MEASURING THE EQUILIBRIUM 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 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, earnings, and employment in general equilibrium. Using a proprietary, hand-collected district-level data set from 25 separate, for-profit 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. We also find that wages in the non-tradable sector fall more than in the tradable sector (agriculture), suggesting that one important impact of the microfinance contraction was transmitted through its effect on aggregate demand. We present a simple two period, two-sector model of the rural economy illustrating this channel and show that our wage results are consistent with a simple calibration of the model.

1. INTRODUCTION

A rich theoretical and empirical literature has investigated the consequences of changes in access to financial intermediation on the households and enterprises whose borrowing is directly affected. However, there is also a growing recognition that credit access can affect even non-borrowing households through general equilibrium effects: changes in factor prices resulting from large-scale changes in credit access. Two important channels have emerged linking credit market tightening to adverse labor market outcomes. First, the *investment-finance channel*: constrained firms may decrease labor demand in response to a negative shock to credit supply, leading to a fall in wages and employment. Second, the

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aggregate demand channel: consumers may decrease demand for goods and services when faced with tighter borrowing constraints. The resulting decrease in aggregate demand, in turn, can lead to a fall in labor demand, putting downward pressure on wages and employment, especially in the non-tradable sector. Both channels appear to have been at work in the US financial crisis, for example (Chodorow-Reich 2014, Mian and Sufi 2014).

In this paper, we seek to measure the equilibrium impacts of a large contraction in the supply of microcredit in India. While the loans are typically very small (approximately $200 each at market exchange rates), microcredit nevertheless plays an important role. On one hand, it serves as a vehicle for financing investments in microenterprises for some households (Banerjee et al. 2018, 2017). Moreover, it allows households to accelerate consumption, especially the purchase of durables (Devoto et al. 2012, Tarozzi et al. 2014, Ben-Yishay et al. 2017). Thus, both the investment-finance channel and the aggregate demand channel may, in principle, be at play in the context of microfinance.

Theoretical work examining the role of credit in developing countries has largely focused on the investment-finance channel (Banerjee and Newman 1993, Evans and Jovanovic 1989, Aghion and Bolton 1997). Especially related to our approach is Buera et al. (2017), who explore theoretically the general equilibrium implications of microfinance for labor markets, via the investment-finance channel. Against this backdrop, a body of evaluations of microfinance (discussed below) have tested its impact on business creation, expansion, hiring, profitability and survival – in partial equilibrium – and have found little evidence that, on average, microfinance leads to transformative business growth.

Despite a recognition that microfinance also allows households to bring consumption forward in time, there has been, to our knowledge, little exploration of how microfinance affects the real economy through the aggregate demand channel. We present a simple two period, two-sector model of the rural economy which focuses on this pathway. Firms come in two types, tradable (agriculture) and non-tradable (non-agriculture), and hire two types of labor, high- and low-skilled, from the local labor market. Households consume tradable and non-tradable goods out of their cash on hand (earnings plus credit). Importantly, the product market for non-tradable goods is limited to local demand.

In the simplest version of this framework, households borrow only to bring forward consumption. A contraction in credit supply decreases the cash on hand of households, thus decreasing their total consumption demand. This triggers a fall in demand for non-tradable products and a subsequent fall in labor demand in the non-tradable sector, which puts downward pressure on wages.

Because the aggregate demand channel is, by definition, an equilibrium phenomenon, shedding empirical light on its importance is challenging. To estimate the equilibrium effects of microfinance on labor markets, one needs a shock to microfinance access which is exogenous, large in magnitude, and which plays out at the level of whole labor markets. We study a unique natural experiment that satisfies all three of these conditions.

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 nationwide shock to the liquidity of lenders. According to data from the Microfinance Information Exchange (MIX), the aggregate gross loan portfolio of Indian microlenders fell by approximately 20%, or more than \$1 billion, between fiscal year 2010 and fiscal year 2011. Panel A of Figure 1 plots India-wide levels of microlending from 2008 to 2013. The drop in lending post-2010 is visible in the figure.

With the help of the largest trade association of for-profit microlenders in India, the Microfinance Institutions Network (MFIN), we hand-collected proprietary district-level data from 25 separate, for-profit microlenders detailing their loan portfolios from 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 (AP), before the crisis, interacted with pre-crisis variation in the geographical footprint of each lender outside of AP. We show that districts that borrowed more from lenders with portfolio exposure to AP witnessed much larger declines in lending between 2010 and 2012 than similar districts with the same amount of overall pre-crisis lending, but whose lenders did not have balance sheet exposure to AP. Panel B of Figure 1 plots the trends in district-level GLP separately for districts with high and low balance sheet exposure to AP. 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] We use this massive, differential 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

[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 maturation of existing loans. This means that we only observe changes in district microfinance levels with a 6-12 month delay.

employment. Our empirical strategy only considers districts outside of AP, which were not directly affected by the ordinance and where individuals did not default on their outstanding loans. This natural experiment is a unique opportunity to study large, exogenous, labor-market level shocks to microfinance credit supply in a setting where there were no concurrent demand shocks.

The impacts of this reduction in microcredit were large enough to affect the labor market. 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. Consequently, the reduction in credit supply causes a decrease in wage labor earnings for the average rural household. We also find that households experience significant reductions in both non-durable and durable consumption. The fall in the wage implies that even non-borrowing laborers may experience declines in earnings and consumption when the local economy is hit by reduced access to credit.

While agricultural products are tradable and should not respond very intensively to changes in local demand, non-agricultural businesses mainly engage in services, construction, or petty trading, all of which are non-tradable and sensitive to changes in local demand. Indeed, we find that the wage response in high exposure districts is almost three times larger for non-agricultural wages than for agricultural wages, suggesting that the aggregate demand channel is an important part of the ramifications of the AP crisis.

We directly examine district-level outcomes for the tradable sector by studying crop yields. On one hand, firms in the tradable sector, which experiences no adverse shock to demand, will benefit from lower wage bills. But, on the other hand, some of these firms may be forced to scale back as liquidity constraints bind more tightly. Thus, the net impact on tradable sector output is ambiguous. We find a fairly precise zero effect for an index of yields of major crops. This suggests that, in aggregate, any benefits from a fall in the wage are offset by reductions in the scale of production by constrained businesses.

We then consider the distributional implications of the contraction of microcredit, aggregating across the two sectors. Using landholdings as a proxy for wealth, we show that the effects on labor market earnings are most pronounced for the poorest quintile of households, for whom casual wage employment is the largest contributor to income. Moreover, we find that intermediate-wealth households, whose ability to accelerate consumption (or invest in a business) may be most dependent on microfinance, experience the largest declines in non-durable and durable consumption.

Finally, we conduct a set of back-of-the-envelope exercises to provide further support for our results. First, we decompose our estimated effects on consumption and durable investment into implied effects on business profits, which we do not observe directly. Reassuringly, we find implied effects on business profits that are within the range of estimates from the RCT literature. Second, we show that our wage results are consistent with a simple calibration of our model.

We provide a battery of robustness tests in support of our identification strategy. We replicate the approach of Khwaja and Mian (2008) to further support our claim that our identification strategy captures a change in credit supply, rather than demand. We also use the NSS 70th round "Debt and Investment" survey to obtain a measure of households' total credit portfolios. The reduction in MFI credit is clearly present in this dataset, demonstrating that it is not an artefact of the fact that not all MFIs are represented in our balance sheet data. We also show that our findings are robust to a number of alternative specifications.

The paper is directly related to an active debate on the role of microfinance as a tool for business growth and poverty reduction. A recent wave of papers use RCTs to measure the partial equilibrium impacts of microcredit expansions. 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. Increased access to microfinance in partial equilibrium is generally found to cause modest business creation and business expansion. While there is evidence that borrowers do purchase more household durables and business assets, there is almost no support for a large average impact on business profits or on non-durable consumption one to two years post intervention.[2] In a quasi-experimental study, Kaboski and Townsend (2012) find a very large short-run consumption response to an expansion of village microcredit in Thailand, consistent with many households using the loan proceeds for consumption. Fink et al. (2017) show that, in Zambia, access to lean-season credit is associated with increased consumption and higher village-level wages.

Our study differs from RCT studies in several ways. Most important is the magnitude and scale of the shock. The Andhra Pradesh crisis moved credit by a large amount, both as a percentage reduction in credit and in aggregate: more than a billion dollars were wiped out of the market. Moreover, this shock played out at the level of entire districts, a large enough area to encompass whole labor markets. Achieving variation at this scale via an RCT would be extremely challenging. We are also able to study effects on average borrowers in mature markets, as opposed to studying new markets or marginal (complier) borrowers.

[2]In a meta-analysis of the RCT evidence Meager (2016) confirms this general appraisal of small, positive, but statistically undetectable effects on most key outcomes.

We attempt to provide complementary evidence to the RCT literature and to fill one of the gaps in the literature highlighted by Banerjee et al. (2015b):

> We have only scratched the surface of identifying spillover and general equilibrium effects ... Nonborrowing wage earners could benefit from increased employment opportunities.

More broadly, the paper is related to the literature on financial access for the poor, especially Burgess and Pande (2005), who show evidence that bank expansions decrease rural poverty. This paper also builds on the large literature in macroeconomics and finance studying the effects of credit supply shocks and bank balance sheet effects.[3] A smaller literature stemming from Peek and Rosengren (2000) traces out effects of such credit supply shocks on real activity.[4] Our paper is also related to recent work examining general equilibrium effects of large-scale programs and economic shocks in developing countries.[5]

Our paper proceeds as follows. In section 2, we discuss the setting and describe the predictions of a simple model exploring the effects of a credit shock on labor markets, via investment by borrowing entrepreneurs. Section 3 discusses the data and empirical strategy. Section 4 presents our main results, Section 5 discusses evidence on the firm liquidity and aggregate demand mechanisms, and Section 6 discusses the results in relation to the RCT literature and discusses profit imputation and calibration exercises that benchmark the magnitudes of our results. Section 7 concludes.

2. Setting, Framework, and Empirical Predictions

2.1. 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 stated that it was worried about widespread over-borrowing by its citizens and alleged abuses by microfinance collection agents. On October 28, 2010, the Wall Street Journal ran the headline "India's Major Crisis in Microlending: Loans Involving Tiny Amounts of Money Were a Good Idea, but the Explosion of Interest Backfires." Other voices in the microfinance debate claimed that the government was using the ordinance to promote its own preferred financial inclusion initiative, bank-financed self-help groups

[3]Many papers, such as Khwaja and Mian (2008), have shown that in diverse settings, negative shocks to bank liquidity are often passed on to borrowers through reductions in lending. Also see Paravisini (2008), Khwaja and Mian (2008), and Schnabl (2012).

[4]Other related papers include Chodorow-Reich (2014), Jiménez et al. (2014), and Greenstone et al. (2014).

[5]See Imbert and Papp (2015), Muralidharan et al. (2017), Jayachandran (2006), Mobarak and Rosenzweig (2014), Akram et al. (2017).

(SHGs).[6] On November 4, 2010, the Harvard Business Review Published an article entitled "India's Microfinance Crisis is a Battle to Monopolize the Poor."

Regardless of the origins of the Ordinance, its provisions brought the activities of MFIs in the state to a complete halt. Under the law, MFIs were not permitted to approach clients to seek repayment and were further barred from disbursing any new loans.[7] In the months following the ordinance, almost 100% of borrowers in AP defaulted on their loans.Furthermore, fearing similar problems in other states, Indian banks pulled back tremendously on their willingness to lend to any MFI across the country. The effects of the crisis can be seen in the aggregate country-wide patterns displayed in Figure 1. Using data from the Microfinance Information Exchange (MIX), the figure shows that total microfinance loan portfolios fell by over one billion dollars following the crisis.[8]

Important for this paper, lending even in areas outside of Andhra Pradesh was affected by the crisis. Notably, the shock in AP was transmitted to other districts through the balance sheets of the lenders – that is, MFIs with high exposure to the defaults in AP were forced to reduce their lending in other states that were not directly affected. In general, they were not able to secure additional financing from the Indian banks to maintain their desired levels of lending. In many cases, exposed lenders ceased lending in some districts outside AP altogether. Figure B.1 shows the number of MFIs per district, before and after the crisis: throughout India, reductions in the number of MFIs active are visible in many districts, illustrating geographical variation in the footprint of the crisis.

Perhaps surprisingly, the defaults in Andhra Pradesh did not spread across the country: individuals continued to make their regular loan repayments even though they may have anticipated that their lender would not be able to give them more credit immediately upon full repayment.[9] Thus there was no direct "windfall" effect outside of AP.

Bank lending to MFIs resumed in mid-2012 when the RBI exerted its regulatory authority over the sector, resolving concerns that another state might promulgate a similar ordinance. Note that Figure 1 also shows that lending had begun to recover by 2013.

[6]In Section 4.1, we investigate whether SHGs were able to offset the decrease in microcredit.

[7]However, it was not illegal for borrowers to seek out their lenders to make payments.

[8]Note that the crisis hit the lender's loan portfolio with a lag. Given the year-long maturity of most microloans, it took up to twelve months for the loans to fully default. Further, many MFIs waited to write off their non-performing loans.

[9]In conversations with executives from six different lenders, we learned that MFIs went to great lengths to manage the expectations of borrowers. In many cases, individuals were able to observe the delayed loan disbursements of peers. In these cases, the loan officers played a significant role in explaining the delays and answering borrower questions.

2.2. **Framework.** In this section we lay out a simple, illustrative model of microfinance credit supply, aggregate demand, and the labor market. Full details and proofs are in Appendix A. We focus on the aggregate demand channel for several reasons. One is the empirical evidence that microfinance has limited effects on business expansion for the average business. Another is to illustrate that the aggregate demand channel alone is able to generate a number of testable predictions, for which we will find support in the data. We also discuss below an extension in which some households have an opportunity to invest in a business, but lack the wealth to do so, creating another motive to borrow.[10]

The model spans two periods – today and the future. Impatience combined with predicted income growth creates a desire to bring consumption forward in time, and therefore, a demand for consumption credit. The economy comprises two sectors: Tradables (mainly agricultural commodities), and Non-tradables (locally-priced goods and services).

Consumers and workers. Household i obtains utility from consuming goods from both sectors, tradables (T) and non-tradables (NT), via a Cobb-Douglas aggregator:

$$C_i = {C_{T,i}}^{\alpha} {C_{NT,i}}^{1-\alpha} \tag{2.1}$$

Consumers are risk neutral, but impatient, and discount period 2 consumption by $\beta < 1$. Moreover, each household is endowed with deterministic non-labor income in each period, y_t. We assume this income is growing over time: $y_2 > y_1$. This, along with $\beta < 1$, ensures a consumption smoothing motive for borrowing.[11]

All households are endowed with fixed amounts of two types of human capital: high-skilled (e.g., numeracy), and low-skilled (e.g., physical strength).[12] We assume for simplicity that households supply labor inelastically. The aggregate endowment of low-skilled human capital is N^{ℓ}, and that of high-skilled human capital is N^h.

MFI borrowing and the AP Crisis. We model microfinance as a source of a fixed amount of credit. If microfinance is available in a community, the MFI will be willing to extend a loan of size B with gross interest rate R to all individuals who wish to borrow. The loans are disbursed in period 1 and repaid in period 2. The assumption that all loans have the same terms matches the stylized fact in our data that MFIs standardize their loan offers.

[10]See Mian et al. (2017) for a model of credit supply that includes both channels.

[11]Consistent with this, the microfinance literature finds robust increases in durable purchases. Another potential motive for borrowing is to mitigate idiosyncratic shocks. However, the microfinance contract structure is not particularly well-suited for risk-smoothing (Field et al., 2013; Greaney et al., 2016).

[12]We refer to the two labor types as high- and low-skilled for simplicity, but the distinction could also capture horizontal differentiation, such as interpersonal skills vs. mechanical skills.

We model the balance sheet effects of the crisis as reducing the amount of microcredit available in exposed districts, so that households, who, in the absence of the crisis could have borrowed more to bring consumption forward, are now more constrained.

Firms and Equilibrium. District-level equilibrium occurs as follows: In both the tradable and non-tradable labor markets, the wage is set in each period by market clearing, such that labor supply equals labor demand, for both high- and low-skilled labor.

Labor markets are likely to be somewhat, but not completely, segmented.[13] Thus, we allow for imperfect segmentation across the high- and low-skilled labor markets. We assume that the tradable (agricultural) sector employs only low-skilled labor, but the non-tradable (non-agricultural) sector employs both low- and high-skilled labor, which are combined via a constant elasticity of substitution aggregator. Production functions in each sector are:

$$Y^T = A^T \left(L^{T,\ell}\right)^\gamma \tag{2.2}$$

$$Y^{NT} = A^{NT} \left((L^{NT,\ell})^\rho + \theta (L^{NT,h})^\rho\right)^{\frac{\gamma}{\rho}} \tag{2.3}$$

In equilibrium, the wage must be such that the non-tradable sector employs the full endowment of high-skilled labor, and the tradable and non-tradable sectors together employ the endowment of low-skilled labor. The tradable good price is normalized to 1 and the relative price of the non-tradable good is pinned down by supply and demand.

With partially segmented labor markets, it is not possible to obtain closed-form solutions for the high- and low-skilled wages.[14] The following result gives the signs and relative magnitudes of how high- and low-skilled period 1 wages respond to credit supply B.

Proposition: When high- and low-skilled labor are imperfect substitutes in the non-tradable sector, $\frac{dw_1^h}{dB}\frac{B}{w_1^h} > \frac{dw_1^\ell}{dB}\frac{B}{w_1^l} > 0$.
Proof: See Appendix A.

The proposition implies that the equilibrium high-skilled, period 1 wage falls when B falls, due to the aggregate demand effect. Moreover, a reduction in aggregate demand also induces non-tradable firms to substitute toward the now-cheaper high-skilled labor, pushing down the low-skilled wage across both sectors. There is a higher elasticity of high-skill wages to borrowing than of low-skilled wages to borrowing. The proposition also implies

[13] Emerick (2017) shows that increases in agricultural productivity in rural India increase the labor share of the non-agricultural sector.

[14] In Appendix D we consider the case of fully segmented labor markets, which has the advantage of producing closed form solutions.

that, if the marginal product of high-skilled labor is higher than that of low-skilled labor,[15] a reduction in credit access will also cause the high-skilled wage to fall by more in Rupees.

2.3. **Empirical Predictions.** This framework delivers several key predictions about the effects of exposure to the AP crisis. We focus here on predictions for the first period in the model, $t = 1$, to match the timing of our empirical results.[16]

Note that, in our data, we do not observe wages separately for high- and low-skilled workers. We instead observe sectoral wages, w^{NT} and w^{T}, which are weighted averages of the wages for the high- and low-skilled human capital considered above.[17] There will be a decrease in average daily wage in both sectors when credit access falls, due to the reduction in labor demand resulting from the drop in aggregate demand as households are less able to borrow to bring consumption forward. The fall in the wage will be particularly strong for non-agricultural businesses (non-tradables), who are directly hit by the reduction in aggregate demand. The tradable sector will experience a smaller wage decline, resulting from some (low-skilled) workers shifting into the tradable from the non-tradable sector.

The model also predicts declines in total labor earnings for all laborer households at $t = 1$. Consumption falls, both in response to the decline in wages and the reduction in consumption credit.[18]

Investment Channel. The above framework only allows microfinance to affect equilibrium wages through a reduction in consumption and, thus, a reduction in aggregate demand in the non-tradable sector. However, a rich theoretical literature has analyzed the potential for credit directed at poor households to matter via the channel of business creation and expansion (e.g., Banerjee and Newman 1993, Buera et al. 2017, Ahlin and Jiang (2008)). In practice, some businesses supplying rural areas are not owned by urban shareholders, but by rural households who may face credit constraints. While the RCT literature finds

[15]This assumption is consistent with the fact that non-tradable wages are higher in the data in our setting.

[16]That MFIs resumed lending outside of AP after 2012 makes our empirical setting less well-suited to examine longer-term effects. Moreover, the two-period nature of our model is extremely stylized and is not equipped to make predictions about any given year following the shock.

[17]One might worry that our model predicts changes in the allocation of low-skilled labor across sectors. However, our empirical test is able to detect a pure decrease in the high-skilled wage. Note that a decrease in credit supply should lead to relative reallocation of skilled labor to the tradable sector. However, if anything, this composition effect should make it *more* difficult to detect a fall in the non-tradable wage.

[18]An additional implication of our model is that the relative non-tradable good price will fall. However, we are unable to empirically test this prediction as the NSS does not collect information on quantities consumed for either services or durable goods.

little evidence of effects of microfinance on business scale or profitability for the average complier, some borrowers do use microfinance to expand profitable businesses.[19]

Adding an investment channel to our framework would strengthen the magnitude of the predicted effects of reduced access to microfinance on tradable and non-tradable wages, labor earnings and consumption. If (some) businesses are forced to scale back employment or close their businesses due to the direct effects of the credit decrease, this will cause labor demand to decline in both the tradable and non-tradable sectors, magnifying the wage drop. Moreover, in an occupational ladder model (Banerjee and Newman 1993), adding this channel suggests that the effects may be heterogeneous across the wealth distribution. See Section 6.3 for a discussion and calibration of a version of the model that incorporates both the aggregate demand and investment channels.

We now turn to testing these predictions, after detailing the data and empirical strategy.

3. Data and Empirical Strategy

3.1. **Data.** We use data from several sources in our empirical analysis. Appendix E provides additional details.

Hand-Collected MFI Data. The first requirement for our proposed analysis of the AP crisis is a measurement of district-level balance sheet exposure to Andhra Pradesh pre- October 2010. Because no commonly-available datasets contain such information, we partnered with the Microfinance Institutions Network (MFIN), the primary trade organization of for-profit MFI-NBFCs (non-bank, financial corporations).[20] MFIN allowed us to ask each of their 42 members for district level balance sheet snapshots from 2008 to 2012; 25 of MFIN's 42 member organizations agreed to share their data for the study.

Given that we do not have the whole universe of Indian lenders, we explore the sample composition. We are able to cross-check our sample with the aggregate data that many firms choose to report to MIX Market, an online repository of information about global microfinance. We examine characteristics of MFIs in 2009, the year before the AP crisis. In total, 115 Indian MFIs provide 2009 data to MIX. Of the 25 MFIs in our sample, 21 report to MIX; these comprise 36% of all reporting for-profit lenders in India. Our sample represents approximately 18% of the total microfinance market by loan volume.

Table 1 examines the selection of reporting firms into the sample. In panel A, we observe that the reporting firms are smaller: they have fewer borrowers, and fewer borrowers per

[19] Banerjee et al. (2018) show that households who selected into entrepreneurship before getting access to microfinance experience sustained positive treatment effects of microfinance, including effects on hiring.
[20] Non-profit lenders represent a very small slice of total loan volume in India.

staff member. This is not surprising given that several of the largest lenders in India, who have achieved greater economies of scale, chose not to participate in our study.[21] However, the loan-level details look much more similar between reporting and non-reporting institutions; the average loan sizes are very similar (around $180) and are not statistically different, and the default rates (write-offs and 30-day portfolio at risk) are quite low in both samples. (Though the 30-day portfolio at risk is significantly lower in the reporting sample.)

In Panel B, we restrict the sample to reporting firms, and examine whether the characteristics of firms exposed to the crisis (i.e., firms with loans in AP on the eve of the crisis; see below) have different characteristics than those which are not exposed. Whereas differences between reporting firms and non-reporting firms in Panel A affect the external validity of our results, any differences between exposed and unexposed lenders could pose a threat to internal validity. Reassuringly, exposed and unexposed firms look quite similar in terms of loan size, number of borrowers, borrowers per staff member, write-off ratio and portfolio at risk. We examine an additional outcome within this sample: the MFI's age, as measured by the first year it reports positive loan volume in our data. (We cannot examine this outcome in Panel A since it is only available for reporting firms.) Exposed and unexposed firms are also similar in this dimension.

Based on the final MFI data set, Table 2 shows that the total 2012 gross loan portfolio in districts where lenders were not exposed to the crisis is 1694 lakhs (roughly INR 170 million). Scaled by the number of rural households, this translates to INR 411 per household (averaging across borrowers and non-borrowers) in the average non-exposed district.

Measuring exposure to the AP Crisis. In order to calculate the level of exposure of each district to the AP crisis, we proceed as follows. 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 pre-crisis, where the weights are that lender's total loan portfolio in the state, $GLP_{dl,Oct2010}$:

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

[21] This is likely because the larger lenders had more outside equity holders and wanted to maintain data privacy and also had the most to fear from negative press coverage.

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 $ExpAP_d^{Total} = \frac{.4+0}{2} = 0.20$.

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. Our primary outcome measures come from the Indian National Sample Survey (NSS). We use household data from waves 64, 66, and 68 of the NSS, which correspond to years 2007-2008, 2009-2010, and 2011-2012, respectively.[22] We focus on the schedules containing household composition, consumption and employment. Key variables are summarized in Table 2. (We summarize the 2012 values in low exposure districts for ease of comparison to the reduced form results, below.) Household total weekly earnings average INR 855. The agricultural casual daily wage averages INR 140, and the non-agricultural casual daily wage averages INR 195.[23] Almost a third (29%) of households report engaging in non-agricultural self-employment.

The NSS waves 64, 66, and 68 do not contain detailed data on household indebtedness. However, as discussed below, we can use the NSS 70th wave contains a "Debt and Investment" survey, collected in 2012 and 2013. Its questions are asked to allow a researcher to reconstruct a household's total credit outstanding on June 30, 2012. The average household in a low-exposure district had INR 347 of MFI loans (narrowly defined). Using a broader definition that likely captures some microloans that the narrower one does not, average holdings of uncollateralized loans from formal sources other than banks are INR 2103. (Note that these measures average across borrowers and non-borrowers.)

Auxiliary Data Sources. Finally, throughout our analysis we introduce several outcomes and covariates from several complementary data sources. These cover variables such as rainfall, inter-district travel times, political party affiliation, and crop yields. We describe

[22]As discussed below in Section 4.1, we also use the credit module of the 70th wave of the NSS to provide an alternate measure of the credit response to the crisis.

[23]We exclude work performed as part of public works programs such as NREGA from the wage calculations since NREGA wages are set administratively, not via market clearing.

the sources of those variables when we introduce the empirical specifications and results, below; more detail is available in Appendix E.

3.2. **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

$$y_{idt} = \alpha + \delta_t + \delta_d + \beta \times Exposure_d \times Post_t + X'_{idt}\gamma + \varepsilon_{idt} \tag{3.3}$$

where y_{idt} 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 (discussed below); 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; and dummies for quintiles of 2008 and 2010 gross loan portfolio, interacted with round. Note that we do not observe a household panel, but rather repeated cross-sections, which form a district-level panel. Standard errors are clustered at the district level.

We use two measures of exposure to the AP crisis, both based on $ExpAP_d$ (defined in equation 3.2). First is the log of the exposure ratio (defined by equation 3.2) plus one. Second is a dummy for the presence of a lender that had any exposure to the AP crisis. The proportion of districts with a positive exposure ratio is 37.3%; the proportion of household-level observations located in these districts is very similar, at 36.9%.

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 and 2010 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% APR, weekly or monthly meetings, meetings held in groups, similar loan sizes, and similar dynamic incentives. Given this standardization, the identifying assumption appears *a priori* reasonable. Moreover, we present robustness and placebo checks below that lend direct support to this assumption.

As a way to shed light on our identification strategy, Table C.1 compares baseline characteristics of exposed vs. unexposed districts. (Recall that, since we use a difference-in-difference strategy, *level* differences across exposed vs. unexposed districts do not in and of themselves pose a concern, but *trend* differences would be a concern.) Columns 1 and

2, respectively, examine whether exposed districts are closer to AP or more likely to border AP. Unsurprisingly, they are: MFIs that operated in AP also operated in nearby districts. In Section 4.3, we will show a variety to checks to rule out that differential trends by distance are driving our results. Columns 3 through 7 shows that exposed and unexposed districts do not differ in their baseline levels of agricultural or non-agricultural daily wages, weekly labor earnings, or non-durable or durable consumption.

4. Results

4.1. **First Stage.** Table 3 presents the first stage, estimated by equation 3.3 with a measure of credit outstanding in 2012 on the left-hand side. We show results for the district-level total gross loan portfolio (column 1), the gross loan portfolio per rural household (column 2) and the log of the district-level total gross loan portfolio (column 3). Row 1 of column 1 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 roughly INR 33,680,000 (337 lakhs) less credit outstanding in the district in 2012 (significant at 1%). The second row of column 1 indicates that those districts with an AP-exposed lender have INR 110,550,000 (1106 lakhs) less credit outstanding in 2012 (also significant at 1%), corresponding to a drop of almost two thirds compared to similar districts whose lenders were not exposed to the crisis. Row 1 of column 2 shows that a 1 log point increase in exposure to the crisis is associated with INR 97 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 308 less credit outstanding per rural household in 2012 (significant at 1%), compared to other similar districts whose lenders were not exposed to the crisis. Column 3 shows an analogous specification in logs; again, the effects are large and highly significant.

These effects imply 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, due to uncertainty in the aftermath of the AP Crisis. 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 have been smaller in size.

Did banks fill the gap? To understand the effects of the crisis on total access to credit, it is important to understand whether other sources, such as commercial bank lending, filled some or all of the gap left by the reduction in access to microcredit. To examine this, we use information from the Reserve Bank of India (RBI) "District-Wise Classification of Outstanding Credit of Scheduled Commercial Banks." These data allow us to examine whether more-exposed districts saw a differential change in commercial bank lending after the AP crisis. We focus on the category of agricultural loan accounts as this category includes most forms of lending to households, including "artisans," i.e. non-agricultural microenterprises. Results are shown for the log of number of accounts and the log of the total amount outstanding.

Table 4 reports the results. There is no effect of exposure to the crisis on the number of agricultural loan accounts, nor the amount outstanding. When we distinguish direct accounts (largely made to individuals) from indirect counts (largely made to other entities, including MFIs, for on-lending) we again see no effect for direct accounts or amounts, and a fall in indirect accounts, likely reflecting reduced lending to MFIs in response to regulatory uncertainty surrounding the MFI sector. In sum, there is no evidence that commercial bank lending filled the gap.[24]

Alternative Credit Data. Our hand-collected credit data is not without limitations. In particular, it represents approximately 18% of the Indian market by loan volume: a large share of the market was comprised of MFIs who declined to share their data with us. If the responding firms are a random sample of all firms, this will only add noise to our measure of exposure, attenuating our measures of the effect of exposure to the crisis toward zero. However, one may worry that the subset of firms who responded is somehow non-random.

As a check, we draw on an alternative source of data, based on survey reports of household indebtedness, rather than MFI reports of their loan portfolios. The source we use is the NSS 70th round "Debt and Investment" survey, collected in 2012 and 2013. Its questions are asked in such a way as to allow researchers to reconstruct a household's total credit outstanding on June 30, 2012.

This is an entirely different data source than that used in Table 3. It is reported by households, not MFIs, and covers a nationally representative sample of Indian households. Thus, to the extent that we observe similar patterns in this data and in the data we collected with

[24]Neither the NSS nor RBI data allows us to examine the effect of the crisis on informal lending; however, the results in Table 5, discussed below, show that the effect on total lending is negative and large, albeit imprecisely estimated, so there is no evidence that informal lending filled the gap. This is intuitive since the credit shock was aggregate to districts, so the social networks of affected households were themselves affected.

MFIN, it confirms that the patterns of exposure we observe are not artefacts of MFI reporting decisions. However, the "Debt and Investment" data is not without its own drawbacks: most significantly, we only have this data for 2012, so we are unable to use our preferred differences-in-differences empirical strategy. We must instead rely on cross-sectional comparisons.[25] This should be viewed as complementary to our analysis above.

Another challenge with the "Debt and Investment" data relates to the classification of MFI loans. The credit survey asks households to enumerate each loan outstanding and aims to capture detailed data on the type of lender. There are 17 different lender types. The NSS handbook (NSSO, 2014) states that for-profit microfinance should be grouped as SHG-NBFC (self-help group - non-banking financial company); however, non-profit microfinance and bank-linked SHGs are grouped under SHG-BL (self-help group - bank-linked). Further, there are three other categories that describe non-bank formal loans from financial institutions, which can be collateralized or uncollateralized. In sum, there is uncertainty about how respondents and surveyors would choose to treat a MFI loan.[26]

To address this ambiguity, we construct two measures intended to capture MFI borrowing. First, we present a measure based on the narrow NSS definition, those classified as SHG-NBFC. Because microloans are almost always uncollateralized, we also present a measure that captures all uncollateralized non-bank credit from formal institutions. We include in this definition all non-collateralized SHG loans, some of which may be linked to a bank. As well as addressing mis-classification, our broader definition allows us to capture impacts on microcredit that are *net* of any offsetting SHG supply response.

Table 5 presents OLS regressions of household credit on our pre-crisis AP exposure variables. Because we cannot use our differences-in-differences strategy, we instead control for numerous pre-crisis, district-level covariates.[27] In columns 1 and 5 we consider impacts on the narrow definition of microfinance, SHG-NBFC.[28] Remarkably, we find impact estimates that are strikingly close to those in Table 3. Districts that are exposed to AP

[25]The NSS collected a small household indebtedness survey as a part of Round 66. However, the module was given only to landless agricultural households, and cannot adequately capture district-level microloan access.
[26]Our experience in the field suggests that these differences in legal structure of loans—e.g., whether an MFI lender is for-profit or non-profit—are not always salient to respondents.
[27]MFI balance sheet controls include levels and quintiles of GLP measured in 2008 and 2010. RBI controls include amount of credit outstanding and number of accounts for agricultural loans, direct loans, and indirect loans. NSS 66 controls include average monthly household expenditures, annual durables expenditures, weekly earnings from and days worked in self-employment and non-self employment, daily wage, and percent of weekly earnings from self-employment.
[28]Columns 1 to 4 use data winsorized at the 99th percentile of non-zero observations, while columns 5 to 8 use logs. Non-winsorized levels data give very similar results.

pre-crisis experience a decrease in per household microcredit outstanding of INR 310 (col 1, row 2); the corresponding figure in Table 3 was INR 308 (col 2, row 2).

Next, in columns 2 and 6, we examine the impacts of high exposure on the broader measure of non-collateralized formal credit. Here, we find that pre-crisis exposure reduces outstanding credit in 2012 by Rs. 1,353. As with the narrower measure, this represents a large fall compared to the control mean of INR 2395. This suggests that SHGs did not in fact fill the void left by reduced access to microcredit loans. It also suggests that it is indeed likely that some for-profit microfinance loans were mis-classified in the NSS surveys as SHG-BL rather than SHG-NBFC loans.

In columns 3, 4, 7 and 8, we present bank credit and total credit as outcomes. While the coefficients are estimated imprecisely, we again find, in column 3, no evidence that bank credit increased and thereby offset the fall in microcredit. (A finding which is consistent with Table 4, which uses a different source of data, namely RBI data on banks' balance sheets.) Finally, we observe a negative, but imprecisely measured, coefficient on total credit outstanding, suggesting that, as expected given the aggregate nature of the shock, other sources such as informal lending could not compensate for the loss of microcredit.

Importantly, the fact that this was a microfinance shock matters for aggregate outcomes, over and above its impact on total district-level credit. The propagation of a credit supply shock will depend critically on the uses to which the credit would have been put, and microcredit serves specific needs, namely accelerating lumpy consumption and financing business investment, that are not well met by other sources.

The results from the "Debt and Investment" survey data are reassuring in that they find very similar patterns as those seen in the MFIN data. Thus, the first-stage effects of exposure to the crisis are not an artefact of differential reporting to MFIN or of geographical clustering across MFIs.

Khwaja and Mian (2008) exercise. As an additional check on the first stage, we conduct an exercise exploiting within-district variation, modeled after Khwaja and Mian (2008). We focus on districts with both exposed and unexposed MFIs, and show that the fall in credit is driven by exposed MFIs. This also serves as an additional test of the identifying assumption that exposed and unexposed districts would have had similar counterfactual outcomes in the absence of the crisis: if exposed districts differed in some unobservable way, or suffered a demand shock due to being exposed to the AP crisis via other channels, we would expect unexposed lenders' portfolios to fall in those districts as well.

We examine this relationship via the following regression:

$$\Delta y_{ld12-10} = \alpha + \delta_d + \beta \times Exposure_l \times Post_t + X_{ld}'\gamma + \varepsilon_{idt} \tag{4.1}$$

where $\Delta y_{ld12-10}$ is the change in per rural household GLP lent by MFI l to district d between September 2010 and March 2012. The δ_d are district fixed effects, and $Exposure_l$ is the exposure of lender l to the AP crisis, measured by either the share of its portfolio in Andhra Pradesh as of September 2010, or a dummy equal to one if the MFI operated in Andhra Pradesh in September 2010. In some specifications, X_{ld}' is a control for the log of the MFI's size September 2010, measured by its total GLP *outside* AP (so that size is not proxying for exposure).

Appendix table C.2 shows the results. Column 1 shows that moving from 0 to 100% exposure of the MFI, captured by the share of its portfolio in Andhra Pradesh as of September 2010, is associated with a INR 281 fall in GLP per rural household over 2010 to 2012. The constant reflects any excess change GLP for an unexposed MFI in a district where some MFIs were exposed; it is very small and not significantly different from zero. Column 2 uses an exposure dummy equal to one if the MFI operated in Andhra Pradesh on the eve of the crisis. Exposed MFIs saw an average decline in GLP per rural household of INR 153; again, the constant shows that unexposed MFIs saw no excess change. Columns 3 and 4 show that controlling for MFI size does not change the results. (Note that the constant no longer has the same interpretation as it reflects the average positive growth rate of an MFI that was very small in 2010.)

4.2. **Reduced Form Results.**

Labor Outcomes. We begin by examining how the reduction in distract-level credit access observed in Table 3 affects the local labor market. Table 6 reports treatment effects on casual daily wages, household total labor supply, total labor earnings, involuntary unemployment and entrepreneurship. We begin by noting that the reduction in credit did have economically and statistically significant effects on the casual daily wage. Exposed districts experienced a fall in the daily wage of INR 8.9, significant at the 1% level, which is displayed in row 2 of column 1. This represents roughly a 6% reduction from the unexposed district mean of INR 153. We next ask if this decrease in wage affected total household labor supply and total labor earnings. Column 2 shows that there are no detectable effects on total days worked in self-employment and wage employment combined. However, column 3 shows that household days worked in casual daily wage labor did decrease by almost half a day on a base of 3.5 person days. Given that wages and paid days worked both fell, this leads to an overall decline in household weekly labor market earnings of

INR 75 in exposed districts relative to unexposed districts after the AP crisis, significant at the 5% level (column 4). 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). Thus we do not find evidence the the crisis resulted in rationing in the market for casual labor, suggesting that adjustments to the crisis were equilibrated via the wage. Column 6 examines effects on the likelihood that a household has a business which employs others. Pooling across agricultural and non-agricultural employers, the point estimate on the extensive margin of being an employer is negative, but not significant at conventional levels ($p = .199$ for the binary indicator). (Of course, the businesses we capture in this measure are likely only a small fraction of total labor demand, as many businesses will not be owned by rural households; the data also do not allow us to examine the intensive margin of labor demand.)

Our strong wage and labor earnings results echo the predictions of Buera et al. (2017) and highlight the importance of incorporating general equilibrium effects into the analysis of the effects of credit access.

Consumption. Table 7 reports the effects of reduced credit access on total expenditure and its components: nondurables and durables, measured on a monthly basis. Column 1, row 1 shows that a 1 log point increase in exposure to the crisis is associated with a reduction of INR 84 in per household monthly total expenditures in 2012 (significant at 1%). Column 1, row 2 indicates that those districts with an AP-exposed lender have INR 319 lower per household monthly total expenditure (significant at 1%), compared to other similar districts whose lenders were not exposed to the crisis. Column 2 examines per household monthly nondurable expenditures. Row 1 shows that a 1 log point increase in exposure to the crisis is associated with a reduction of INR 69 (significant at 1%), and row 2 shows that those districts with an AP-exposed lender have INR 247 lower per household monthly nondurable expenditure (significant at 5%). Column 3 repeats the analysis for per household monthly durable expenditures. Row 1 shows that a 1 log point increase in exposure to the crisis is associated with a reduction of INR 16 (significant at 5%), and row 2 shows that those districts with an exposed lender have INR 80 lower per household monthly durable expenditure (significant at 1%). In sum, reduced credit access resulted in reduced total consumption, stemming from falls in both nondurables and durables. In the context of our model, this consumption fall arises both from reduced labor earnings and tighter constraints on the ability to borrow against future income.

In column 4, we also examine whether exposure to the crisis has any effect on whether households are below the poverty line.[29] We find no significant effect on this outcome, suggesting that the reduction in consumption is concentrated higher up in the distribution. We should also note that poverty headcounts in India have fallen substantially since the banking reform studied by Burgess and Pande (2005). During the timeframe of their study, 48% of rural households were classified as below the poverty line. In our data from 2010, the poverty count is only half as large, at 25%.

4.3. **Robustness checks.** We next provide evidence to rule out several key threats to identification.

Placebo regression. To provide support for the identifying assumption that exposed and unexposed districts had similar counterfactual outcomes in the absence of the balance sheet effects of the crisis, Table 8 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 spurious "effects" in round 66. Reassuringly, for none of the main outcomes is the placebo treatment significant at standard levels. Moreover, the point estimates are all much smaller in magnitude than those of the main regressions and can be statistically distinguished from the main treatment effects. This suggests that pre-existing differential trends are not driving our results.

Geographical Distance to AP. Recall from Table C.1 that exposure to the AP crisis is correlated with distance to Andhra Pradesh. Thus, if places closer to AP systematically had different (worse) economic trends post 2010, then our identification strategy would be compromised. Moreover, it is also conceivable that the direct fallout of the AP crisis could have "spilled over" onto nearby districts through channels other than the MFI balance sheet effect we measure (such as economic uncertainty, decreased trade, etc.). We perform several tests to check that our results are not simply capturing such an effect.

In Table 9, we conduct three robustness exercises using distance measures to Andhra Pradesh. First, in Panel A, we rerun our main specification for key consumption and labor supply outcomes, but drop districts with a geographical border with Andhra Pradesh. Second, in Panel B, we instead include the geographical ("as the crow flies") distance of each district from AP, interacted with survey round. While the district fixed effects control for time invariant correlates with distance, this specification allows for differential trends by distance. Raw geographical distance may not adequately capture some types of relationships between districts, such as trade costs, due to variation in the quality of infrastructure.

[29]See Appendix E for details on the construction of the below poverty line variable.

As a third distance measure, we add the travel times between a given district and Hyderabad, as measured in Allen and Atkin (2016). Panel C of Table 9 displays the results. Across these iterations, the results look very similar to those in our main specification.

Finally, we also conduct Altonji-type tests in Appendix Table C.3, systematically dropping each state from the analysis. We find that no single state is driving the results, even those bordering AP.

Randomization Inference. As a further check of the possibility that our results are spurious, Table C.5 performs randomization inference (RI) by performing 500 permutations, in each of which a different draw of 132 districts was selected to be assigned the status of "exposed." As noted by Blattman et al. (2017), randomization inference estimates p-values based on the empirical distribution of all treatment effects that could arise under a given research design and dataset. If our results arise from a chance correlation between exposure to the crisis and negative outcomes, then many permutations that randomly assign "exposure" will generate similar patterns. On the other hand, if the observed results are far in the tails of the distribution generated by the RI procedure, this suggests that they are not arising by chance. Reassuringly, for all five of the key consumption and labor market outcomes examined, the p-values are 0.024 or smaller, meaning that the actual coefficients are unlikely to be due to spurious correlation.

Placebo Shocks. Another, related, concern is that the states that were exposed to AP might also have been exposed, via trade or other linkages, to negative shocks originating elsewhere and thus, we might attribute effects to exposure to the AP crisis that were instead due to some other factor. To address this issue, we permute the identity of the state in which the placebo "crisis" takes place. There are 23 states other than AP in our data, but only 22 unique placebo shocks, because a single MFI in our sample operated in both Sikkim and Tripura before the AP crisis, and therefore these states are counted as a single permutation. Thus, we construct 22 placebo measures of exposure (via MFI balance sheets): exposure to Assam, exposure to Bihar, etc. Table C.5 reports the results. For all five of the key consumption and labor market outcomes examined, the true measure of exposure (to AP) generates outcomes that are the lowest or second-lowest in the distribution.

Political Affinity with AP. While distance and trading relationships represent the most serious threats to identification, we also investigate whether the shock to AP may have spread to other places with similar political ideologies, for instance because of greater concern about a default episode occurring in politically-similar states. Appendix Table C.6 tests for the possibility that states with greater exposure to the crisis may have been more "aligned" with Andhra Pradesh through having similar political parties in power. We add as controls indicator variables for the political party of the state's chief minister in 2010, at the time of the crisis, interacted with round. This allows all states with a certain party in power to be on a differential trend. Again, our results remain robust.

Rainfall and Other Economic Conditions. Finally, we also check that our results are not coming from time-varying differences in other economic characteristics. First, we check that the differences between high and low exposure districts after 2010 are not coming from (random but unlucky) differences in rainfall. We construct an index for abnormal rainfall using the methodology of Jayachandran (2006). In Appendix Table C.7, we run our main specification, including time varying rainfall realizations, and find no major differences with our main results.

Finally, in Appendix Table C.8 we allow for differential trends by baseline economic conditions. We allow districts with different levels of baseline consumption, poverty, casual wage, or self-employment to evolve differently. Our results remain robust, showing that differential trends by initial level of development cannot explain our findings.

4.4. **Scaling the Reduced Form Treatment Effects.** Due to the concerns with both our pre-crisis measure of exposure and with our ex post measure of the drop in credit, one needs to use caution when thinking about scaling the reduced form, intent-to-treat (ITT) effects into treatment on the treated (TOT) effects.

One issue with our MFI balance sheet data is a slight timing mis-match. The post-crisis data reflects balance sheets as of March 2011 and March 2012. Credit likely bottomed out around the end of 2011, by which time all of the loans outstanding at the time of the crisis would have rolled over; this is consistent with Figure 1. Thus, our data likely misses the bottoming-out of the market and hence the full magnitude of the credit contraction. Our NSS "Debt and Investment" data measures credit at an even later point of time, June 2012. The outcomes data, on the other hand, come from the NSS round 68 and were measured for most households at the end of 2011, likely reflecting the full brunt of the credit contraction. Thus, scaling the reduced form impacts by the measured first stage may imply TOT effects that are too large, since the denominator may be too small.

Another issue, discussed above, is that the first stage based on the balance sheet data, as used in Table 3, only measures lending from the subsample of MFIs who provided their data. This will attenuate the first stage relationship. A similar issue is present in the narrow definition of MFI borrowing from the "Debt and Investment" data, to the extent that some MFI lending is misclassified.

In sum, any scaling of reduced form effects by first stage estimates should be done with caution. If a first stage number is desired for back-of-the-envelope purposes, the broader measure of microfinance in Table 5, column 2 (Rs. -1353) is arguably most appropriate.

5. Mechanisms and Incidence

Exposure to the AP crisis reduced access to microfinance loans. This credit contraction, in turn, caused significant drops in daily casual wages, labor earnings, and durable and nondurable consumption. We now examine several intermediating variables that shed light on the mechanisms that give rise to these impacts.

5.1. **Impacts on Tradable and Non-tradable Sectors.** We next consider the effect of the AP crisis-induced credit crunch on wages, separately for agriculture (tradable) and non-agriculture (non-tradable). Table 10 presents the results.

Column 1 shows the pooled wage result across both genders and sectors, which is identical to the estimate in Table 6. Columns 2 and 3 disaggregate the wage by sector. We find negative effects on the wage in both the tradable and non-trabable sectors, but the wage effects are much stronger for non-agricultural work: the wage drop associated with the binary measure of exposure is INR 5.15 (significant at 10%) for the agricultural sector, and INR 15.4 (significant at 1%) for the non-agricultural sector. While the average level of agricultural wages is lower, the effect on the non-agricultural wage is also larger in percentage terms: it falls by 8.4% of the control mean, compared with 4% for the agricultural wage.

Columns 4 and 5 further disaggregate the results, showing effects on men's wages in the agricultural (tradable) and the non-agricultural (non-tradable) sector, respectively. As in the results pooling genders, the wage effects are much stronger for non-agricultural work. The fall in the wage associated with the binary measure of exposure is INR 5.14 $(p = .1026)$ for the agricultural sector, and INR 16.65 $(p = .0014)$ for the non-agricultural sector.

Columns 6 and 7 show the wage effect, by sector, for women's wages. The effects are not significantly different from zero, partly reflecting the smaller number of observations for women. The treatment effect on women's agricultural wages is very similar in magnitude to that received by men. For non-agricultural wages, the effect on women's wages is notably smaller in magnitude than that for men, likely reflecting women working in different non-agricultural jobs, such as domestic work and services, where the aggregate demand channel is less strong since these services cannot be bought on credit.

Finally, columns 8 and 9 examine effects on the likelihood that a household employs wage workers in an agricultural or non-agricultural business, respectively. There is no effect on the extensive margin of being an agricultural employer. However, column 9 shows that there is a negative and significant effect on the likelihood that a household has a non-agricultural business which employs others. Thus, one of the channels whereby exposure to the crisis reduced wages is a reduction in the number of potential employers.

This pattern of results is consistent with the predicted impacts of a negative shock to labor demand through the business investment channel, affecting both tradables and non-tradables, combined with a reduction in aggregate demand putting additional downward pressure on employment and wages in the non-tradable sector. The asymmetric treatment effects on both wages and hiring suggest that a reduction in aggregate demand is an important factor driving the fall labor demand and hence, wages.

Agricultural wages and nominal rigidity. If agricultural wages display downward rigidity (Kaur, 2015), a crucial determinant of wages may be whether they adjust upward when demand is at its peak. To address this possibility, we examine whether the effects of (lack of) access to microcredit differ in times of peak agricultural labor demand.

Appendix Table C.9 presents the effects of exposure to the crisis for the subsample of households surveyed in peak demand periods and those surveyed in non-peak periods. Column 1 shows that the effect on the agricultural wage is almost three times larger during peak periods than non-peak periods. Column 2 shows that the effect on the non-agricultural wage shows no similar pattern—in fact the effect in non-peak periods is slightly larger. This is as expected since we have focused on peak periods of *agricultural* labor demand and reaffirms that agricultural and non-agricultural labor markets are somewhat segmented. The total effect on weekly labor earnings (column 4) is markedly stronger in peak periods. As a result, the peak effects on total consumption are also larger.

5.2. **Impacts on Agricultural Output.** We next look for district-level impacts of the credit supply shock on output in the tradable (agricultural) sector. While tradables experienced no shock to product demand, the effect on total output is nevertheless unsigned. On one hand, agricultural firms will benefit from lower wage bills, but on the other hand, some of these farms may be forced to scale back as liquidity constraints bind more tightly.

We examine district-level crop yields to shed light on this question. Given the importance of agriculture to rural Indian economies, effects of microfinance on crop yields are also of independent interest. We use data from the Ministry of Agriculture, Directorate of Economics and Statistics, which collects information on crop production. Following Jayachandran (2006), we consider a weighted average of log yield (production in tonnes per area cropped, in hectares) for the five major crops: rice, wheat, sugar, jowar (sorghum), and groundnuts.[30] We also consider each crop separately. The results appear in Table 11. We find a fairly precise zero effect for the index and for all crops but sugarcane, where the effect is less precise but still insignificant. This suggests that, in aggregate, for the agricultural (tradable) sector, the benefit from the wage reduction cancels out the cost from tighter liquidity constraints.

5.3. **Distributional Effects.** Another question of interest is how the effects of the credit contraction are felt across the wealth distribution. 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.

Table 12, reports effects on key outcomes separately for each quintile of the within-district land distribution. Column 1 shows the first stage: the second quintile of the land distribution experiences the largest percentage reduction in credit access. Column 2 shows the effects on household weekly labor earnings associated with a high exposure to the crisis. Given that the poorest households are most likely to supply casual labor, households in quintile 1 (landless and near-landless) experience the largest fall in earnings (INR 21.5, significant at 5%). For higher land households, the effects are insignificant, with a pattern of point estimates that are generally shrinking in magnitude as land holdings increase.

Column 3 shows effects on monthly consumption. The largest magnitude effects are seen in the fourth quintile of the distribution, where monthly consumption falls by INR 139 (significant at 1%). Households in the poorest quintile see a fall of INR 49 ($p = .113$); those in the third quintile see a fall of INR 80 (significant at 10%). The effect for the wealthiest is insignificant. Thus the effects are largest for intermediate-wealth households. Finally, column 4 examines monthly durable consumption, and finds a similar pattern: large and highly significant effects for the fourth quintile of the distribution, where monthly durable consumption falls by INR 30 (significant at 1%). The effects at both lower and higher quintiles are smaller in magnitude, suggesting that intermediate wealth households are particularly forced to scale back purchases of household/business durables.

This pattern suggests that medium-sized landholders, whose ability to accelerate consumption or invest in a business may be most sensitive to microfinance access, respond to reduced credit supply by reducing consumption and investment in household businesses (proxied by durable spending). The landless and near-landless experience falls in earnings, due to the reduced wage arising from reduced labor demand from local businesses.

[30] As in Jayachandran (2006), the weights are the district-average revenue share of the crop.

6. Discussion: Putting the Treatment Effects in Context

The fall in consumption resulting from exposure to the AP crisis results from three distinct channels: the reduction in credit that, for some, would have been used for consumption; the change in business profits for those who would have borrowed for entrepreneurship; and the reduction in labor earnings from the fall in the wage stemming from the aggregate demand and business financing channels. Unfortunately, we cannot observe business profits in our data, and moreover, the repeated cross section nature of the data does not allow us to identify ex ante entrepreneurs. So, we cannot directly decompose these three channels. Instead we put our results in context in three ways: a back-of-the envelope exercise to examine if implied effects on business profits are plausible; a comparison of our results with other GE results; and a calibration of our model. Each exercise requires its own assumptions, but they all give similar conclusions, namely, that the magnitudes of the effects we find are consistent with related findings in the literature.

6.1. **What are we implicitly assuming about profits?** Here, we present a back-of-the envelope exercise to try to understand the extent to which changes in profits might be driving the consumption response. Recall that the microfinance RCT literature typically finds modest, often statistically insignificant, partial equilibrium treatment effects (Banerjee et al. 2015b). Thus, one goal of the exercise is to check whether our implied effects on profits seem plausible in light of this previous evidence.

Of course any such exercise requires a set of assumptions. We begin with the simple observation that, in the absence of consumption credit, $HH\ Consumption = MPC \times Income = MPC \times (LaborEarnings + BizProfits)$. For this exercise, we make the conservative assumption that households do not consume directly from microcredit (i.e., we shut down the aggregate demand channel). Note that we observe total consumption and labor earnings in our data. Thus if we knew the marginal propensity to consume (MPC), we could back out business profits. Our strategy is to calculate this implied profits effect for a range of possible MPCs.

Table 13 steps through this exercise. Panel A contains the treatment effects estimated in Section 4.2 used for the calculation along with other key assumptions. It is likely that households include expenses for their businesses in their NSS survey responses regarding durables spending. Thus, we first approximate the portion of total consumption that is *not* used to purchase a business durable. We use the fraction of durables purchased which are for business use from the RCT results of Banerjee et al. (2015a) in this calculation, along with the total treatment effect we find on durables consumption. Panel B shows the implied IV treatment effect on profits, assuming different MPCs. The estimates range from approximately Rs. 0 in profits per Rs. 1 in credit when MPC = 0.9 to Rs. 0.265 in profits per Rs. 1 in credit for MPC = 0.4.

We do not have a credible way to estimate the MPC for our setting, so we look to the development literature for guidance. Gertler et al. (2012) and Ravallion and Chen (2005) calculate MPCs of 61% for a permanent shock and 50% for a semi-permanent shock in Mexico and China, respectively. Again to be conservative, we assume MPC = 0.4 and compare the Rs. 0.265 treatment effect to the RCT results. Our implied effect is in the range of the RCT findings. The estimates in Crépon et al. (2015) imply an IV profits effect of 0.210 Moroccan dirham per 1 dirham of credit (reduced form significant at the 10% level), and those of Banerjee et al. (2015a) imply an effect of Rs. 0.275 per Rs. 1 of credit (insignificant) in their study in Hyderabad, India.

We view this exercise as a sanity check of sorts and show that under generally conservative assumptions, our results are consistent with the RCT literature.

6.2. **GE Effects in the Development Literature.** Another way of benchmarking our results is to compare them to related empirical findings. The development literature has recently made considerable progress in measuring GE effects of public and private interventions in the labor and financial markets. Table 14 presents the results of five studies in South and Southeast Asia that measure the impacts of large programs or other types of large shocks on wages. Two of the papers, Burgess and Pande (2005) and Kaboski and Townsend (2012) measure the change in the wage in response to an increase in access to finance. Burgess and Pande (2005) study the coordinated expansion of rural bank branches in India and find a 7% agricultural wage increase from one additional branch per 100,000 people. Kaboski and Townsend (2012) find a comparable agricultural wage response to a 43% increase in short term credit stemming from an increase in rural credit supply provided by the Thai government. Consistent with our results, Kaboski and Townsend (2012) find a much larger wage impact for jobs in construction, a non-tradable sector. They also find large short-run consumption effects which are consistent with an aggregate demand story.

We believe that the pathway from credit to wages is likely mediated through labor demand in our setting. Businesses hit with an aggregate demand shock hire less, and constrained entrepreneurs that close or shrink their businesses when credit dries up also reduce labor demand. The table highlights two studies of the impacts of a change in labor demand on the wage. Both study NREGA, India's nationwide work-fare program, as the source of the shock. Imbert and Papp (2015) use the staggered roll-out of the program to show that agricultural wages increase by 4.7% as a result of a 1.3% demand shift from NREGA. Muralidharan et al. (2017) improve the functioning of NREGA through digitization of worker payments and cause a 6% increase in demand from NREGA. This shift in labor demand is accompanied by a 6.1% increase in the total wage. In Bangladesh, Akram et al. (2017) studies the change in wage resulting from a change in labor supply due to out-migration. The authors conduct a field experiment that encourages a 30% increase in migration from rural villages to urban centers and find that wages rise by 4.5-6.6%. These estimates point to reasonably high elasticities of wages to labor demand and supply. We take this as suggestive evidence that in our setting, the credit shock does not need to cause an implausibly large drop in labor demand or supply to lead to wage effects of the estimated magnitude.

6.3. **Model Calibration.** A drawback of the approach above is that it is difficult to compare directly our wage results to those in Table 14 due to the varying nature of the interventions they evaluate. As an alternative, we extend and calibrate the simple model presented in Section 2.2. Of course, this requires us to make a number of additional assumptions and to shut down plausible channels for which we do not have sufficient information. As with the back-of-envelope profits exercise, we view this calibration largely as a sanity check, showing that plausible parameter values can deliver wage effects in the range of our estimated magnitudes.

Additional Model Assumptions. We adjust the model in several ways to more closely match our empirical setting. First, rather than businesses being owned by urban shareholders, we allow some rural households to own and operate businesses, each with production functions of the type in Equations 2.2 and 2.3. Second, and related, we allow the possibility that some microcredit is used to invest in starting and operating a profitable business, rather than assuming that borrowing is only for accelerating consumption.

Calibrated Parameters of the model. Appendix F provides details on the parameter values. We calibrate the parameters describing households' skilled and unskilled labor endowments and tradable and nontradable consumption shares using NSS data. Production function parameters (TFP and returns to scale) are chosen to match those for India in Buera et al. (2017). Finally, the credit market parameters are chosen to match the real interest rate charged by Indian microlenders, the size of a loan, as a share of annual labor earnings and the share of households who borrow from microfinance. We examine how our results change as we vary the share of microcredit borrowers who borrow for business investment.

Calibration Results. We present the calibrated treatment effects on wages in the tradable and non-tradable sectors in Figure 2. We calculate these effect sizes for a range of assumptions on the extent to which microfinance is used to invest in profitable businesses.

Recall that the estimated effects, pooling men and women, are a 4.01% fall in the agricultural (tradable) wage and a 8.36% drop in the non-agricultural (non-tradable) wage (see table 10, columns 2 and 3). When approximately one third of microfinance is used for business investment, and the remainder is used for consumption smoothing, the wage effects implied by the calibrated model can match the treatment effect that we estimate on the non-tradable (non-agricultural) wage. The finding that roughly one-third of microfinance loans are used for businesses in the non-agricultural sector is consistent with Banerjee et al. (2018), who show that the top tercile of urban households experiences persistent and positive effects on business profitability and scale from the Hyderabad microfinance RCT.

The estimated treatment effect in the tradable sector is matched by the calibration when approximately 20% of microfinance loans are used for business investment. The finding that the implied investment share is smaller in the agricultural sector is consistent with the widely-acknowledged fact that microfinance is less well-suited to agriculture (Morvant-Roux, 2011), due to e.g., the lag between investment and production.

The fact that the calibration can match our estimated effects with plausible parameter values demonstrates that the aggregate demand and business investment channels together can deliver the wage effects we find. We should note, however, that there are other, unmodeled, channels which could also contribute to the size of the empirical effects. A precautionary savings motive as in Kaboski and Townsend (2011) would amplify the aggregate demand effect as households save to re-build buffer stocks. And a labor supply response as in Jayachandran (2006) would magnify the wage fall, as households respond to consumption drops by increasing labor supply.

7. Conclusion

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 and the extent of the crisis, which wiped roughly a billion dollars off of lenders' balance sheets, this episode presents a unique opportunity to study the impacts of microfinance in general equilibrium.

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 creditworthy borrowers in other states, which in turn led to decreased wages, earnings and consumption. This episode shows that microfinance, despite its small loan sizes, can have meaningful impacts on rural economies.

Insofar as credit not borrowed today does not need to be repaid in the future, one might think that, over time, the net effect of the crisis will "wash out." However, for poor households, utility is likely quite concave and so the volatility in the credit market, which translates into volatility in wages, earnings, and consumption, may be quite costly. The loss in total welfare resulting from a pronounced short term consumption fall will not be fully offset by a future stream of slightly higher consumption. Moreover, some effects of the credit crunch could persist, due to, for instance, durable investment or adjustment costs.

Ultimately, we believe that our findings complement the RCT literature. Randomized evidence has documented that microfinance has modest effects and has largely explored the direct effects on likely borrowers. By studying quasi-exogenous variation in credit supply at a larger level of aggregation, we find evidence of important equilibrium effects through changes to labor demand. These results together can paint a more complete picture than either taken alone.

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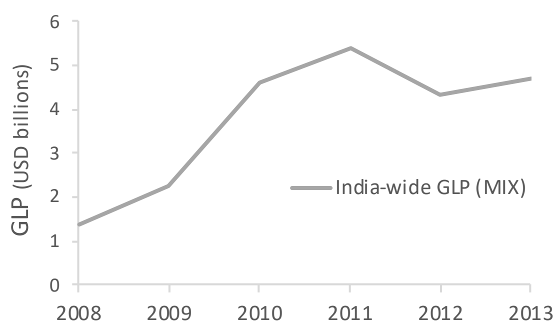
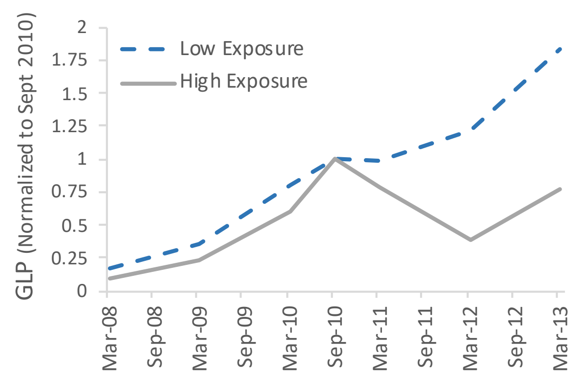
FIGURES



(A) Panel A: India-Wide GLP



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

FIGURE 1. Growth of Microfinance Gross Loan Portfolio: India and Analysis Sample

Note: Panel A plots the India-wide gross loan portfolio (GLP) aggregated across microfinance institutions and states as reported in USD in the MIX database. Panel B shows the evolution of microfinance using the hand-collected data (reported in Indian rupees) from 25 microfinance institutions. The figure in Panel B splits the districts between low and high AP exposure (ex AP). High and Low exposure are defined as in Section 3.1. GLP in each year is scaled by the pre-crisis district level of microcredit on September 30, 2010.

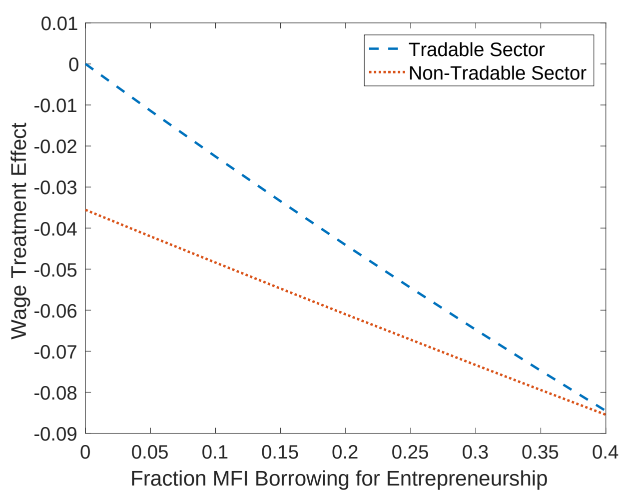


FIGURE 2. Calibrated Wage Effects by Share Borrowing for Entrepreneurship

Note: The figure shows the percentage drops in the sector-specific wages resulting from a withdrawal of access to credit in the calibrated model. The x-axis is the fraction of borrowers who borrow to invest in a business. For details and parameter values, see Section 6.3 and Appendix F.

TABLES

TABLE 1. Sample Selection

	(1) Average Loan per Borrower	(2) Number of Borrowers	(3) Borrowers per Staff Member	(4) Write-off Ratio	(5) Portfolio at Risk, 30 Days	(6) MFI Age
Panel A: Selection into the Sample						
MFI in the Sample	-25.164	-34132.611	-72.491**	-0.002	-0.017***	
	(21.324)	(103178.714)	(35.782)	(0.002)	(0.006)	
Control mean	176.064	245201.611	267.591	0.005	0.023	
Control SD	198.024	782389.257	256.144	0.012	0.047	
Observations	114	115	113	82	84	
Panel B: Sampled MFIs, relation to exposure						
Exposure to AP	-0.750	166780.191	72.574	-0.002	0.002	0.132
	(8.776)	(241593.920)	(56.126)	(0.002)	(0.006)	(0.500)
Control mean	152.000	177160.059	179.176	0.004	0.007	1.118
Control SD	29.180	215349.208	103.882	0.005	0.007	0.993
Observations	21	21	21	18	18	21

Note: Data from the Microfinance Information Exchange (MIX). In panel A, the left-hand side variable is a dummy indicating if the institution is in our sample. Write-off ratio and Portfolio at risk are fractions of the overall portfolio. In panel C, the left-hand side variable is a dummy indicating if the MFI was exposed to the AP crisis. The left-hand side variable in column (6) refers to the number of years before 2010 that the MFI reports positive GLP; it is a measure of age in 2010, top-censored at 2 years (2008). Since it is available only for sampled MFIs, this dependent variable is used only in Panel B. Robust standard errors in parentheses.

TABLE 2. Summary Statistics

Variable	Obs	Mean	Std. Dev
District-level variables from balance sheet data			
Any exposed lender, 2010	354	0.35	0.48
Gross loan portfolio in lakhs (100,000 INR)	145	1693.74	1895.74
Gross loan portfolio, per rural household	145	410.97	528.93
Household-level variables from NSS (round 68)			
HH Weekly Labor Earnings	16340	854.81	1434.83
Casual Daily Wage: Ag	1176	140.53	58.53
Casual Daily Wage: Non-Ag	2460	194.71	107.40
HH Weekly Days Worked: Total	16340	10.28	6.74
Household weekly days worked in self-employment	16340	6.55	7.04
Household weekly days worked in non-self-employment	16340	3.73	5.16
Any HH Member Invol. Unemployment	16340	0.10	0.30
HH size	16340	4.52	2.23
(mean) num_hh_earners	16340	1.89	0.35
HH Monthly Consumption: Total	16340	5643.40	4531.70
HH Monthly Consumption: Durables	16340	382.25	1891.40
Any non-Ag. Self Employment	16340	0.22	0.41
Household-level variables from NSS (round 70)			
MFI amt outstanding, win	17961	391	4005
Uncollateralized formal non-bank amt outstanding, win	17961	2395	13201
Total loan amt outstanding	17961	53256	128823

Note: Outcomes variables in first panel are from the balance sheet data collected with MFIN; see text for details. Sample is restricted to only low exposure districts with some MFI activity in 2010. However, the "Any exposed lender" measure is computed based on the full sample. Outcome variables in the second panel are from NSS round 68 (2012). Outcomes variables in the third panel are from NSS round 70 (2014) and are winsorized at the 99th percentile.

TABLE 3. Exposure to the AP Crisis and total MFI lending: Balance sheet data

	(1) District total gross loan portfolio in lakhs (100,000 INR)	(2) District gross loan portfolio per household (INR)	(3) District total gross loan portfolio in lakhs (in logs)
Log(Exposure Ratio) × Post 2010	-336.801***	-97.232***	-0.478***
	(43.314)	(11.133)	(0.084)
Any exposed lender × Post 2010	-1105.546***	-308.068***	-1.786***
	(178.472)	(44.942)	(0.370)
Control mean	1693.7	411.0	6.814
Control SD	1895.7	528.9	1.365
Observations	1048	1048	1048

Note: Outcomes data from MFI balance sheets. Each cell provides coefficients from separate differences-in-differences 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 esposure to AP. The outcome of interest in column 1 is total district-level credit outstanding (GLP) in lakhs (100,000 INR), while column 2 scales this value by the number of rural households. In all columns, controls include round and district fixed effects, number of rural households times round, number of rural households squared times round, GLP quintiles in 2008 dummies times round, GLP quintiles in 2010 dummies times round. Standard errors are clustered at the district level.

TABLE 4. Exposure to the AP Crisis and commercial bank lending: RBI data

	(1) No. accounts (agriculture) (logs)	(2) Amt outstanding (agriculture) (logs)	(3) No. accounts (direct) (logs)	(4) Amt outstanding (direct) (logs)	(5) No. accounts (indirect) (logs)	(6) Amt outstanding (indirect) (logs)
Log(HH Exposure Ratio) × Post 2010	-0.001	0.006	0.008	0.010	-0.150***	-0.067**
	(0.008)	(0.015)	(0.009)	(0.011)	(0.038)	(0.034)
Any Exposed Lender × Post 2010	0.009	0.026	0.038	0.046	-0.514***	-0.285**
	(0.032)	(0.047)	(0.033)	(0.040)	(0.150)	(0.131)
Control mean	11.564	15.944	11.509	15.795	8.113	13.659
Control SD	0.732	0.773	0.711	0.772	1.402	1.143
Observations	1031	1031	1031	1031	1031	1031

Note: Outcomes data from RBI "District-Wise Classification of Outstanding Credit of Scheduled Commercial Banks". Each cell provides coefficients from separate differences-in-differences regressions. 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 round and district fixed effects, quintiles of rural households times round, quintiles of total households times round, GLP quintiles in 2008 dummies times round, GLP quintiles in 2010 dummies times round. Standard errors are clustered at the district level.

TABLE 5. Exposure to the AP Crisis and total MFI lending: NSS round 70 data

	(1) MFI amt outstanding, win.	(2) Uncollateralized formal non-bank amt outstanding, win.	(3) Bank amt outstanding, win.	(4) Total loan amt outstanding, win.	(5) MFI amt outstanding, log.	(6) Uncollateralized formal non-bank amt outstanding, log.	(7) Bank amt outstanding, log.	(8) Total loan amt outstanding, log.
Log(HH Exposure Ratio)	-88.242***	-390.241***	-170.543	-926.577	-0.046***	-0.132***	0.028	-0.083
	(26.619)	(111.150)	(582.900)	(893.325)	(0.014)	(0.026)	(0.046)	(0.060)
Any exposed lender	-310.893***	-1352.917***	-1798.924	-3496.923	-0.159***	-0.436***	0.043	-0.317
	(99.591)	(385.963)	(2198.649)	(3413.070)	(0.054)	(0.101)	(0.175)	(0.232)
Control mean	391.485	2394.640	29531.260	69353.672	0.191	0.904	2.618	7.492
Control SD	4004.849	13200.690	104467.426	142601.618	1.345	2.834	4.715	4.950
Observations	38492	38492	38492	38492	38492	38492	38492	38492

Note: Otcomes data from the NSS 70th round "Debt and Investment" survey reflecting outstanding credit on June 30, 2012. Each cell provides coefficients from separate OLS regression specification. The first row reports coefficients from separate regressions using 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 columns 1 and 5 is total SHG-NBFC credit outstanding. Columns 2 and 6 consider total formal, non-bank, non-collateralized credit, with individual-liability bank credit in column 3 and 7, and total credit in column 4 and 8. The dependent variables in columns 1 to 4 are in levels and winsorized at the bottom and top 1 percentile, and in log(X+1) transformation for columns 5 to 8. All columns include pre-crisis district-level controls. Balance sheet controls include levels and quintiles of GLP measured in both 2008 and 2010. RBI controls include amount of credit outstanding and number of accounts for agricultural loans, direct loans, and indirect loans. NSS 66 controls include average monthly household expenditures, annual durables expenditures, weekly earnings from and days worked in self-employment, daily wage, and percent of weekly earnings from self-employment. Standard errors are clustered at the district level.

TABLE 6. Labor Outcomes

	(1) Casual Daily Wage	(2) HH Weekly Total Days Worked	(3) HH Weekly Casual Days Worked	(4) HH Weekly Labor Earnings	(5) Any HH Member Invol. Unemployed	(6) HH is Employer
Log(Exposure Ratio) × Post 2010	-2.179***	-0.031	-0.091**	-16.522**	0.003	-0.001
	(0.640)	(0.046)	(0.042)	(7.124)	(0.003)	(0.001)
Any exposed lender × Post 2010	-8.866***	-0.066	-0.431**	-74.784**	0.011	-0.004
	(2.887)	(0.190)	(0.176)	(29.285)	(0.011)	(0.003)
Control mean	153.361	10.275	3.455	854.812	0.098	0.026
Control SD	87.097	6.738	5.134	1434.832	0.297	0.160
Observations	40584	119668	119668	119668	119668	119668

Note: Outcomes data from NSS rounds 64, 66, 68. Each cell provides coefficients from separate differences-in-differences regressions. 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 round and district fixed effects, survey month, quintiles of household size, number of rural households times round, number of rural households squared times round, GLP quintiles in 2008 dummies times round, GLP quintiles in 2010 dummies times round. Standard errors are clustered at the district level.

TABLE 7. Consumption Outcomes

	(1) HH Monthly Consumption: Total	(2) HH Monthly Consumption: Nondurables	(3) HH Monthly Consumption: Durables	(4) Below Proverty Line
Log(Exposure Ratio) × Post 2010	-82.845***	-68.694***	-15.729**	0.003
	(25.666)	(23.024)	(6.415)	(0.004)
Any exposed lender × Post 2010	-319.339***	-246.690**	-80.170***	-0.004
	(118.234)	(107.493)	(24.421)	(0.019)
Control mean	5643.397	5278.214	382.247	0.254
Control SD	4531.698	3694.260	1891.396	0.435
Observations	111692	119668	111692	111692

Note: Outcomes data from NSS rounds 64, 66, 68. Each cell provides coefficients from separate differences-in-differences regressions. Notice that due to missing values the sample size for durable consumption is lower than for nondurable consumption. Total consumption and poverty are then considered missing when durable consumption is missing. 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 round and district fixed effects, survey month, quintiles of household size, number of rural households times round, number of rural households squared times round, GLP quintiles in 2008 dummies times round, GLP quintiles in 2010 dummies times round. Standard errors are clustered at the district level.

TABLE 8. Robustness: Placebo

	(1) HH Monthly Cnsumption: Total	(2) HH Monthly Consumption: Durables	(3) HH Weekly Labor Earnings	(4) HH Weekly Casual Days Worked	(5) Casual Daily Wage
Log(HH Exposure Ratio) × Post 2008	-4.426	1.156	-1.235	-0.003	-0.378
	(19.966)	(3.487)	(5.908)	(0.051)	(0.369)
Any Exposed Lender × Post 2008	-67.405	15.685	-2.525	0.009	-1.441
	(83.994)	(16.217)	(23.065)	(0.198)	(1.634)
Observations	75850	75850	83826	83826	30506

Note: Outcomes data from NSS rounds 64 and 68. Each cell provides coefficients from separate differences-in-differences regressions. 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 round and district fixed effects, survey month, quintiles of household size, number of rural households times round, number of rural households squared times round, GLP quintiles in 2008 dummies times round.

TABLE 9. Robustness: Distance to Andhra Pradesh

	(1) HH Monthly Consumption: Total	(2) HH Monthly Consumption: Durables	(3) HH Weekly Labor Earnings	(4) HH Weekly Casual Days Worked	(5) Casual Daily Wage
Panel A: Drop border districts					
Log(HH Exposure Ratio) × Post 2010	-74.149***	-15.083**	-13.691*	-0.082**	-1.899***
	(28.573)	(6.962)	(7.754)	(0.041)	(0.698)
Any Exposed Lender × Post 2010	-258.567**	-75.449***	-60.469**	-0.382**	-7.718**
	(125.869)	(25.769)	(30.367)	(0.172)	(3.010)
Observations	105801	105801	113346	113346	37774
Panel B: Control for distance to AP × round					
Log(HH Exposure Ratio) × Post 2010	-81.465***	-17.952***	-19.080***	-0.039	-2.552***
	(27.210)	(6.609)	(7.125)	(0.043)	(0.682)
Any Exposed Lender × Post 2010	-306.946**	-87.093***	-82.724***	-0.251	-9.992***
	(122.320)	(25.401)	(29.113)	(0.175)	(3.027)
Observations	111692	111692	119668	119668	40584
Panel C: Control for travel time to Hyderabad × round					
Log(HH Exposure Ratio) × Post 2010	-91.124**	-23.649***	-19.581**	-0.041	-2.339**
	(36.117)	(8.242)	(9.771)	(0.054)	(0.903)
Any Exposed Lender × Post 2010	-342.418**	-103.610***	-81.661**	-0.277	-8.210**
	(160.153)	(34.365)	(38.492)	(0.222)	(3.802)
Observations	63071	63071	67939	67939	22868

Note: Outcomes data from NSS rounds 64, 66, 68. In each panel, each cell provides coefficients from separate differences-in-differences regressions. 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 round and district fixed effects, survey month, quintiles of household size, number of rural households times round, number of rural households squared times round, GLP quintiles in 2008 dummies times round, GLP quintiles in 2010 dummies times round. In the first panel, the sample is restricted to districts that share no border with Andhra Pradesh. In the second panel, the linear distance to Andhra Pradesh interacted with the round is also included as control. In the third panel, we use instead the road travel time between each district and Hyderabad as calculated by Allen and Atkin (2016). Standard errors are clustered at the district level.

TABLE 10. Casual Daily Wages by Sector

	(1) Casual Daily Wage: Pooled	(2) Casual Daily Wage: Ag	(3) Casual Daily Wage: Non-ag	(4) Casual Daily Wage: Men, Ag	(5) Casual Daily Wage: Men, Non-ag	(6) Casual Daily Wage: Women, Ag	(7) Casual Daily Wage: Women, Non-ag	(8) Ag. Employer	(9) Non-ag Employer
Log(Exposure Ratio) × Post 2010	-2.179***	-1.310**	-4.167***	-1.241*	-4.579***	-1.113	-1.105	-0.000	-0.001**
	(0.640)	(0.663)	(1.162)	(0.732)	(1.224)	(0.732)	(1.765)	(0.001)	(0.000)
Any exposed lender × Post 2010	-8.866***	-5.151*	-15.399***	-5.140	-16.647***	-3.717	-4.043	-0.001	-0.003**
	(2.887)	(2.995)	(4.998)	(3.149)	(5.222)	(3.426)	(7.904)	(0.003)	(0.001)
Control mean	153.361	128.581	184.242	140.534	194.709	102.236	113.578	0.017	0.009
Control SD	87.097	57.000	106.180	58.525	107.398	43.071	61.620	0.131	0.093
Observations	40584	23444	17140	14554	14939	8890	2201	119668	119668

Note: Outcomes data from NSS rounds 64, 66, 68. Each cell provides coefficients from separate differences-in-differences regressions. 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 round and district fixed effects, survey month, quintiles of household size, number of rural households times round, number of rural households squared times round, GLP quintiles in 2008 dummies times round, GLP quintiles in 2010 dummies times round. Standard errors are clustered at the district level.

TABLE 11. Crop Yields

	(1) Crop Yield Index	(2) Rice Yield	(3) Wheat Yield	(4) Jowar Yield	(5) Sugarcane Yield	(6) Groudnut Yield
Log(Exposure Ratio) × Post 2010	0.011	0.015	0.025	0.010	-0.852	-0.009
	(0.013)	(0.026)	(0.025)	(0.017)	(1.031)	(0.019)
Any exposed lender, 2010	0.050	0.113	0.053	0.032	-2.802	-0.062
	(0.057)	(0.108)	(0.103)	(0.067)	(4.789)	(0.080)
Control mean	0.145	2.706	2.714	1.033	73.480	1.674
Control SD	0.192	0.880	1.116	0.433	38.551	0.926
Observations	963	910	783	622	833	758

Note: Outcomes data from the Ministry of Agriculture, Directorate of Economics and Statistics. Index in column 1 is a revenue-weighted average of the log of yield for the five major crops: rice, wheat, sugarcane, jowar (sorghum), and groundnuts. Yields in columns 2-6 are in tonnes per hectare. In all columns, controls include round and district fixed effects, survey month, number of rural households times round, number of rural households squared times round, GLP quintiles in 2008 dummies times round, GLP quintiles in 2010 dummies times round, and rainfall shocks. Standard errors are clustered at the district level.

TABLE 12. Heterogeneity: Land

	(1) Uncollateralized amount outstanding log	(2) HH Weekly Labor Earnings	(3) HH Monthly Consumption: Total	(4) HH Monthly Consumption: Durables
1st Quintile District Land Dist.	-0.146***	-21.467**	-48.883	-7.792
	(0.048)	(10.582)	(30.961)	(5.850)
2st Quintile District Land Dist.	-0.203***	-15.627	-16.474	-12.040*
	(0.038)	(17.284)	(39.958)	(7.142)
3st Quintile District Land Dist.	-0.125***	1.984	-78.924*	-9.294
	(0.037)	(19.320)	(43.764)	(6.245)
4st Quintile District Land Dist.	-0.106**	-14.441	-139.061***	-29.671***
	(0.042)	(10.583)	(36.428)	(10.051)
5st Quintile District Land Dist.	-0.143***	-2.355	-90.256	-11.101
	(0.052)	(14.204)	(59.235)	(28.719)

Note: For column (1), outcomes data are from NSS round 70; for columns (2)-(4), outcomes data are from NSS rounds 64, 66, 68. Each cell provides coefficients from a different regression. All specifications use the continuous exposure measure. The rows report the sample restriction by quintile of the district wealth distribution. The columns reflect different outcomes. In all cells of column (1), we included pre-crisis district-level controls. Balance sheet controls include levels and quintiles of GLP measured in both 2008 and 2010. RBI controls include amount of credit outstanding and number of accounts for agricultural loans, direct loans, and indirect loans. NSS 66 controls include average monthly household expenditures, annual durables expenditures, weekly earnings from and days worked in self-employment, daily wage, and percent of weekly earnings from self-employment. In all cells of columns (2)-(4), controls include round and district fixed effects, survey month, quintiles of household size, number of rural households times round, number of rural households squared times round, GLP quintiles in 2008 dummies times round, GLP quintiles in 2010 dummies times round. For column (1), the number of observations are, for quintiles one to five, respectively 7,471, 7,330, 7,351, 7,327 and 7,366. For columns (2)-(4), the number of observations are, for quintiles one to five, respectively 30,238, 21,906, 21,527 and 19,251. Standard errors are clustered at the district level.

TABLE 13. Decomposing Effects into Profits, Capital and Consumption

Panel A: Calibrated Effects from the Empirical Results			
(1)	Total Consumption		319
(2)	Total Durables		80
(3)	Business Durables, (2)$\times 0.64$		51
(4)	Non-business Consumption, (2)-(3)		268
(5)	Labor Earnings		320
(6)	Credit		1319
Panel B: Effects for Different Assumptions on the Marginal Prop. to Consume			
(7)	(8)	(9)	(10)
Marginal Prop. to Consume	Implied Profits + Labor Earnings $\frac{(4)}{(7)}$	Implied Profits (8)-(5)	"IV": Implied Profits per Credit $\frac{(8)}{(9)}$
0.9	298	-23	-0.017
0.8	335	15	0.011
0.7	383	62	0.047
0.6	447	126	0.096
0.5	536	216	0.163
0.4	670	350	0.265

Note: Values (1) and (2) are from table 7. Value (5) is from table 6. Value (6) is from table 5. Share of durables for business purposes used in (3) is from Banerjee et al. (2015a).

TABLE 14. General Equilibrium Effect Studies

Channel	Study	Country	Wage Impact	"First Stage" Scaling
Credit Supply	Burgess and Pande (2003)	India	7% (ag wage)	1 bank branch per 100,000 people
	Kaboski and Townsend (2012)	Thailand	7% (avg wage) 28% (construction wage)	43% increase in short term credit
Labor Demand	Imbert and Papp (2014)	India	4.7% (ag wage)	1.3% demand shift from NREGA
	Muralidharan *et al* (2017)	India	6.1% (total wage)	6% demand shift from NREGA
Labor Supply	Akram *et al* (2017)	Bangladesh	2.8% (ag wage)	10% increase in emigration

Online Appendix

APPENDIX A. MODEL APPENDIX

A.1. **Setting up the Problem.** [31] Firms come in two sectors: $S \in \{T, NT\}$, and workers in two types: $k \in \{\ell, h\}$. The NT sector uses both types of labor, while the T sector uses only ℓ labor. Production functions are:

$$Y^T = A^T \left(L^{T,\ell}\right)^{\gamma} \tag{A.1}$$

$$Y^{NT} = A^{NT} \left(L^{NT,\ell\rho} + \theta L^{NT,h\rho}\right)^{\frac{\gamma}{\rho}} \tag{A.2}$$

where $\rho < \gamma < 1$.

Firms sell their products for price P^S. We normalize $P^T = 1$ and denote $P^{NT} = P$. Firms make hiring decisions by maximizing profits, which are given by:

$$\Pi^S = P^S Y^S - w_\ell L^{S,\ell} - w_h L^{S,h} \tag{A.3}$$

Consumers of worker type k maximize within-period utility subject to a budget constraint:

$$\max_{C^{T,k}, C^{NT,k}} \left(C^{T,k}\right)^{\alpha} \left(C^{NT,k}\right)^{1-\alpha} \tag{A.4}$$

$$s.t. C^{T,k} + PC^{NT,k} \leq w_k + y + B$$

For simplicity, we normalize $y = 0$. Given the Cobb-Douglas structure, consumers will spend constant budget shares on each good:

$$C^{T,k} = \alpha \left(w_k + B\right)$$

$$C^{NT,k} = \frac{1-\alpha}{P} \left(w_k + B\right)$$

A.2. **Equilibrium Conditions.** Both labor markets and the non-tradable product market clear:

$$L^{T,\ell} + L^{NT,\ell} = N^\ell \tag{A.5}$$

$$L^{NT,h} = N^h \tag{A.6}$$

$$N^\ell C^{NT,\ell} + N^h C^{NT,h} = A^{NT} \left(L^{NT,\ell\rho} + \theta L^{NT,h\rho}\right)^{\frac{\gamma}{\rho}} \tag{A.7}$$

[31] We are particularly grateful to Bruno Barsanetti for developing an elegant method of proving these results.

A.3. **Solving the Problem.** T firms solve the following FOC:

$$\gamma A^T \left(L^{T,\ell}\right)^{\gamma-1} = w_\ell$$

Rearranging,

$$L^{T,\ell} = \left(\frac{\gamma A^T}{w_\ell}\right)^{\frac{1}{1-\gamma}}$$

The maximization problem of NT firms yields the following FOCs:

$$\gamma P A^{NT} \left(L^{NT,\ell\rho} + \theta L^{NT,h\rho}\right)^{\frac{\gamma}{\rho}-1} L^{NT,\ell\rho-1} = w_\ell$$

$$\gamma \theta P A^{NT} \left(L^{NT,\ell\rho} + \theta L^{NT,h\rho}\right)^{\frac{\gamma}{\rho}-1} L^{NT,h\rho-1} = w_h$$

Simplifying,

$$L^{NT,h} = L^{NT,\ell} \left(\frac{w_\ell \theta}{w_h}\right)^{\frac{1}{1-\rho}}$$

$$L^{NT,\ell} = \left[\frac{\gamma P A^{NT}}{w_\ell} \left(1 + \theta \left(\frac{w_\ell \theta}{w_h}\right)^{\frac{\rho}{1-\rho}}\right)^{\frac{\gamma-\rho}{\rho}}\right]^{\frac{1}{1-\gamma}}$$

Plugging the demands into the equilibrium conditions yields:

$$\left(\frac{\gamma A^T}{w_\ell}\right)^{\frac{1}{1-\gamma}} + \left[\frac{\gamma P A^{NT}}{w_\ell} \left(1 + \theta \left(\frac{w_\ell \theta}{w_h}\right)^{\frac{\rho}{1-\rho}}\right)^{\frac{\gamma-\rho}{\rho}}\right]^{\frac{1}{1-\gamma}} = N^\ell$$

$$\left[\frac{\gamma P A^{NT}}{w_\ell} \left(1 + \theta \left(\frac{w_\ell \theta}{w_h}\right)^{\frac{\rho}{1-\rho}}\right)^{\frac{\gamma-\rho}{\rho}}\right]^{\frac{1}{1-\gamma}} \left(\frac{w_\ell \theta}{w_h}\right)^{\frac{1}{1-\rho}} = N^h$$

$$N_1 \frac{1-\alpha}{P} \left(w_\ell + y\right) + N_2 \frac{1-\alpha}{P} \left(w_h + y\right) = A^{NT} \left(L^{NT,1^\rho} + \theta L^{NT,2^\rho}\right)^{\frac{\gamma}{\rho}}$$

To simplify, we can solve for P using the third equation

$$\frac{1-\alpha}{A^{NT} \left(L^{NT,\ell\rho} + \theta L^{NT,h\rho}\right)^{\frac{\gamma}{\rho}}} \left(N^\ell w_\ell + N^h w_h + B\left(N^\ell + N^h\right)\right) = P$$

and we can substitute $L^{NT,\ell} = L^{NT,h} \left(\frac{w_\ell \theta}{w_h}\right)^{\frac{-1}{1-\rho}} = N^h \left(\frac{w_\ell \theta}{w_h}\right)^{\frac{-1}{1-\rho}}$. So,

$$P = (1-\alpha) \frac{N^\ell w_\ell + N^h w_h + B\left(N^\ell + N^h\right)}{A^{NT} N_h^\gamma \left(\left(\frac{w_\ell \theta}{w_h}\right)^{\frac{-\rho}{1-\rho}} + \theta\right)^{\frac{\gamma}{\rho}}}$$

Similarly, from the equilibrium condition of the type 2 workers,

$$P = \left(1 + \theta\left(\frac{w_\ell \theta}{w_h}\right)^{\frac{\rho}{1-\rho}}\right)^{\frac{\rho-\gamma}{\rho}} \frac{w_\ell}{\gamma A^{NT}}\left(\frac{w_\ell \theta}{w_h}\right)^{\frac{-(1-\gamma)}{1-\rho}} N_h^{1-\gamma}$$

Combining the P equations yields

$$N^\ell w_\ell + N^h w_h + B\left(N^\ell + N^h\right) = \frac{w_\ell}{\gamma(1-\alpha)}\left(\left(\frac{w_h}{w_\ell \theta}\right)^{\frac{1}{1-\rho}} + \frac{w_h}{w_\ell}\right) N^h$$

Rearranging and using the first condition A.5, we can collapse the equilibrium conditions:

$$\left(\frac{\gamma A^T}{w_\ell}\right)^{\frac{1}{1-\gamma}} + N^h\left(\frac{w_h}{w_\ell \theta}\right)^{\frac{1}{1-\rho}} - N^\ell = 0$$

$$\frac{w_\ell}{\gamma(1-\alpha)}\left(\left(\frac{w_h}{w_\ell \theta}\right)^{\frac{1}{1-\rho}} + \frac{w_h}{w_\ell}\right) N^h - N^\ell w_\ell + N^h w_h + B\left(N^\ell + N^h\right) = 0$$

To solve the system and derive comparative statics, we introduce a change of variables.

- $\omega = \frac{w_h}{w_\ell}$ be the relative wage to high-skill (non-tradable) workers;
- $\nu = \frac{1}{w_\ell}$ be the inverse of low-skill (tradable) wages.

If we divide the second equation by w_ℓ and replace the variables, our system becomes:

$$\left(\gamma A^T \nu\right)^{\frac{1}{1-\gamma}} + N^h\left(\frac{\omega}{\theta}\right)^{\frac{1}{1-\rho}} - N^\ell = 0$$

$$\frac{N^h}{\gamma(1-\alpha)}\left(\left(\frac{\omega}{\theta}\right)^{\frac{1}{1-\rho}} + \omega\right) - N^\ell - N^h\omega - y\left(N_1 + N^h\right)\nu = 0$$

We can isolate ν in the second equation to obtain:

$$\nu = \frac{\frac{N^h}{\gamma(1-\alpha)}\left[\left(\frac{\omega}{\theta}\right)^{\frac{1}{1-\rho}} + \omega\right] - N^\ell - N^h\omega}{B(N^\ell + N^h)}$$

$$\nu = \frac{n_h\left(\frac{\omega}{\theta}\right)^{\frac{1}{1-\rho}} + n_h\omega[1 - \gamma(1-\alpha)] - n_\ell}{\gamma(1-\alpha)B}$$

where $n_i = \frac{N_i}{N_1 + N^h}$. If we replace ν in the first system equation, after rearranging we have:

$$\frac{(1-\alpha)B}{A^T} = \frac{n_h\left(\frac{\omega}{\theta}\right)^{\frac{1}{1-\rho}} + n_h\omega[1 - \gamma(1-\alpha)] - n_1}{[N^\ell - N^h\left(\frac{\omega}{\theta}\right)^{\frac{1}{1-\rho}}]^{1-\gamma}}$$

The LHS is a linear and increasing function of B, and the RHS is strictly increasing in the relative wages ω. Hence, $\frac{w_h}{w_\ell}$ is increasing in B; that is, the elasticity of the high-skilled wage (with respect to B) will be higher than the elasticity of the low-skilled wage. If $w_h > w_\ell$ in equilibrium, then the absolute change in $w_h$will be larger than for w_ℓ.

Finally, we can show that both wages go up with B. First, notice that:

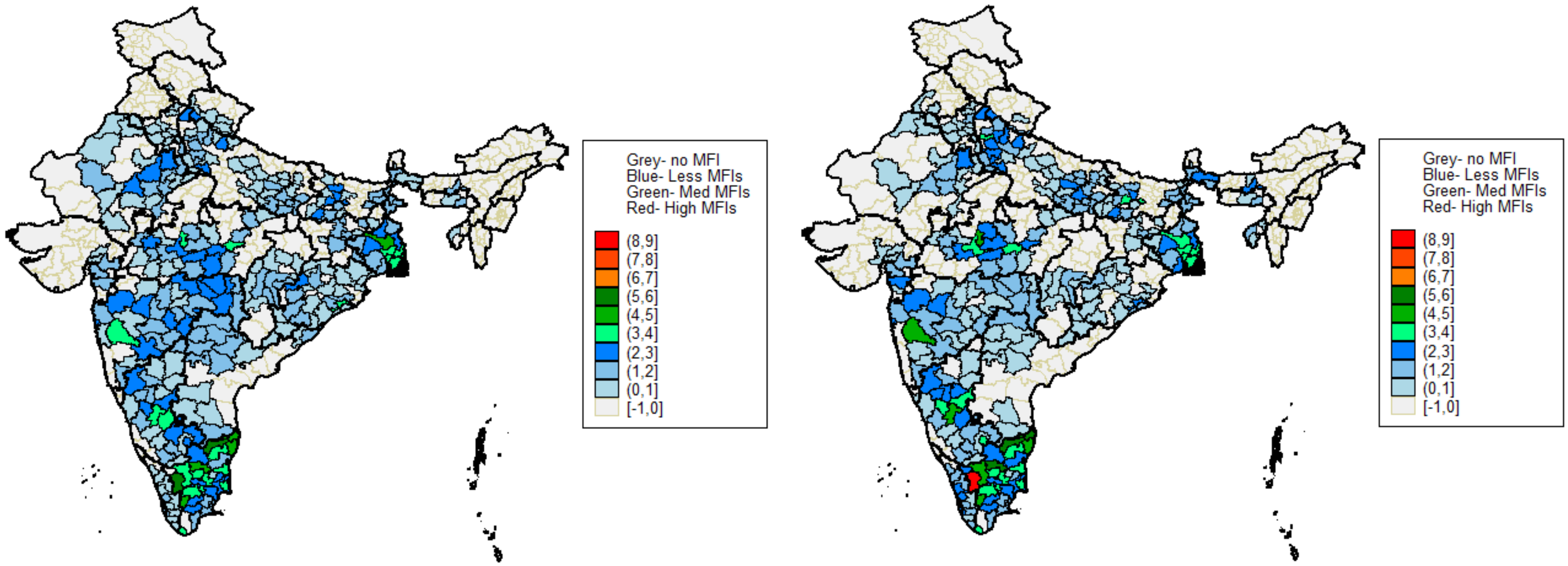
$$[n_h(\frac{\omega}{\theta})^{\frac{[1}{1-\rho}} + n_h\omega[1-\gamma(1-\alpha)] - n_\ell = \frac{(1-\alpha)B}{A^T}[N^\ell - N^h(\frac{\omega}{\theta})^{\frac{1}{1-\rho}}]^{1-\gamma}$$

And so we can substitute in the expression for ν to get:

$$\nu = \frac{1}{A^T}[N^\ell - N^h(\frac{\omega}{\theta})^{\frac{1}{1-\rho}}]^{1-\gamma}$$

which depends on B only through ω. Hence, ν is decreasing in B, so both w_ℓ and w_h are increasing in B.

Appendix B. Supplementary Figures



(A) September 2010 (B) March 2012

EDIT

Figure B.1. Number of MFIs by District

Note: These maps present visualizations of the hand-collected data from 25 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 25 lenders in our sample were lending in those districts at the time.

APPENDIX C. SUPPLEMENTARY TABLES

TABLE C.1. Baseline Balance

	(1) Distance to AP	(2) District Borders AP	(3) Casual Daily Wage: Agriculture	(4) Casual Daily Wage: Non-agriculture	(5) HH Weekly Labor Earnings	(6) HH Monthly Consumption: Non-durables	(7) HH Monthly Consumption: Durables
Log(Exposure Ratio)	-15.126**	0.043***	0.062	-0.368	-9.761	4.417	-2.575
	(5.860)	(0.012)	(0.382)	(0.412)	(8.378)	(29.966)	(5.578)
Any exposed lender	-44.747*	0.102***	0.789	-1.131	-23.374	-23.734	19.022
	(24.634)	(0.035)	(1.488)	(1.419)	(29.110)	(104.108)	(18.838)
Observations	354	354	340	340	340	340	340

Note: Outcomes from NSS round 66 . Each row provides coefficients from separate regressions. 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 dependent variable is the average across households in each district in round 66. In all columns, controls include state-dummies, number of rural households, number of rural households squared, GLP quintiles in 2008 dummies, and GLP quintiles in 2010. In columns (3) to (7), the average of the dependent variable in round 64 is also used as a control. Robust standard errors in parenthesis.

TABLE C.2. First Stage Results Using Within-District Variation in MFI Exposure

	(1)	(2)	(3)	(4)
Fraction of Exposed GLP	-281.283*		-282.694*	
	(153.899)		(153.442)	
Exposed MFI Dummy		-153.173*		-154.444*
		(79.348)		(78.635)
Logarithm of MFI Size			-9.250***	-9.320***
			(2.888)	(2.872)
Constant	2.635	8.174	194.447***	201.537***
	(6.806)	(9.313)	(60.549)	(60.720)
Observations	426	426	426	426

Note: Analysis uses within-district variation modeled after Khwaja and Mian (2008). All identifying variation comes from districts with both exposed and unexposed MFIs. Outcomes data from MFI balance sheets. In each column, the dependent variable is the difference of per rural household GLP by the MFI to the district between September 2010 and March 2012. In columns (1) and (3), exposure of the MFI is captured by the share of its portfolio in Andhra Pradesh as of September 2010. In columns (2) and (4), we use a exposure dummy equal to one if the MFI operates in Andhra Pradesh. All specifications include district dummies. In columns (3) and (4), the logarithm of the total portfolio of the MFI is also used as control. The sample is restricted only to MFI-district pairs with positive GLP. Standard errors are clustered at the district level.

Table C.3. Robustness: Sequential Exclusion of States

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
Excluding:	AS	BR	CG	GJ	HR	HP	JH	KA	KL	MP	MH	OD	PB	RJ	TN	UP	UK	WB
Total consumption:																		
Log(HH Exposure Ratio) × Post 2010	-117.7***	-119.9***	-116.2***	-110.9***	-110.6***	-115.8***	-116.7***	-109.5***	-95.6***	-106.4***	-135.1***	-109.8***	-112.3***	-124.6***	-119.9***	-126.5***	-115.9***	-121.6***
	(27.2)	(27.9)	(27.5)	(27.3)	(27.2)	(27.3)	(27.7)	(30.0)	(26.4)	(28.0)	(30.2)	(27.9)	(27.2)	(27.0)	(26.8)	(28.0)	(27.3)	(28.2)
Any Exposed Lender × Post 2010	-426.5***	-443.3***	-418.7***	-386.2***	-398.2***	-418.9***	-421.3***	-375.9***	-316.8***	-397.6***	-508.0***	-373.3***	-403.1***	-449.0***	-438.7***	-468.8***	-421.2***	-458.3***
	(119.9)	(124.1)	(120.8)	(120.0)	(119.6)	(120.0)	(121.6)	(126.6)	(115.8)	(122.8)	(125.8)	(124.2)	(119.6)	(120.8)	(119.9)	(126.4)	(120.6)	(127.5)
Labor earnings:																		
Log(HH Exposure Ratio) × Post 2010	-16.8**	-14.0*	-15.4**	-16.7**	-16.1**	-16.6**	-15.1**	-17.1**	-14.1**	-13.5*	-23.3***	-14.8**	-16.1**	-16.8**	-16.5**	-20.2***	-16.5**	-19.0***
	(7.1)	(7.4)	(7.2)	(7.2)	(7.2)	(7.1)	(7.1)	(7.6)	(7.2)	(7.6)	(6.8)	(7.2)	(7.1)	(7.4)	(7.1)	(7.2)	(7.1)	(7.3)
Any Exposed Lender × Post 2010	-75.4**	-63.7**	-70.8**	-74.0**	-72.7**	-74.8**	-68.8**	-73.4**	-62.2**	-63.2**	-95.5***	-64.4**	-72.5**	-76.0**	-79.3***	-97.2***	-74.4**	-87.4***
	(29.3)	(30.4)	(29.5)	(29.7)	(29.5)	(29.3)	(29.1)	(30.3)	(29.4)	(30.1)	(28.3)	(30.1)	(29.3)	(30.2)	(29.4)	(29.9)	(29.3)	(30.9)
Observations	119412	115856	118756	117471	118229	119668	118612	114937	114675	114651	109971	114983	118844	113512	117188	107536	119138	112646

Note: Outcomes data from NSS rounds 64, 66, 68. In each panel, each row provides coefficients from separate differences-in-differences regressions. 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 round and district fixed effects, survey month, quintiles of household size, number of rural households times round, number of rural households squared times round, GLP quintiles in 2008 dummies times round, GLP quintiles in 2010 dummies times round. In the first panel, the dependent variable is monthly total expenditures. In the second panel, the dependent variable is weekly labor earnings. In each column, observations in the state indicated at the top of the column are excluded from the sample; all other 17 states are included.

TABLE C.4. Randomization Inference: District Level Permutations

	(1) HH Monthly Cnsumption: Total	(2) HH Monthly Consumption: Durables	(3) HH Weekly Labor Earnings	(4) HH Weekly Casual Days Worked	(5) Casual Daily Wage	(6) Casual Daily Wage Non-ag
Estimated Coefficient	-319.339	-80.170	-74.784	-0.431	-8.866	-16.647
Distribution Mean	-6.622	-2.262	-0.029	-0.013	0.031	0.074
Distribution Standard Deviation	122.794	28.715	28.938	0.176	3.239	6.564
Rank	3/500	0/500	3/500	6/500	1/500	1/500
P-value	0.012	0.000	0.012	0.024	0.004	0.004

Note: The estimated coefficient refers to the dummy exposure variable. The mean and standard deviation refer to the distribution of estimated coefficients on permutations of the exposure dummy across districts. There were 500 iterations; at each iteration, 132 districts were randomly selected to have an exposure dummy equal to 1, while the remaining districts had an exposure dummy equal to 0. The rank indicates how the estimated coefficient in the data is located in the distribution of simulated coefficients. The p-value refers to a two-sided test based on the distribution of the coefficients.

TABLE C.5. Randomization Inference: State Level Permutations

	(1) HH Monthly Consumption: Total	(2) HH Monthly Consumption: Durables	(3) HH Weekly Labor Earnings	(4) HH Weekly Casual Days Worked	(5) Casual Daily Wage	(6) Casual Daily Wage Non-ag
Estimated Coefficient	-319.339	-80.170	-74.784	-0.431	-8.866	-16.647
Distribution Mean	7.581	-31.057	-0.477	-0.148	1.334	2.846
Distribution Standard Deviation	220.512	42.478	47.457	0.211	6.615	12.476
Rank	1/22	1/22	1/22	0/22	1/22	2/22

Note: The estimated coefficient refers to the dummy exposure variable. The mean and standard deviation refer to the distribution of estimated coefficients on permutations of the exposure dummy across MFIs; a district is exposed if an exposed MFI operated in it in 2010. There were 23 permutations; at each permutation, a single state was selected and a district was exposed if in October 2010 there was an MFI which operated in both the district and the selected state. For each regression, the sample does not include Andhra Pradesh or the selected "exposed" state. Since a single MFI in our sample operated in both Sikkim and Tripura before the AP crisis, these states are counted as a single permutation. The rank indicates how the estimated coefficient in the data is located in the distribution of simulated coefficients.

TABLE C.6. Robustness: Political Party

	(1) HH Monthly Consumption: Total	(2) HH Monthly Consumption: Durables	(3) HH Weekly Labor Earnings	(4) HH Weekly Casual Days Worked	(5) Casual Daily Wage
Log(HH Exposure Ratio) × Post 2010	-75.001**	-9.689	-11.749	-0.031	-1.934***
	(30.614)	(8.180)	(7.473)	(0.047)	(0.673)
Any Exposed Lender × Post 2010	-254.151*	-56.830*	-57.786*	-0.208	-7.950***
	(132.944)	(29.861)	(29.566)	(0.200)	(3.029)
Observations	111692	111692	119668	119668	40584

Note: Outcomes data from NSS rounds 64, 66, 68. Each row provides coefficients from separate differences-in-differences regressions. 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 round and district fixed effects, survey month, quintiles of household size, number of rural households times round, number of rural households squared times round, GLP quintiles in 2008 dummies times round, GLP quintiles in 2010 dummies times round, and the party affiliation of the state prime-minister in 2010 times round.

TABLE C.7. Robustness: Rainfall

	(1) HH Monthly Consumption: Total	(2) HH Monthly Consumption: Durables	(3) HH Weekly Labor Earnings	(4) HH Weekly Casual Days Worked	(5) Casual Daily Wage
Log(HH Exposure Ratio) × Post 2010	-70.244***	-13.235**	-15.950**	-0.094**	-1.931***
	(24.723)	(6.085)	(7.232)	(0.042)	(0.622)
Any Exposed Lender × Post 2010	-264.535**	-69.667***	-72.200**	-0.442**	-7.832***
	(114.737)	(23.040)	(29.886)	(0.177)	(2.796)
Observations	111692	111692	119668	119668	40584

Note: Outcomes data from NSS rounds 64, 66, 68. Each row provides coefficients from separate differences-in-differences regressions. 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 round and district fixed effects, survey month, quintiles of household size, number of rural households times round, number of rural households squared times round, GLP quintiles in 2008 dummies times round, GLP quintiles in 2010 dummies times round, and rainfall shocks. Rainfall data is from the Global Precipitation Climatology Centre (GPCC) and rainfall shocks are calculated as in Jayachandran (2006): if rainfall in a year is above the 80-th percentile of the rainfall distribution from 1950-2014, then the rainfall shock equals 1; if it is below the 20-th percentile, the rainfall shock equals -1; otherwise, its value is zero.

TABLE C.8. Robustness: Initial Economic Conditions

	(1) HH Monthly Consumption: Total	(2) HH Monthly Consumption: Durables	(3) HH Weekly Labor Earnings	(4) HH Weekly Casual Days Worked	(5) Casual Daily Wage
Panel A: consumption in round 66 × round					
Log(HH Exposure Ratio) × Post 2010	-61.210**	-11.079*	-11.740*	-0.082*	-2.183***
	(25.201)	(6.117)	(7.116)	(0.043)	(0.643)
Any Exposed Lender × Post 2010	-202.059*	-55.587**	-49.466*	-0.386**	-9.007***
	(117.382)	(22.866)	(29.687)	(0.184)	(2.898)
Observations	111692	111692	119668	119668	40584
Panel B: Poverty head count × round					
Log(HH Exposure Ratio) × Post 2010	-78.831***	-15.346**	-15.188**	-0.086**	-2.168***
	(25.410)	(6.397)	(7.182)	(0.043)	(0.641)
Any Exposed Lender × Post 2010	-293.339**	-77.841***	-67.286**	-0.405**	-8.865***
	(117.852)	(24.688)	(29.863)	(0.187)	(2.882)
Observations	111692	111692	119668	119668	40584
Panel C: Casual wage in round 66 × round					
Log(HH Exposure Ratio) × Post 2010	-95.272***	-17.867**	-18.721**	-0.081	-2.330***
	(26.556)	(6.682)	(7.122)	(0.042)	(0.658)
Any Exposed Lender × Post 2010	-365.082***	-88.237***	-83.363***	-0.389**	-9.424***
	(123.455)	(25.763)	(29.098)	(0.177)	(2.944)
Observations	111692	111692	119668	119668	40584
Panel D: Share of self-employment × round					
Log(HH Exposure Ratio) × Post 2010	-70.127***	-16.578***	-15.747**	-0.087**	-2.160***
	(25.513)	(6.227)	(7.116)	(0.042)	(0.639)
Any Exposed Lender × Post 2010	-264.565**	-83.072***	-71.395**	-0.412**	-8.824***
	(119.442)	(24.389)	(29.059)	(0.173)	(2.880)
Observations	111692	111692	119668	119668	40584

Note: Outcomes data from NSS rounds 64, 66, 68. In each panel, each row provides coefficients from separate differences-in-differences regressions. 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 round and district fixed effects, survey month, quintiles of household size, number of rural households times round, number of rural households squared times round, GLP quintiles in 2008 dummies times round, GLP quintiles in 2010 dummies times round, and rainfall shocks In each panel, additional controls are included: average district consumption in round 66 times round (first panel), district poverty head count in round 66 times round (second panel), average casual wage in agriculture in round 66 times round (third panel), and district share in self-employment times round (fourth panel) . Standard errors are clustered at the district level.

TABLE C.9. Heterogeneity: Peak agricultural labor demand periods

	(1) Casual Daily Wage: Ag	(2) Casual Daily Wage: Non-Ag	(3) HH Weekly Casual Days Worked	(4) HH Weekly Labor Earnings	(5) HH Monthly Consumption: Total
Peak labor demand periods					
Log(HH Exposure Ratio) × Post 2010	-2.234*	-4.962**	-0.182**	-32.372***	-81.428*
	(1.214)	(2.136)	(0.078)	(11.671)	(42.206)
Any Exposed Lender × Post 2010	-9.941*	-18.366**	-0.641**	-108.163**	-324.969*
	(5.366)	(9.102)	(0.302)	(48.983)	(182.678)
Observations	2515	3482	25625	25625	25625
Non-peak labor demand periods					
Log(HH Exposure Ratio) × Post 2010	-0.693	-5.589***	-0.110*	-13.829	-61.961*
	(1.010)	(1.505)	(0.056)	(9.559)	(31.727)
Any Exposed Lender × Post 2010	-3.339	-20.195***	-0.534**	-65.540	-220.215
	(3.980)	(6.131)	(0.227)	(39.747)	(146.863)
Observations	12039	11457	94043	94043	94043

Note: Outcomes data from NSS rounds 64, 66, 68. Households are administered the NSS survey on a rolling basis throughout the year. Thus, we split the calendar year into two-week bins and, for a given district, calculate the percentage of households who report that they are employed in agricultural. We identify peak demand periods as the 6 two-week bins with the highest agricultural employment. Each row provides coefficients from separate differences-in-differences regressions. 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 round and district fixed effects, survey month, number of rural households times round, number of rural households squared times round, GLP quintiles in 2008 dummies times round, GLP quintiles in 2010 dummies times round.

TABLE C.10. Robustness: Heterogeneous Covariates as Outcomes

	(1)	(2)	(3)	(4)	(5)
	Land Quintiles				
	1	2	3	4	5
Log(Exposure Ratio) × Post 2010	-0.004	0.005	-0.001	0.002	0.001
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
Any exposed lender × Post 2010	-0.012	0.016	0.000	0.012	0.003
	(0.013)	(0.014)	(0.012)	(0.010)	(0.008)
Observations	119668	119668	119668	119668	119668

Note: Each cell corresponds to a different regression. The top row uses the continuous exposure indicator, while the second row uses the binary exposure indicator. In all specifications, controls include round and district fixed effects, survey month, quintiles of household size, number of rural households times round, number of rural households squared times round, GLP quintiles in 2008 dummies times round, GLP quintiles in 2010 dummies times round. Standard errors are clustered at the district level.

APPENDIX D. SUPPLEMENTARY MODEL APPENDIX

Here, we solve for the limiting case of fully segmented labor markets. This has the advantage of producing simple, closed form solutions for equilibrium wage levels.

D.1. **Setting up the Problem.** Recall from Section 2.2 that firms come in two sectors: $S \in \{T, NT\}$, and workers in two types: $k \in \{\ell, h\}$. Here we assume that the NT sector uses only h labor, while the T sector uses only ℓ labor. Production functions are:

$$Y^T = A^T \left(L^{T,\ell}\right)^\gamma \tag{D.1}$$

$$Y^{NT} = A^{NT} \left(L^{NT,h}\right)^\gamma \tag{D.2}$$

where $\gamma < 1$.

All assumptions about consumers, goods prices, and borrowing are the same as in the full model with partially segmented labor markets.

D.2. **Equilibrium Conditions.** Again, both labor markets and the non-tradable product market clear:

$$L^{T,\ell} = N^\ell \tag{D.3}$$

$$L^{NT,h} = N^h \tag{D.4}$$

$$N^\ell C^{NT,\ell} + N^h C^{NT,h} = A^{NT} \left(L^{NT,h}\right)^\gamma \tag{D.5}$$

D.3. **Solving the Problem.** The FOCs of T and NT firms yield:

$$L^{T,\ell} = \left(\frac{\gamma A^T}{w_\ell}\right)^{\frac{1}{1-\gamma}} = N^\ell$$

$$L^{NT,h} = \left(\frac{\gamma P A^{NT}}{w_h}\right)^{\frac{1}{1-\gamma}} = N^h$$

From here, we can solve for w_ℓ

$$w_\ell = \frac{\gamma A^T}{\left(N^\ell\right)^{1-\gamma}}$$

Note that w_ℓ is only a function here of model preliminaries, and is not a function of B. Thus $\frac{dw_\ell}{dB} = 0$.

Plugging the consumption demands, w_ℓ, and P into the equilibrium condition yields:

(D.6)

$$\left(N^\ell + N^h\right) B + N^\ell \left(\frac{\gamma A^T}{\left(N^\ell\right)^{1-\gamma}}\right) + N^h \left(w_h\right) = \frac{\frac{\left(N^h\right)^{1-\gamma}}{A^{NT}\gamma} w_h}{1-\alpha} A^{NT} \left(N^h\right)^\gamma$$

(D.7)
$$w_h = \frac{\gamma\left(1-\alpha\right)}{1-\gamma\left(1-\alpha\right)} \left(\frac{\left(N^\ell + N^h\right)}{N^h} B + \frac{N^\ell}{N^h}\left(\frac{\gamma A^T}{\left(N^\ell\right)^{1-\gamma}}\right)\right)$$

Finally, note that $\frac{dw_h}{dB} = \frac{\gamma(1-\alpha)}{1-\gamma(1-\alpha)} \frac{\left(N^\ell + N^h\right)}{N^h} > 0$. Thus $\frac{dw_h}{dB} > 0$ and $\frac{dw_\ell}{dB} = 0$ when the labor market is fully segmented

Appendix E. Data Appendix

E.1. **Household Survey Data.** Household level data are from several rounds of the National Sample Survey (NSS). Most of the analysis in the paper refers to rounds 64, 66 and 68. Round 64 was conducted from July 2007 until June 2008. Round 66 was conducted from July 2009 until June 2010. Finally, round 68 was conducted from July 2011 until June 2012, after the Andhra Pradesh crisis in October 2010. We also used the round 70 of the NSS (January 2013 - December 2013), in particular the Debt and Investment schedule.

We now discuss how household level variables are constructed from the National Sample Surveys, rounds 64, 66 and 68. All the questions refer to the questionnaire from Schedule 10 ("Employment, Unemployment and Migration Particulars").

Labor and Earnings Variables In round 64, labor information is from block 5, while for rounds 66 and 68 it is from block 5.3. Casual labor wages are calculated at the household level as the ratio between the sum of total weekly earnings across household members and the total number of days worked in the week. Earnings are in column 17 and worked days are in column 14. Wages and earnings are restricted to status 51 ("casual labor in non-public works"). Prime age individuals are those between 18 to 45 years old. We classify the work as agricultural if the 2-digit NIC-2004 code is 1, and as non-agricultural otherwise. Total weekly days worked correspond to the sum of column 14 among household members with activity status (column 4) below 72, so it excludes domestic activities and education time. Casual weekly days worked correspond to the sum of column 14 among household members with activity status 41 ("casual wage labor in public works other than NREG public works"), 42 ("casual wage labor in NREG public works"), or 51 ("casual labor in non-public works"). Household weekly labor earnings correspond to the sum of column 17 among all household members with activity status (column 4) below 72. A household has a member in unemployment if the status (column 4) equals 81 ("did not work but was seeking and/or available for work") for some household member. A household has any non-agricultural self employment if the status (column 4) is less or equal than 21 and the 2-digit NIC-2004 code is larger than 1 for some household member.

Consumption Variables From round 64, monthly household total consumption expenditure is the sum of the answers to items 16 ("sub-total (items 1 to 15)") and 21 ("sub-total (items 17 to 20)") of block 7 ("household consumer expenditure"), with the latter normalized to represent monthly expenditure, instead of yearly. Durable consumption expenditure is from the answer to item 20 of block 7, again scaled to reflect the monthly average in the past year. Non-durable consumption expenditure is given by summing item 16 with items 17-19 of block 7, the latter normalized to reflect the monthly average. From round

66, monthly household total consumption expenditure is the answer to item 40 of block 9. Durable consumption expenditure is the sum of items 29 to 37 of block 9, scaled to reflect the monthly average in the past year. Non-durable consumption is the sum of item 23 and the monthly equivalent of the sum of item 24 to 28. From round 68, monthly household total consumption expenditure is the answer to item 40 of block 8. Durable consumption expenditure is the sum of itens 29 to 37 of block 8, scaled to reflect the monthly average in the past year. Non-durable consumption is the sum of item 23 and the monthly equivalent of the sum of item 24 to 28. Finally, the poverty dummy is constructed by comparing per capita household total consumption with the state-round specific rural poverty line from the Planning Commission, Government of India, "Report of the Expert Group to Review the Methodology for Measurement of Poverty", 2014.

Household Size and Landholdings For any round, household size is the answer to item 1 of block 3 and household land holdings are from item 7 of block 3.

E.2. **Banking Data.** District-level banking data is from the Basic Statistical Returns of Scheduled Commercial Banks in India provided by the Reserve Bank of India (RBI). This information is available at `http://dbie.rbi.org.in/DBIE/dbie.rbi?site=publications#!9`. In particular, the data comes from Table 5.9., "District-Wise Classification of Outstanding Credit of Scheduled Commercial Banks".

E.3. **Poverty Data.** An indicator for whether a household is below the poverty line is constructed by comparing total per capita monthly consumption with the state-specific rural poverty lines presented in the document "Report of the expert group to review the methodology for measurement of poverty" (Government of India Planning Commission 2014). This report is available at `http://planningcommission.nic.in/reports/genrep/pov_rep0707.pdf`. See Table B1, pg. 28 and B2,B3,B4 pgs. 29-31. Values for 2007-08 are obtained by inflation-adjusting the 2009-10 values.

E.4. **Crop Yield Data.** District-level crop yield data is constructed from the Crop Production Statistics Information System, Directorate of Economics and Statistics, Ministry of Agriculture and Farmers Welfare (`http://aps.dac.gov.in/APY/Index.htm`). The crop index is constructed in a similar way as in Jayachandran (2006). For each district and each of the five crops, (Sugarcane, Rice, Groundnut, Wheat and Sorghum), we normalize yields to 1 in 2008 and take the weighted average of the logarithms. Weights are the revenue share of each crop. The only difference to the measure in Jayachandran is that we normalize the yields by the initial yields, instead of the average yield across all periods. Also, Jayachandran (2006) uses local prices in order to measure the revenue associated to each crop, while we use a national 2008 price index for each crop. The price indexes are available from FAOSTAT.

E.5. **Rainfall.** Rainfall data is from the Global Precipitation Climatology Center (GPCC), available at `http://www.esrl.noaa.gov/psd/data/gridded/data.gpcc.html`. The original dataset contains a 0.5x0.5 degree grid on monthly precipitation, which is interpolated from weather station data. For each district in our sample, we assign the rainfall of the grid point closest to the district centroid. Monthly rainfall is averaged at the year level. We construct rainfall shocks as in Jayachandran (2006). If rainfall in a year is above the 80-th percentile of the rainfall distribution for that district from 1950-2014, then the rainfall shock equals 1; if it is below the 20th percentile, the rainfall shock equals -1; otherwise, its value is zero.

E.6. **Political Parties.** The political party variable is defined as the party affiliation of the chief minister of the state in September, 2010 (on the eve of the crisis). Party affiliation information was collected from states' websites and google searches.

E.7. **Road Travel Time.** The time travel between Indian districts is from Allen and Atkin (2016). The dataset is available at the authors'websites. We use the travel time calculated for the year 2011.

E.8. **Hand-collected MFI balance sheet data.** We partnered with MFIN, the primary trade organization of for-profit MFI-NBFCs (non-bank, financial corporations). We worked with MFIN to ask each of their 42 members for total principal outstanding on active loans, by district, at annual intervals between September 2008 and September 2012. In total 25 of MFIN's 42 member organizations agreed to share their data for the study.

APPENDIX F. CALIBRATION APPENDIX

Here, we provide details about the calibrations used in Section 6.3. We allow both channels, the aggregate demand as well as the investment channel, to operate. Households are heterogeneous: some are unconstrained entrepreneurs (who borrow from sources other than microfinance), others are permanently constrained workers (who cannot borrow from microfinance), while we also allow for some individuals to be potential microfinance customers. To match the previous literature, we allow some microfinance borrowers to have a consumption motive, while others use microfinance to start a productive business.

F.1. **Workers.**

All households are endowed with a labor endowment in both the tradable and non-tradable sector. Worker households supply (ℓ_T, ℓ_{NT}) inelastically to each market.

Worker households (denoted by type ω) maximize utility, subject to the within-period budget constraints:

$$\max_{C_t^{T,\omega}, C_t^{NT,\omega}} C_1 + \beta C_2$$
$$s.t. C_t = \left(C_t^{T,\omega}\right)^{\alpha}\left(C_t^{NT,\omega}\right)^{1-\alpha}$$
$$C_t^{T,\omega} + PC_t^{NT,\omega} \leq \ell_T w_{T,t} + \ell_{NT} w_{NT,t} + y_t + B_t - RB_{t-1}$$

where β is the household's discount rate, $w_{k,t}$ is the period t wage in sector k, y_t is non-labor income, and B_t is the amount borrowed, discussed below. R is the interest rate on last period's borrowing. Households are fully savings constrained and can only move money between periods by borrowing, if available.

Given the Cobb-Douglas structure, consumers will spend constant budget shares on each good each period:

$$C_t^{T,\omega} = \alpha\left(\ell_T w_{T,t} + \ell_{NT} w_{NT,t} + y_t + B_t - RB_{t-1}\right)$$
$$C_t^{NT,\omega} = \frac{1-\alpha}{P_t}\left(\ell_T w_{T,t} + \ell_{NT} w_{NT,t} + y_t + B_t - RB_{t-1}\right)$$

where P_t is the relative price of the non-tradable good. (We normalize the price of the tradable good each period to 1).

F.2. **Entrepreneurs.**

Some households are endowed with entrepreneurial ability in one of two sectors, $S \in \{T, NT\}$. If they choose to operate a business, the production functions are:

$$Y^T = A^T \left(L^{T,\ell}\right)^\gamma$$
$$Y^{NT} = A^{NT} \left(L^{NT,h}\right)^\gamma$$

where $\gamma < 1$. Note here, that for simplicity, we assume a fully segmented labor market. As before, entrepreneurs maximize profits, $\Pi_t^S = P_t^S Y_t^S - L_t^S w_S$, where $L_t^S w_S$ is shorthand for the total input costs of the sector-specific type of labor and P_t^S is the price of the good produced by sector S in period t.

We assume that running a business in either sector requires the entrepreneur's full human capital. Therefore, potential-entrepreneur households must choose whether to run a business or to supply their labor to the wage labor market. Finally, we assume that opening a business for the first time requires the payment of a fixed cost $\bar{B}$. We assume that unconstrained entrepreneurs are all incumbents and have paid the cost in the past.

Thus, unconstrained entrepreneurs maximize the same objective function as the workers, subject to an entrepreneur and sector-specific budget constraint:

$$C_t^{T,E:S} + PC_t^{NT,E:S} \leq \Pi_{S,t} + y_t$$

We need to check that in equilibrium, all unconstrained entrepreneurs receive more utility from running their business than from closing the business and opting into the wage labor market.

F.3. **Microfinance Borrowing.** While in Section 2.2, we considered small changes in the quantities of microfinance available to borrowers, in reality, the AP Crisis led to a large discrete decrease in the loan size. We model the change in credit supply for as a fall in B from $\bar{B}$ to 0. As shown above in the worker's budget constraint, consumption borrowing increases resources in period 1 by B at a cost of RB in the future.

Microfinance lenders generally target borrowers in the middle of the village income distribution. The poorest individuals are viewed as unable to repay, while the richest households are already less constrained and would have lower demand for credit. Consistent with the empirical facts, we allow for only a fraction of constrained individuals to be able to avail themselves of microcredit.

We also allow there to be some potential entrepreneurs who have the ability to enter entrepreneurship, but who have not yet paid the fixed cost to set up the business. For these constrained entrepreneurs, they can use the loan to pay this cost. This leads to the following budget constraint for the $EB : S$ types (entrepreneurial borrowers in sector S).

$$C_t^{T,EB:S} + PC_t^{NT,EB:S} \leq \Pi_{S,t} + y_t - RB_{t-1}$$

For an interior microfinance borrowing equilibrium, three conditions must be satisfied:

(1) Borrowers with a consumption motive must have a higher utility from borrowing the fixed quantity $\bar{B}$ than from borrowing 0 and consuming all labor and non-labor earnings.
(2) Constrained T entrepreneurs must prefer to borrow to start a business than to borrow for consumption.
(3) Constrained NT entrepreneurs must prefer to borrow to start a business than to borrow for consumption.

F.4. **Types.** To summarize the above discussion, the model leads to six different types of agents:

(1) Unconstrained T Entrepreneurs ($E : T$)
(2) Unconstrained NT Entrepreneurs ($E : NT$)
(3) Partially Constrained T Entrepreneurs ($EB : T$)
(4) Partially Constrained NT Entrepreneurs ($EB : T$)
(5) Partially Constrained Workers (ω^B)
(6) Fully Constrained Workers (ω)

We can then define the fraction of agents of each type τ by θ_τ. The following objects are particularly important: the total fraction of worker households (both borrowers and non-borrowers) θ_ω; the total fraction of T entrepreneurs θ_T; and the total fraction of NT entrepreneurs θ_{NT}. Note $\theta_\omega + \theta_T + \theta_{TE} = 1$. The weights will change as a function of the microfinance regime.

F.5. **Equilibrium Conditions.** As in the pure model of aggregate demand, in equilibrium, the labor markets and the non-tradable product market must clear:

$$\theta_T L^{T,\ell} = \theta_\omega \ell_T$$
$$\theta_{NT} L^{NT,h} = \theta_\omega \ell_N T$$
$$\sum_\tau N^\tau C^{NT,\tau} = \theta_{NT} A^{NT} \left(L^{NT,h}\right)^\gamma$$

As mentioned above, it also needs to be the case that entrepreneurs of both types prefer to use their human capital to run a business rather than to supply labor to the market.

F.6. **Parameter Assumptions.** To calibrate the model, we have to make numerous simplifying assumptions. We describe our assumptions by family of parameters:

Production function parameters. $\left(\gamma, A^T, A^{NT}\right)$: We set $A^T = A^{NT} = 4.6$. This value is chosen to match the TFP parameter in Buera et al. (2017). We set the returns to scale parameter, $\gamma = 0.535$, again using the value from Buera et al. (2017).

Household parameters. $(\ell_T, \ell_{NT}, \alpha, y_1, y_2)$: We set $\ell_{NT} = 89.2216, \ell_T = 104.7384$. The relative endowments of labor in the tradable and non-tradable sectors are set to match the share of casual labor hours supplied in agriculture (53.6%) and non-agriculture (46.4%) in the 2012 NSS in control (unexposed) districts.[32]

We set the weight on tradables in the utility function to $\alpha = 0.55$. This is the share of total household expenditure that is food and tobacco in the 2012 NSS in control (unexposed) districts. Finally, we set $y_1 = 22.4, y_2 = 60$. The high value of y_2 relative to y_1 is chosen to capture, in a reduced form way, the factors that make households desire consumption credit.[33]

Types. θ_τ We assume that 25% of households are unconstrained entrepreneurs. Given the unavailability of detailed business information, we make the assumption that 50% of businesses are tradable and 50% are nontradable. Finally, the share who borrow from microfinance is set to $.0932$, which is the share of households who have a microloan in the NSS 70 data, using the broad definition of microfinance, namely non-collateralized formal lending from a non-bank source. As we discuss in Section 4.4, this is the measure that best captures households' total borrowing from microfinance sources.

Borrowing parameters. $\left(\bar{B}, R\right)$: We set the size of a microloan to $\bar{B} = 16$, chosen to be 58% of economy-wide avergage labor earnings, which is the size of a typical microloan as a share of labor earnings in the 2012 NSS in control (unexposed) districts. This number appears large because entrepreneurial households report zero labor earnings and thus bring down the average. We set $R = 1.15$. A typical Indian microloan carries a nominal APR of approximately 25%, and inflation was approximately 10%.

[32]In the calibrated version of the model we assume full segmentation between the two labor markets, so this is equivalent to choosing the endowments of low- and high-skilled labor.

[33]These factors could include rational expectations of higher income in the future, but also myopic/time-inconsistent preferences or lack of understanding of the terms of microloans.