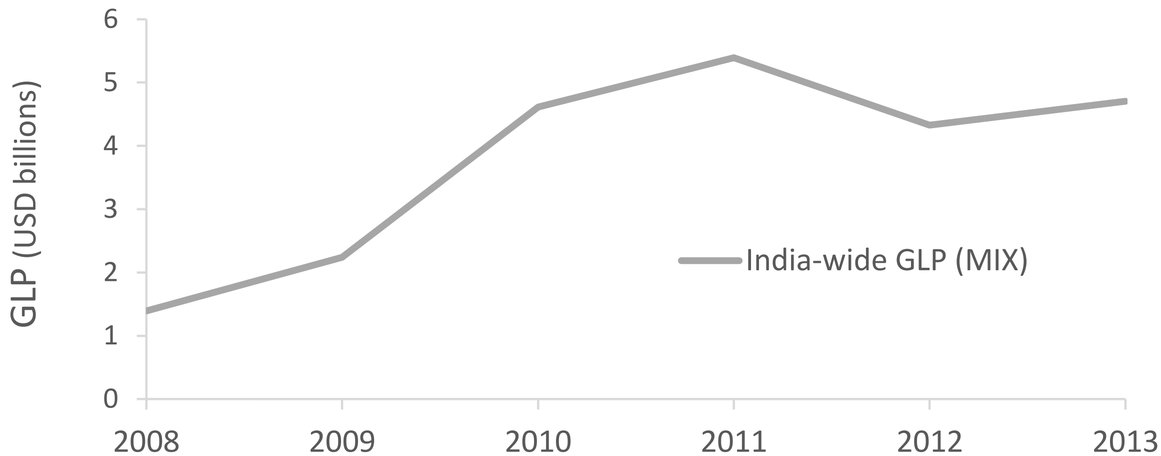
Figures

Panel A: India-Wide GLP



Panel B: GLP in High vs. Low Exposure Districts (ex Andhra Pradesh)

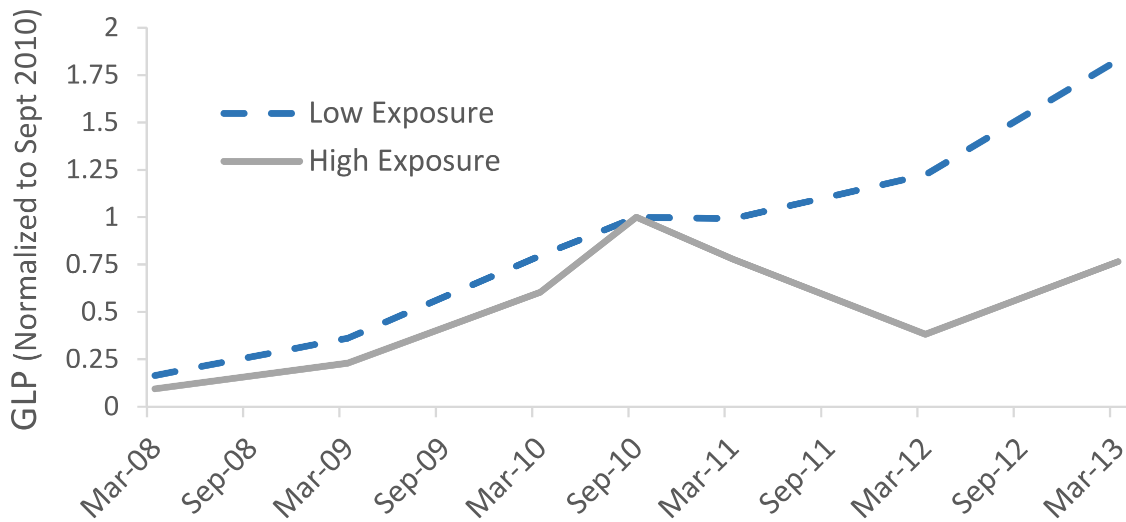
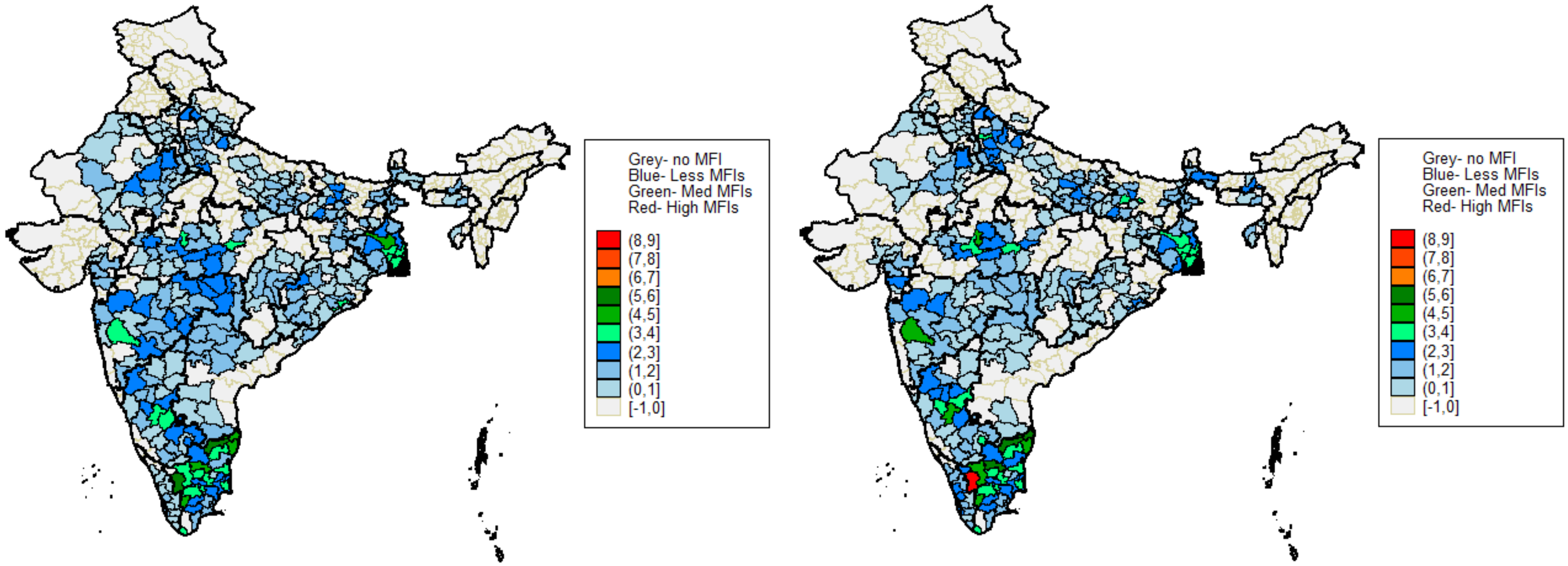


Figure 1. Growth of Microfinance Gross Loan Portfolio (GLP) in India and in Analysis Sample

Note: Panel A plots the India-wide gross loan portfolio (GLP) from 2008 to 2013 aggregated across microfinance institutions and states as reported in USD in the MIX database. Reporting to the MIX is voluntary, and thus the reporting dates may vary by lender. Panel B shows the evolution of microfinance using the hand-collected data (reported in Indian rupees) from 27 microfinance institutions. The figure in Panel B splits the set of districts between low and high AP exposure. A district is defined to have low exposure if it did not have any loans from an MFI that did have outstanding loans in Andhra Pradesh in September 2010. GLP in each year is scaled by the pre-crisis district level of microcredit on September 30, 2010.



(A) September 2010

(B) March 2012

FIGURE 2. Number of MFIs by District

Note: These maps present visualizations of the hand-collected data from 27 microfinance institutions. The first subfigure plots the number of lenders per district in our dataset in September 2010, on the eve of the AP crisis. Subfigure 2 plots the number of lenders per district after the contraction in lending was underway in March 2012. Districts without coloration indicate that none of the 27 lenders in our sample were lending in those districts at the time.

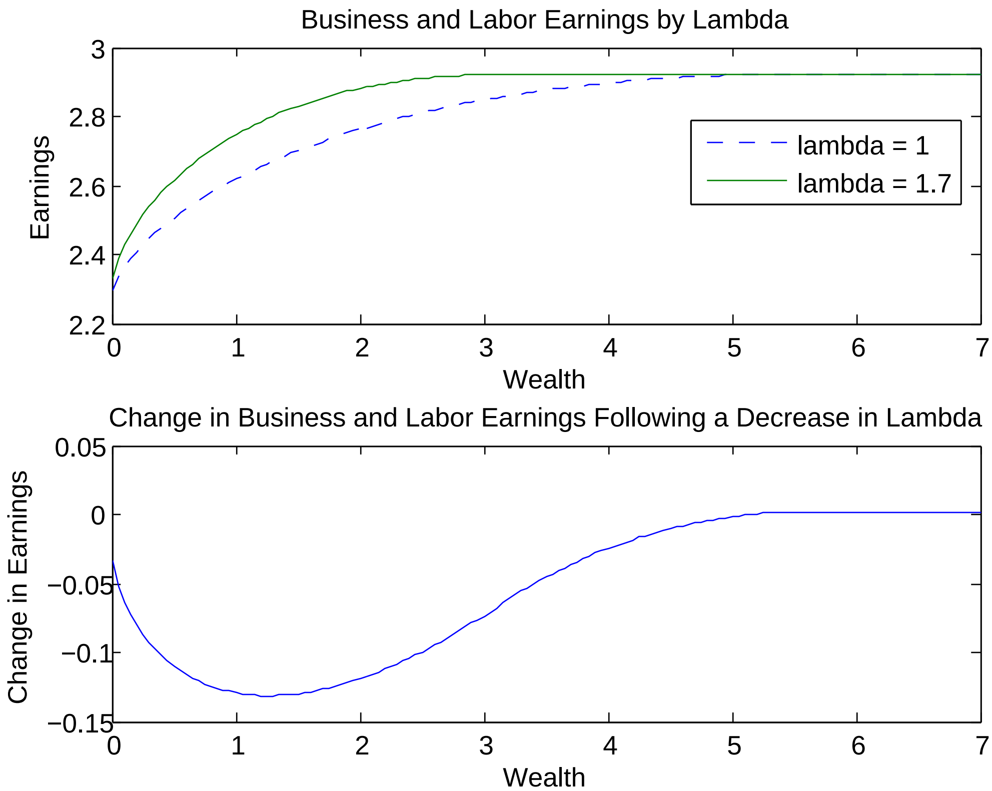


FIGURE 3. Modeled Earnings under Different Credit Supply Regimes

Tables

Table 1. Summary Statistics, 2012 NSS

Variable	Obs.	Mean	Standard Deviation
District GLP 2012	16340	1.72E+08	1.85E+08
HH Weekly Labor Earnings	16340	1086.03	1996.49
Casual Daily Wage: Ag	1176	149.28	72.07
Casual Daily Wage: Non-Ag	2460	215.33	118.54
HH Weekly Days Worked	16340	10.59	7.04
Any HH Member Invol. Unemployed	16340	0.10	0.30
HH Monthly Consumption: Total	16340	6945.68	6518.77
HH Annual Consumption: Durables	16340	7901.78	36548.95
Any non-Ag Self Employment	16340	0.37	0.48

Note: Outcomes variables from from NSS round 68 (2012). Sample is restricted to only low exposure districts (control group).

Table 2. Exposure to the AP Crisis and total lending

	(1) District Total GLP	(2) District Household GLP
Log(HH Exposure Ratio) x Post 2010	-2.095e+07***	-66.253***
	(2526405.770)	(6.958)
High HH Exposure x Post 2010	-7.394e+07***	-223.416***
	(10926630.030)	(27.695)
Observations	119,670	119,670

Note: Outcomes data from MFI balance sheets. Each row provides coefficients from separate regression specifications. The first row reports specifications that use the continuous exposure measure. The second row reports coefficients from separate regressions using the binary indicator for high exposure to AP. The outcome of interest in column 1 is total district-level credit outstanding (GLP), while column 2 scales this value by the number of rural households. In all columns, controls include month fixed effects, round fixed effects, district fixed effects, HH size, number rural HH * round, num rural HH^2 * round, presence of MF in 2008 dummy * round, GLP quintiles in 2008 dummies * round. Standard errors are clustered at the district level.

TABLE 3. Reduced Form: Labor Outcomes

	(1) HH Weekly Labor Earnings	(2) Casual Daily Wage: Ag	(3) Casual Daily Wage: Non-Ag	(4) HH Weekly Days Worked	(5) Any HH Member Invol. Unemployed
Log(HH Exposure Ratio) x Post 2010	-18.042**	-1.247*	-4.568***	-0.044	0.003
	(7.155)	(0.731)	(1.192)	(0.043)	(0.003)
High HH Exposure x Post 2010	-77.759***	-5.288*	-16.353***	-0.119	0.010
	(29.693)	(3.149)	(5.195)	(0.182)	(0.011)
Observations	119,668	14,554	14,939	119,668	119,668

Note: Outcomes data from NSS rounds 64, 66, 68. Each row provides coefficients from separate regression specifications. The first row reports specifications that use the continuous exposure measure. The second row reports coefficients from separate regressions using the binary indicator for high exposure to AP. In all columns, controls include month fixed effects, round fixed effects, district fixed effects, HH size, number rural HH * round, num rural HH^2 * round, presence of MF in 2008 dummy * round, GLP quintiles in 2008 dummies * round.

TABLE 4. Reduced Form: Consumption and Self-Employment

	(1) HH Monthly Consumption: Total	(2) HH Annual Consumption: Durables	(3) Any non-Ag Self Employment
Log(HH Exposure Ratio) x Post 2010	-86.233***	-197.326***	-0.004
	(25.792)	(76.099)	(0.003)
High HH Exposure x Post 2010	-345.071***	-982.335***	-0.015
	(117.914)	(291.745)	(0.012)
Observations	119,668	111,692	119,668

Note: Outcomes data from NSS rounds 64, 66, 68. Each row provides coefficients from separate regression specifications. The first row reports specifications that use the continuous exposure measure. The second row reports coefficients from separate regressions using the binary indicator for high exposure to AP. In all columns, controls include month fixed effects, round fixed effects, district fixed effects, HH size, number rural HH * round, num rural HH^2 * round, presence of MF in 2008 dummy * round, GLP quintiles in 2008 dummies * round. Standard errors are clustered at the district level.

Table 5. Heterogeneous effects: Land

	(1) HH Weekly Labor Earnings	(2) HH Monthly Consumption: Total	(3) HH Annual Consumption: Durables	(4) Any non-Ag Self Employment	Obs.
Log(HH Exposure Ratio) x Post 2010					
1st Quintile District Land Dist.	-25.137**	-55.345*	-103.591	0.001	30,238
	(10.242)	(31.176)	(69.520)	(0.005)	
2nd Quintile District Land Dist.	-18.569	-23.526	-154.630*	0.001	21,906
	(17.350)	(39.688)	(83.459)	(0.006)	
3rd Quintile District Land Dist.	1.876	-76.283*	-120.615	-0.007	21,527
	(19.479)	(43.363)	(74.708)	(0.006)	
4th Quintile District Land Dist.	-16.341	-141.434***	-358.184***	-0.009**	21,981
	(10.530)	(35.735)	(119.248)	(0.004)	
5th Quintile District Land Dist.	-2.985	-71.092	-122.266	-0.006	19,917
	(14.495)	(56.831)	(342.928)	(0.006)	

Note: Each row contains treatment effect estimates from a different regression. The rows report the sample restriction by quintile of the district wealth distribution. The columns reflect different outcomes. All specifications use the continuous exposure measure. Outcomes data from NSS rounds 64, 66, 68. In all columns, controls include month fixed effects, round fixed effects, district fixed effects, HH size, number rural HH * round, num rural HH^2 * round, presence of MF in 2008 dummy * round, GLP quintiles in 2008 dummies * round. Standard errors are clustered at the district level.

Table 6. Heterogeneous effects: Employees

	(1) HH Weekly Labor Earnings	(2) HH Monthly Consumption: Total	(3) HH Annual Consumption: Durables	Obs.
Log(HH Exposure Ratio) x Post 2010				
<6 Employees	-17.063**	-84.217***	-213.754***	69,970
	(7.540)	(27.922)	(79.137)	
>=6 Employees	2.869	204.611	-109.069	1,327
	(56.211)	(244.715)	(795.341)	
High HH Exposure x Post 2010				
<6 Employees	-77.235**	-308.565**	-1,101.087***	69,970
	(31.534)	(124.251)	(320.394)	
>=6 Employees	43.348	671.329	-812.644	1,327
	(215.790)	(1,008.614)	(3,089.220)	

Note: Each row contains treatment effect estimates from a different regression. The rows report the sample restriction by number of employees in the household business. The top two row report results using the continuous exposure measure, while the bottom two rows use the binary measure. The columns reflect different outcomes. Outcomes data from NSS rounds 64, 66, 68. In all columns, controls include month fixed effects, round fixed effects, district fixed effects, HH size, number rural HH * round, num rural HH^2 * round, presence of MF in 2008 dummy * round, GLP quintiles in 2008 dummies * round. Standard errors are clustered at the district level.

Online Appendix

Appendix A. Supplementary Tables

Table B.1. Robustness: Distance to Andhra Pradesh

VARIABLES	(1) Household average total monthly expenditure	(2) Household expenditure on durables, last 365 days	(3) Household weekly labor earnings	(4) Household weekly days worked	(5) Household weekly days worked in self-employment	(6) Household weekly days worked in non-self-employment	(7) Househol wage f casual l
Drop border districts							
Log(HH exposure ratio) x Post 2010	-73.203**	-187.797**	-14.848*	-0.020	0.061	-0.081**	-1.524
	(28.571)	(83.726)	(7.770)	(0.045)	(0.051)	(0.041)	(0.73
High HH exposure x Post 2010	-278.412**	-935.026***	-62.877**	-0.018	0.356*	-0.374**	-6.746
	(125.186)	(310.193)	(30.850)	(0.187)	(0.211)	(0.170)	(3.26
Observations	113,346	105,801	113,346	113,346	113,346	113,346	38,80
Control for distance to Andhra Pradesh X round							
Log(HH exposure ratio) x Post 2010	-87.748***	-220.348***	-20.123***	-0.035	0.010	-0.045	-1.584
	(26.944)	(79.336)	(7.096)	(0.045)	(0.055)	(0.042)	(0.74
High HH exposure x Post 2010	-347.189***	-1,067.981***	-84.904***	-0.080	0.181	-0.261	-6.736
	(120.966)	(307.325)	(29.350)	(0.189)	(0.220)	(0.170)	(3.35
Control mean, round 68	5334.8	3870.1	768.4	10.6	6.8	3.8	139.
Observations	119,668	111,692	119,668	119,668	119,668	119,668	41,20

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Data from NSS rounds 64, 66, 68. In all columns, controls include month fixed effects, round fixed effects, district fixed effects, HH size, number rural HH * round, num rural HH^2 * round, presence of MF in 2008 dummy * round, GLP quintiles in 2008 dummies * round. Standard errors are clustered at the district level.

Table B.2. Robustness: State-by- calendar month controls

VARIABLES	(1) Household average total monthly expenditure	(2) Household expenditure on durables, last 365 days	(3) Household weekly labor earnings	(4) Household weekly days worked	(5) Household weekly days worked in self-employment	(6) Household weekly days worked in non-self-employment	(7) Household daily wage from casual labor
Control for state X month							
Log(HH exposure ratio) x Post 2010	-89.081***	-214.914***	-18.209**	-0.045	0.048	-0.093**	-1.607**
	(24.884)	(72.745)	(7.175)	(0.043)	(0.053)	(0.042)	(0.682)
High HH exposure x Post 2010	-355.4***	-1,052.8***	-77.518***	-0.120	0.317	-0.437**	-6.875**
	(115.335)	(283.883)	(29.363)	(0.183)	(0.213)	(0.173)	(3.108)
Observations	119,668	111,692	119,668	119,668	119,668	119,668	41,264

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Note: Data from NSS rounds 64, 66, 68. In all columns, controls include state-specific calendar month fixed effects, round fixed effects, district fixed effects, HH size, number rural HH * round, num rural HH^2 * round, presence of MF in 2008 dummy * round, GLP quintiles in 2008 dummies * round. Standard errors are clustered at the district level.

Table B.3. Placebo Test: "Treatment" in Round 66

	(1) HH Weekly Labor Earnings	(2) Casual Daily Wage: Ag	(3) Casual Daily Wage: Non-Ag	(4) HH Weekly Days Worked	(5) HH Monthly Consumption: Total	(6) HH Annual Consumption: Durables
Log(HH Exposure Ratio) x Post 2010	-1.872	-0.272	-0.930	-0.014	-7.352	16.798
	(5.769)	(0.422)	(0.952)	(0.056)	(22.916)	(41.793)
High HH Exposure x Post 2010	-2.124	-0.859	-4.081	-0.046	-91.584	188.152
	(22.777)	(1.870)	(3.999)	(0.226)	(91.533)	(194.295)
Observations	83,826	11,791	9,953	83,826	83,826	75,850

Note: Data from NSS rounds 64, 66, 68. In all columns, controls include month fixed effects, round fixed effects, district fixed effects, HH size, number rural HH * round, num rural HH^2 * round, presence of MF in 2008 dummy * round, GLP quintiles in 2008 dummies * round. Standard errors are clustered at the district level.

Table B.4. Robustness: Heterogeneous Covariates as Outcomes

	(1)	(2)	(3)	(4)	(5)	(6)
	Business with >6			Land Quintiles		
	Employees	1	2	3	4	5
Log(HH Exposure Ratio) x Post 2010	0.001	-0.003	0.005	-0.001	0.002	0.000
	(0.001)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
High HH Exposure x Post 2010	0.003	-0.008	0.015	-0.001	0.011	0.002
	(0.002)	(0.013)	(0.014)	(0.012)	(0.010)	(0.007)
Observations	71,297	119,668	119,668	119,668	119,668	119,668

Note: Each row corresponds to a different regression. The top row uses the continuous exposure indicator, while the second row uses the binary exposure indicator. Data from NSS rounds 64, 66, 68. In all columns, controls include month fixed effects, round fixed effects, district fixed effects, HH size, number rural HH * round, num rural HH^2 * round, presence of MF in 2008 dummy * round, GLP quintiles in 2008 dummies * round. Standard errors are clustered at the district level.