The Moneylender as Middleman: Formal Credit Supply and Informal Loans in Rural India

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Abstract

Informal moneylending continues to flourish across the developing world, despite expansions in the formal financial sector. In this paper, I investigate whether the two sectors compete, or are embedded in a vertical relationship in the context of non-agricultural lending. I find that weather-induced increases in incomes raise household borrowing from informal sources primarily due to higher borrowing for purchases of durable goods. This is accompanied by an increase in informal loan interest rates, suggesting a demand response. However, this increase in transacted loans is significantly lower when districts also experience a contraction in the supply of formal credit. To explain this, I turn to primary and secondary survey data, which indicate that moneylenders use formal loans as lending capital, increasing such borrowing when met with shortfalls. Together, these results suggest that informal moneylenders play an intermediating role between borrowers and formal financial institutions, contributing to their persistence in the consumption credit landscape.

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1 Introduction

Underbanked populations across the world are often forced to resort to high-interest non-institutional loans, or rely on their networks for their consumption credit needs. High-interest options range from payday loans in the United States, to loans from informal moneylenders across South Asia. The prevalence of such lending has prompted regulation,[1] and countries across the developing world have looked to expansions in formal finance to reduce high-interest informal debt – which is often considered usurious by policy-makers. Despite this, informal credit markets have continued to thrive (Bell, 1990; Conning, 1996; Guirkinger, 2008; Hoff & Stiglitz, 1998; Karaivanov & Kessler, 2018; Kochar, 1997; Mosley, 1999; Siamwalla et al., 1990).

The literature on credit in developing countries has either assumed that the formal and informal credit sectors compete (Bell, Srinivasan, & Udry, 1997; Giné, 2011; Jacoby, 2008; Jain, 1999; Kochar, 1997), or that informal moneylenders on-lend institutional loans (Floro & Ray, 1997; Hoff & Stiglitz, 1998; Jacoby, 2008). However, most such analyses focus on production loans, and most analyses of consumption credit do not speak to the interaction between the sectors. In this paper, I explore the interaction between the two sectors in rural India. I focus on borrowing outside the main agricultural season and answer the following questions: (1) How does household borrowing respond to transitory income shocks, and how do these responses alter the terms at which informal loans are contracted? (2) Does the availability of formal credit impact an informal lender's ability to meet unanticipated increases in demand?

I combine detailed nationally representative household and loan-level survey data; data from firms, lenders and the banking system; and a primary survey of moneylenders, and a subset of village heads and borrowers in their 'catchment areas' to answer these questions. I exploit the seasonality of agriculture and variation in realized rainfall to estimate the impact of weather-induced income shocks on household borrowing, and establish that this represents a shock to household demand for credit in the non-agricultural season. I then use quasi-random variation in bank credit availability from a shift-share measure of changes in credit supply (Greenstone, Mas, & Nguyen, 2019) to designate which districts experience a reduction in formal credit. The interaction between these two shocks allows me to establish the nature of the relationship between

[1] Anti-usury laws exist across countries, and extant laws regulating moneylending in India date back to as early as 1940 (the Telangana Area Money Lenders Act, 1349F and the Bengal Money Lenders Act, 1940)

the informal and formal credit sectors. I supplement these results with findings from the primary survey, which allows me to directly address moneylenders' decisions and the current structure of moneylending markets.

This paper has three main sets of findings. First, when rural households experience an unanticipated increase in income, measured by an increase in monsoon rainfall in a district, borrowing from informal moneylenders increases. This is accompanied by an increase in the interest rates at which informal loans are contracted. The increase in interest rates on informal loans is not driven by changes in the composition of borrowers as the same borrower is likely to have taken more expensive loans when demand went up. Thus, this represents an increase in demand, rather than a change in supply. Consistent with this, moneylenders in the primary survey report increasing interest rates when there are increases in demand. The higher demand for informal credit following a positive income shock is driven by an increase in loans for purchases of durable goods or consumption assets, likely due to indivisibilities in such goods or assets which require lump-sum expenditures.

Second, when districts experience a contraction in formal credit, moneylenders are no longer able to extend additional loans during periods of increased demand. Both national sample survey data and primary survey data indicate that moneylenders themselves often borrow from both formal and informal sources in order to extend loans to their clients. Thus, when faced with a contraction in lending capital available to them, moneylenders are unable to lend more than their 'business as usual' amounts. Together, these results suggest that moneylenders do have a vertical relationship with formal lenders, and while they do not exclusively source capital from them, formal financial institutions facilitate smoother functioning of the informal market. Finally, in districts where households are unable to take additional loans from moneylenders following an increase in incomes, households borrow more interest-free loans from friends or relatives. These interest-free loans tend to be smaller, and reflect informal reciprocal relationships.

This paper contributes to the literature on the functioning of informal credit markets, and the interaction between formal and informal credit institutions (Bell, 1990; Bell et al., 1997; Bose, 1998; Casson, Giusta, & Kambhampati, 2010; Conning, 1996; Floro & Ray, 1997; Giné, 2011; Guirkinger, 2008; Hoff & Stiglitz, 1990, 1998; Jain, 1999; Karaivanov & Kessler, 2018; Kochar, 1997; Mansuri, 2007; Mosley, 1999; Siamwalla et al., 1990). One strand of this literature sees the two sectors as competing, possibly due to credit constraints in the formal sector; while the other argues that the informal market primarily on-lends formal credit. Madestam (2014) attempts to reconcile these two motives for co-existence of the two sectors by arguing that one or the other might predominate depending on concentration of wealth and the strength of legal institutions in a given context. The set-up in this paper explicitly allows for both competing effects and channeling of funds, and finds evidence consistent with a vertical relationship between the sectors. In addition, this paper focuses on the implications for consumption credit, rather than borrowing for production. This is relevant in the present context in India, which has seen large expansions in formal credit for agriculture and production through priority sector lending and schemes such as the Kisan Credit Card.[2] As a result, over 84% of informal loans (both interest-free and interest-bearing) were taken for non-productive purposes in 2013 (NSSO, 2013a). Relatedly, more recent work demonstrates how informal lenders respond to demand shocks, or competitive pressure (Berg, Emran, & Shilpi, 2013; Demont, 2016; Hoffmann, Rao, Surendra, & Datta, 2020; Mallick, 2011; Mookherjee & Motta, 2016). With its finding that informal lenders do increase interest rates when faced with increases in demand, this paper adds to this body of work.

Household purchases of durable goods and assets could also bolster their ability to deal with unexpected negative shocks, and in this, the paper's findings relate to the extensive literature on risk-coping in agrarian economies. Tests of the permanent income hypothesis in developing country contexts (Friedman, 1957; Wolpin, 1982) indicate that rural households save a larger fraction of transitory income than permanent income (Paxson, 1992). The literature also indicates that in the face of negative shocks, households rely on formal and informal insurance, informal credit, savings, sales of durable assets, labor supply and seasonal migration as strategies to cope with risk and smooth consumption (Coffey, Papp, & Spears., 2015; Eswaran & Kotwal, 1989; Kochar, 1999; Ligon, 2005; Morten, 2019; Paxson, 1992; Rosenzweig & Binswanger, 1993; Rosenzweig & Stark, 1989; Rosenzweig & Wolpin, 1993; Udry, 1994). With its analysis of household borrowing responses to agricultural productivity shocks, this paper's findings also relate to the literature investigating the impact of such shocks on rural economic outcomes in India, such as impacts on wages for agricultural labor, participation in agricultural and non-agricultural labor, and firm outcomes (Colmer, in press; Emerick, 2018; Jacoby & Skoufias, 1998; Jayachandran, 2006; Kaur, 2019;

[2]Kisan is the Hindi word for farmer.

Santangelo, 2019; Wolpin, 1982).

Finally, a strand of literature has considered the impacts of an expansion in formal credit on growth and welfare. Findings from India suggest that early bank expansions (in the 1950s) disrupted the informal saving-by-lending institutions as savings in formal institutions became available (Wolcott, 2017). Later expansions in unbanked regions decreased poverty and increased agricultural output (Burgess & Pande, 2005), increased consumption inequality (Kochar, 2011), and bank nationalization in the 1980s slowed employment gains in trade and services (Cole, 2009). More recent bank branch expansions (since 2005) also increased local GDP (Young, 2019), while financial inclusion initiatives such as the banking correspondent system allowed rural households to increase their savings (Kochar, 2016). Relatedly, India has also seen a spread of bank-linked self-help group programs, as well as microfinance institutions (MFIs), which could be thought of as being in-between formal and informal lenders in a continuum from banks to friends & relatives. Examples of the extensive research on their functioning and impacts both in India and other developing country contexts are Angelucci, Karlan, and Zinman (2015); Attanasio, Augsburg, de Haas, Fitzsimons, and Harmgart (2015); Augsburg, Haas, Harmgart, and Meghir (2015); Banerjee, Duflo, Glennerster, and Kinnan (2015); Banerjee, Karlan, and Zinman (2015); Berg et al. (2013); Breza and Kinnan (2018); Crépon, Devoto, Duflo, and Parienté (2015); deJanvry, McIntosh, and Sadoulet (2010); Demont (2016); Ghatak and Guinnane (1999); Hoffmann et al. (2020); Karlan and Zinman (2009, 2010); Meager (2019); Tarozzi, Desai, and Johnson (2015) among many others. This paper adds to both sets of literature by evaluating the impact of changes in the intensive margin of formal credit supplied to a region, where other work evaluated changes in the extensive margin. While the paper's findings suggest no direct significant impact on rural household borrowing, contractions in formal credit supply reduce the ability of informal lenders to respond to demand shocks.

The remainder of this paper proceeds as follows – section 2 describes both the demand and supply sides of the credit market in rural India, section **??** presents the theoretical framework, section 5 describes the data and empirical strategy used in the paper, section 6 discusses the results, and section 8 concludes.

2 Background

Household Borrowing in Rural India

Around half of all rural households in India are indebted,[3] and the median indebted household owed approximately ₹40,000 to its creditors in 2012-13.[4] Households across all levels of wealth borrow (Banerjee, 2003; NAFIS, 2017), and they do so from both institutional and non-institutional sources. On average, institutional loans are larger than non-institutional loans; but tend to have lower interest rates than interest-bearing non-institutional loans (Figure 2). Non-institutional (or informal) loans are either interest-free or interest-bearing, and the interest-bearing loans are usually from professional moneylenders, pawnbrokers, landlords, input-traders, local shop-keepers or friends and relatives, while interest-free loans tend to be from friends, relatives or patrons (Dréze, Lanjouw, & Sharma, 1998; ICRISAT, 2014). Despite there being no explicit interest charged, these loans come with implicit interest in the form of obligatory reciprocity (Ambrus, Mobius, & Szeidl, 2014; Hayashi, Altonji, & Kotlikoff, 1996; Ligon, 2005; Ligon & Schechter, 2012; Udry, 1994). In 2013, 31% of all loans transacted were interest-bearing non-institutional loans, while 20% of all loans were interest-free (NSSO, 2013b).

Around 70% of all loans are reported as being taken for non-productive needs – consumption expenditures, purchases of assets and durable goods, education and medical expenses (NAFIS, 2017; NSSO, 2013a).[5,6,7] Loans for different purposes tend to be from different sources – loans for production (both agricultural and non-agricultural) are more likely to be from institutional sources, while loans for consumption are more likely to be from non-institutional sources (NSSO, 2013a). More specifically, pawnbrokers might help smooth income, self-help groups and banks might provide loans allowing economic investments, local moneylenders might provide large loans for ceremonies and life-cycle events, and 'mobile lenders' might help with emergency loans

[3] 53% of rural households were indebted in 2012-13 (NSSO, 2013b); 47.4% of them were indebted in 2016-17 (NAFIS, 2017); and this was up from 43% of households in 1993 (NSSO, 2013b)

[4] This is in 2012-13 prices, or Rs. 56,381 in current rupees; and is equivalent to $730 in 2012-13 USD or $796 in current USD

[5] 74% of all loans were for non-productive needs in 2016-17 (NAFIS, 2017)

[6] This is 70% by number of loans and 68% by amount borrowed in 2012-13, (NSSO, 2013b)

[7] This is different from findings in earlier studies such as Timberg and Aiyar (1984), Banerjee (2003) and in NSSO (2013b) data for the year 1991 – all of which indicate that production is main reason households borrow

(Guérin, Roesch, Venkatasubramanian, & D'espalliers, 2012).[8,9]

Non-institutional lenders

Non-institutional lenders,[10] or moneylenders, in developing countries have long been thought of as being monopolistically competitive, since a lender who has "screened an individual and assessed the likelihood of repayment, is an imperfect substitute for any other moneylender" (Hoff & Stiglitz, 1998). In a primary survey of 140 moneylenders in Telangana (Telangana Survey, 2020), I find that 50% of lenders surveyed lend to a new borrower only if someone they know vouches for them; 27% lend based on a subjective notion of creditworthiness;[11] 17% only lend to a new borrower if they own assets (land, gold or a house); and 5% do not lend to new borrowers. This is consistent with older analyses of informal moneylending which suggest that informal lending markets are segmented (Aleem, 1990; Hoff & Stiglitz, 1990) – and it appears that this is along caste and class lines (Khanna & Majumdar, 2018; Telangana Survey, 2020). Multiple lenders operate in a village market, and residents of the median village in the sample (Telangana Survey, 2020) borrowed from 8 different lenders inside, and 2 lenders outside, the village – with each lender lending to around 10 borrowers in the village.

Non-institutional lenders offer loans at interest rates between 6 and 240% annually (Hoffmann et al., 2020; ICRISAT, 2014; NSSO, 2013b; RBI, 2012; TNSMS, 2009), and larger loans tend to have lower interest rates (Banerjee, 2003; Dasgupta, Nayar, & Associates, 1989; NSSO, 2013b). These loans may have interest rates that are daily,[12] weekly, monthly or yearly (ICRISAT, 2014; Jeevika, 2014). While loans do have approximate standard durations (often between a few months and one year) (Telangana Survey, 2020, Figure 3), they can also evolve over time according to the constraints of borrowers and lenders (Guérin et al., 2012). Non-institutional loans tend to have low levels of default (Banerjee, 2003; Timberg & Aiyar, 1984) – and 36% of lenders in the Telangana Survey (2020) sample reported no defaulters, with a total of 95% of lenders (cumulative) reporting

[8] Guérin et al. (2012) observe this in Tamil Nadu, but this is also borne out in qualitative work in Bihar.

[9] The difference between 'mobile lenders' and other moneylenders appears to be that the latter are well-known, established or powerful people in the village and failing to repay such loans leads to a larger loss of status than other types of lenders.

[10] Here I consider non-institutional lenders who provide interest-bearing loans.

[11] Responses indicate this is based on 'family background' or whether the potential borrowers are 'good'; and occasionally, lenders report lending with 'confidence' in addition to the former.

[12] An example of daily interest rates is the case of the street vendors who borrow in the morning and return loans at the close of the day's business in Karlan, Mullainathan, and Roth (2019)

that fewer than 25% of borrowers ever defaulted.[13] Around 89% of lenders (in Telangana Survey, 2020) reported that less than a quarter of borrowers ever repaid late. Default and delayed payments are dissuaded by the mechanisms lenders have in place to deal with these eventualities. For instance, 58% of lenders (in Telangana Survey, 2020) either required land or property documents,[14] gold or other assets, promissory notes or a co-signer.[15] In cases where repayment is delayed, 75% of lenders report charging additional interest, while 17% allow additional time to repay. In cases where lenders fear default, apart from additional interest or taking possession of collateral, lenders also report resorting to coercion or social pressure through the *Panchayat* or co-signer. A few lenders report seizing durables from borrowers' homes, and one lender reported potentially sending goons after the borrower (Telangana Survey, 2020).

Recent empirical evidence suggests that interest rates charged by local moneylenders respond to competitive pressure or to demand shocks, though the evidence is mixed.[16] Specific to the Indian context, Demont (2016) finds that whether informal interest rates rise or fall following entry of microfinance institutions or self-help groups depends on the size and risk-composition of the market that continues to borrow from informal lenders (resulting in a U-shaped relationship between informal interest rates and SHG coverage overall). Hoffmann et al. (2020) find that informal interest rates decline and fewer moneylenders operate in a village following the entry of a self-help group program – suggesting a response to competitive pressure.[17]

Institutional lenders

Institutional credit from banks in India is planned and targeted. Each state in India has a 'State Level Bankers Committee' which determines its Annual Credit Plan (ACP) at the start of the fiscal

[13] This is also verified by qualitative fieldwork in Bihar by my colleague, Shruti Majumdar, who finds that there is no notion of default since there is always some way repayment is worked out – either through compounding interest rates after an initial period, or an agreement relating to a labor or in-kind transaction.

[14] Property is either a house, or rarely, a vehicle

[15] The co-signer is referred to as a witness or middleman, who might be called on to repay the loan upon default.

[16] In Bangladesh, Mallick (2011) and Berg et al. (2013) find that interest rates on informal loans increase when microfinance institutions enter a village market since the borrowers that continue to borrow from informal lenders are the ones who are less creditworthy. While, Kaboski and Townsend (2012) find no statistically significant impact of microfinance lending on informal lender rates in Thailand.

[17] This is also suggested in media reports of moneylenders lowering interest rates following a fall in demand for loans due to the implementation of Generalized Sales Tax (GST) in India in 2017. "GST crashes even money lenders' usurious rates," by Saikat Das (Economic Times).
Accessed on 11/11/2019 at: https://economictimes.indiatimes.com/markets/stocks/news/gst-crashes-even-money-lenders-usurious-rates/articleshow/60919609.cms?from=mdr

year. This plan is an aggregate of district level plans which in turn aggregate plans at the bank branch level. In addition, the Reserve Bank of India requires that all banks lend 40% of bank credit to the 'priority sector' – agriculture, small scale industries and 'weaker sections' (Cole, 2009; RBI, 2018b) – and this is part of the ACPs.[18]

The median district in India had 10,000 adults per bank branch in 2014 (RBI, 2014), and the RBI continues to incentivize banks to open branches in underbanked districts.[19] Formal banks channel credit to rural populations, in particular, through the Kisan Credit Card (KCC) scheme,[20] and aim to facilitate financial inclusion through zero-balance bank accounts and banking correspondents for villages with no nearby bank branches (Kochar, 2018). Other channels through which credit is extended are through MFIs;[21] and the SHG-bank linkage program,[22] through which SHGs can borrow from banks under 'priority sector' lending targets. However, MFI and SHG loans formed only about 9% of loans taken and 3% of the amount borrowed by rural households in 2013 (NSSO, 2013b).[23]

3 A Stylized Model of Informal Lending

4 A Model of Household Borrowing and Informal Moneylending in Rural India

I outline a model of a rural economy with borrowers and lenders to derive testable predictions about the relationship between institutional and non-institutional credit. While households in real-world rural settings borrow for both production and consumption – to make the model

[18] As per the RBI, the following categories of borrowers fall qualify as 'weaker sections' – small and marginal farmers, artisans, village and cottage industries, beneficiaries under government sponsored schemes, scheduled castes and scheduled tribes, self help groups, distressed farmers indebted to non-institutional lenders, persons with disabilities, individual women beneficiaries up to Rs. 0.1 million. The 40% target is pegged to the Adjusted Net Bank Credit in the preceding year

[19] The current policy does this by allotting licenses for branches in metropolitan areas only if banks also open a branch in an underbanked district. This is different from the social banking era that Burgess and Pande (2005) analyze

[20] The KCC offers credit to farmers for agricultural investment, and to meet consumption needs over the agricultural season

[21] Microfinance institutions often operate as RBI-regulated Non-Banking Financial Institutions (NBFCs) (RBI, 2018a) and lend either to individual clients, or adopt the self-help group structure.

[22] self-help groups (SHGs) consist of groups of 10-15 individuals (usually women) who commit to weekly savings, and have access to loans through the group (Hoffmann et al., 2020).

[23] This had gone up to about 20% of loans taken and 10% of amount borrowed by 2017 (NAFIS, 2017) which is after the period considered in the main analyses in this paper.

more tractable, I focus on loans for consumption and agents' decisions following the main agricultural season.[24] The model draws on earlier work relating to household consumption and loan decisions (Hanemann, 1984; Ligon & Worrall, 2020; Ngo, 2018, etc), as well as theoretical literature on informal lending (Hoff & Stiglitz, 1998; Karaivanov & Kessler, 2018, etc).

4.1 Setup

I assume that the local rural economy consists of a continuum of borrowing households, with households indexed by their endowment, θ. This endowment could be thought of as a household's landholdings or wealth, and is distributed over the interval $[\theta_L, \theta_H]$ according to the function, $F(.)$ or density, $f(.)$. I consider a two-season deterministic horizon – this allows me to focus on the relationship between borrowing for durables and income. However, this set-up does not allow uncertainty to play a role in borrowing, and so I cannot address other motives for borrowing (for example, borrowing to enable precautionary savings). Each household derives a per-season utility, $u(.)$ (with $u(0) = 0$, $u'(.) > 0$, and $u''(.) < 0$), from the consumption of a good, c_t. A household may also choose to purchase a durable good, D, in season 1, and in doing so, benefits from the services, d, provided by the durable over both seasons. The good, c_t, is the numeraire good,[25] and the price of the durable good, D, is $p > 1$.

Each household earns a per-season income, $R\theta$, which depends on its endowment and an exogenous productivity parameter, R. R could be thought of as the monsoon realization in a given year, which impacts both agricultural and non-agricultural incomes alike (Table 3). Households also choose whether, and how much to borrow in the first season, and choose between institutional loans, b_B, interest-bearing non-institutional loans, b_m, and interest-free non-institutional loans, b_f. Loans from institutional sources bear interest, r_B, while interest-bearing non-institutional loans cost r. Though interest-free non-institutional loans bear no explicit interest, they do come with *implicit* interest in the form of necessary reciprocity or social obligations (Ambrus et al., 2014; Hayashi et al., 1996; Ligon, 2005; Ligon & Schechter, 2012; Udry, 1994), represented in the model as a utility cost, $\delta(\theta)$, in season 2. In this set-up, consumption loans from institutional sources tend to be cheaper than loans from non-institutional sources, but are only available to relatively

[24]The rain-fed *kharif* season in India, concurrent with the annual monsoon.

[25]I assume that the price remains unchanged across the two-seasons.

wealthier households because they require large collateral.

Assumption 1. *Only households with an endowment greater than a threshold, $\bar{\theta}$, are able to borrow from institutional sources for consumption.*

These households always choose an institutional loan over a non-institutional loan since they are cheaper, i.e., $r_B < r$.

4.1.1 Demand for Informal Credit

For a household that borrows from a moneylender, its utility across the two seasons is $U_{ml} = u(c_1) + d\mathbb{1}\{D = 1\} + \beta\Big[u(c_2) + d\mathbb{1}\{D = 1\}\Big]$. The exogenous productivity parameter, R, is realized at the start of season 1, and each household earns $R\theta$ in both seasons. A household may also borrow in season 1, and in the case of interest-bearing non-institutional loans (or moneylender loans), its consumption is given by:

$$c_1 + p\mathbb{1}\{D = 1\} = R\theta + b_{ml}$$
$$c_2 = R\theta - rb_{ml}$$

Assumption 2. *Households are not able to obtain interest-free non-institutional loans to purchase durables.*

In the case of interest-free non-institutional loans, the household also bears a utility cost, $\delta(\theta)$, which depends on the household's endowment and reflects potential obligations or reciprocity in the future ($\delta(.)$ is an invertible function, with $\delta'(.) > 0$ and $\delta''(.) > 0$). So, the household's utility is $U_f = u(c_1) + \beta\Big[u(c_2) - \delta(\theta)\Big]$, and its consumption is given by:

$$c_1 = R\theta + b_f$$
$$c_2 = R\theta - b_f$$

Assumption 3. *The cost of defaulting on either interest-free or interest-bearing non -institutional loans is high enough to prevent default for all loan sizes, so $\forall\ \theta$, $U_{ml}(repay) > U_{ml}(default)$ and $U_f(repay) > U_f(default)$.*

This assumption is realistic, since moneylenders report very low default rates, and borrowers report that penalties for default are high enough to prevent default (Telangana Survey, 2020); and in fact, over 94% of lenders surveyed report that default rates are between 0 and 25% (the data does not allow further disaggregation). To further simplify the model, I assume that $u(.)$ is the natural log function. A household's demand for a moneylender loan is then given by,

$$b_{ml}^{*} = \frac{(1-\beta r)}{r(1+\beta)} R\theta + \mathbb{1}\{D=1\}\frac{\beta r}{r(1+\beta)} p, \tag{1}$$

while its demand for an interest-free loan is given by,

$$b_{f}^{*} = \frac{(1-\beta)}{(1+\beta)} R\theta \tag{2}$$

Proposition 1. *Only households with an endowment below $\underline{\theta}$ borrow interest-free non-institutional loans, while those with an endowment above $\underline{\theta}$ borrow interest-bearing non-institutional loans. $\underline{\theta}$ is the endowment where the cost of borrowing from either are equal, i.e.,* $\delta(\theta) = \frac{(1+\beta)}{\beta}\ln\left[\frac{2}{1+r}\right] + \frac{1}{\beta}\ln r$ *or* $\underline{\theta} = \delta^{-1}\left[\frac{(1+\beta)}{\beta}\ln\left[\frac{2}{1+r}\right] + \frac{1}{\beta}\ln r\right]$.

Proof. See Appendix A.3. ■

Proposition 2. *Households that borrow from moneylenders choose to purchase the durable good when* $\theta \geq \hat{\theta} = \frac{e^{d}}{(e^{d}-1)}\frac{r}{(1+r)}\frac{p}{R}$.

Proof. See Appendix A.3. ■

Based on these household decisions, the total demand in the local economy for interest-bearing non-institutional loans, or moneylender loans, is given by:

$$L^{*} = \int_{\underline{\theta}}^{\hat{\theta}} b_{m}^{*} f(\theta) d\theta + \int_{\hat{\theta}}^{\bar{\theta}} b_{m,d}^{*} f(\theta) d\theta \tag{3}$$

Proposition 3. *Total demand for moneylender loans is* $L^{*} = \frac{R(1-r\beta)}{r(1+\beta)}\left[\bar{\theta}F(\bar{\theta}) - \underline{\theta}F(\underline{\theta}) - \int_{\underline{\theta}}^{\bar{\theta}} F(\theta)d\theta\right] + \frac{\beta p}{(1+\beta)}\left[F(\bar{\theta}) - F(\hat{\theta})\right]$.

Proof. See Appendix A.3. ■

4.1.2 Supply of Informal Credit

I now restrict attention to the supply of interest-bearing informal credit (loans from informal moneylenders); and following Hoff and Stiglitz (1998), I consider a monopolistically competitive market. Moneylenders tend to offer a menu of interest rates to their borrowers, depending on how urgently loans are required, or the loan purpose. A caveat here is that I abstract away from these factors in this model, and the interest rate here could be thought of as an average within this menu.

Assumption 4. *Lenders are endowed with liquid capital, K, and a production technology, $B(.)$ such that $B(0) = 0$, $B'(.) > 0$, $B''(.) < 0$. There are N_L such lenders in this rural economy, each earning zero profit in the long-run equilibrium.*

Lenders can also borrow, G, from institutional sources, and either lend, invest in $B(.)$, or both. $B(.)$ is scaled up or down by the exogenous productivity parameter, R. A lender that lends, l, in the informal credit market, receives a return of rl in the following season. The lender also invests $K + G - l$ in production, which yields $R \times B(K + G - l)$ in the following season. I consider the symmetric case with N_L identical lenders. Each lender's profit function is defined by,

$$\Pi = rl + RB(K + G - l) - r_B G \tag{4}$$

where $l = \frac{L}{N_L}$, and L is determined by the household's decisions above. Each lender, thus, faces a demand of:

$$l = \frac{L}{N_L} = \frac{1}{N_L} \left\{ \frac{R(1 - r\beta)}{r(1 + \beta)} \left[\bar{\theta} F(\bar{\theta}) - \underline{\theta} F(\underline{\theta}) - \int_{\underline{\theta}}^{\bar{\theta}} F(\theta) d\theta \right] + \frac{\beta p}{(1 + \beta)} \left[F(\bar{\theta}) - F(\hat{\theta}) \right] \right\}$$

In addition, as a result of monopolistic competition, lenders make no economic profit. The zero profit condition is defined by,

$$rl + RB(K + G - l) - r_B G = RB(K + G) - r_B G \tag{5}$$

Proposition 4. *In the symmetric equilibrium, each lender chooses an interest rate, r^*, that satisfies*

$$\frac{R(1-r\beta)}{r(1+\beta)}\left[\bar{\theta}F(\bar{\theta})-\underline{\theta}F(\underline{\theta})-\int_{\underline{\theta}}^{\bar{\theta}}F(\theta)d\theta\right]+\frac{\beta p}{(1+\beta)}\left[F(\bar{\theta})-F(\hat{\theta})\right]=$$

$$\left[RB'(K+G-l)-r\right]\left\{\frac{-R}{r^2(1+\beta}\left[\bar{\theta}F(\bar{\theta})-\underline{\theta}F(\underline{\theta})-\int_{\underline{\theta}}^{\bar{\theta}}F(\theta)d\theta\right]-\right.$$

$$\left.\frac{R(1-r\beta)}{r(1+\beta)}\underline{\theta}f(\underline{\theta})\frac{d\theta}{dr}-\frac{\beta p}{(1+\beta)}f(\hat{\theta})\frac{d\hat{\theta}}{dr}\right\}$$

Proof. See Appendix A.3. ■

4.2 Testable Predictions

I relate the market equilibrium informal interest rate, and quantity borrowed, to changes in the exogenous productivity parameter, R, and changes in the formal or institutional credit supply, G. In the rural Indian context, rainfall during the monsoon increases local incomes (Table 3), and an increase in monsoon rainfall[26] could be thought of as an increase in R.

Proposition 5. *An increase in the exogenous productivity parameter, R, increases the equilibrium informal interest rate, r, i.e., $\frac{dr}{dR} > 0$*

Proof. See Appendix A.3. ■

Proposition 6. *An increase in the exogenous productivity parameter, R, increases the equilibrium amount borrowed from informal moneylenders, L (or $\frac{dL}{dR} > 0$) when $\Phi \geq 0$.*

Proof. See Appendix A.3. ■

With the increase in R, lenders see an increase in returns to their outside option, and this increases the opportunity cost of lending. On the borrowers' side, an increase in R increases the number of households which are able to purchase durables with their loans. As a result, the equilibrium interest rate is higher. At the same time, a higher interest rate also means that more households might now prefer interest-free informal loans to interest-bearing informal loans. This

[26] except in a flood situation

results in some substitution out of the moneylender market. When the substitution into interest-free loans is small, we expect to observe an increase in the total quantity borrowed along with an increase in the interest rates.

Assumption 5. *An exogenous increase in formal credit increases the number of borrowers who can borrow from institutional sources, i.e.,* $\frac{d\bar{\theta}}{dG} < 0$. *Conversely, an exogenous decrease in formal credit decreases the number of borrowers who can borrow from institutional sources, i.e.,* $\frac{d\bar{\theta}}{d(-G)} > 0$.

Proposition 7. *An exogenous contraction in the formal credit supply, G, increases the equilibrium informal interest rate, r, i.e.,* $\frac{dr}{d(-G)} > 0$.

Proof. See Appendix A.3. ■

Proposition 8. *An exogenous contraction in the formal credit supply, G, decreases the equilibrium amount borrowed from moneylenders, L, i.e.,* $\frac{dL}{d(-G)} < 0$ *if* $|\frac{d\bar{\theta}}{dG}| < |\Psi_1|$*, and increases the equilibrium amount borrowed from moneylenders, L, i.e.,* $\frac{dL}{d(-G)} > 0$ *if* $|\frac{d\bar{\theta}}{dG}| > |\Psi_2|$*. The effect is ambiguous when* $|\Psi_1| < |\frac{d\bar{\theta}}{dG}| < |\Psi_2|$

Proof. See Appendix A.3. ■

A contraction in the supply of formal credit might directly increase the demand for loans from moneylenders since fewer borrowers are able to borrow from formal sources. A contraction in formal credit supply might also reduce the capital lenders themselves have, and thus reduce the supply of moneylender loans. Thus, if the direct impact of a contraction in formal credit supply on the number of eligible borrowers from the sector is large, i.e., if $|\frac{d\bar{\theta}}{dG}|$ is large, then the net effect is an expansion in borrowing from informal moneylender; while the converse is true if $|\frac{d\bar{\theta}}{dG}|$ is small.

Proposition 9. *An exogenous increase in the productivity parameter, R, has a smaller impact on the equilibrium informal rate when formal credit supply, G, is low than when it is high (i.e.,* $\frac{d^2 r}{dRd(-G)} < 0$*), provided* $\chi < 0$.

Proof. See Appendix A.3. ■

Proposition 10. *An exogenous increase in the productivity parameter, R, has a smaller impact on the equilibrium amount borrowed when formal credit supply, G, is low than when it is high (i.e.,* $\frac{d^2 L}{dRd(-G)} < 0$*), provided* $\Omega > 0$ *and* $\chi < 0$.

Proof. See Appendix A.3. ■

Propositions 9 and 10 address the impact of an increase in the productivity parameter, R, across environments with high and low supplies of formal credit, G. The intuition behind the two propositions is that if the direct impact of the level of formal credit on demand for informal loans is small (i.e., $|\frac{d\bar{\theta}}{dG}|$ is small), then the effect G has on borrowing and interest rates is largely through its impact on the supply of *informal* credit. At low levels of G, moneylenders have lower levels of lending capital, and this could be seen as an inward shift in the supply curve with resultant higher interest rates. In this environment, an increase in R, does not increase the amount borrowed as much as when G is higher.

5 Data and Empirical Strategy

5.1 Datasets

Household credit data is primarily constructed from the Indian National Sample Survey (NSS)'s Debt and Investment rounds. The survey is representative of India's over 600 districts,[27] and this paper focuses on the rural sample. Each survey round was conducted over a calendar year (2003 and 2013), and each household was visited twice within each round. The first visit references a household's assets and liabilities as on June 30$^{\text{th}}$ June, 2002 or 2012, and the second, as on June 30$^{\text{th}}$, 2003 or 2013. In addition, the survey also records all loan transactions between the end of the reference period and the day of the survey. As a result, there is a stacked household panel of all loans taken in a year that are outstanding at the end of the survey reference year; and another panel of all loans taken between the end of the survey reference year and the date of the survey. The surveys also record expenditures on land, capital assets and savings.

A second source of data on household borrowing is the ICRISAT[28] Village Dynamics survey, with data from 866 households[29] in 18 villages in 9 districts in the states of Andhra Pradesh,[30] Maharashtra, Karnataka, Gujarat, and Madhya Pradesh. Each household is surveyed every month between 2010 and 2014,[31] and the survey records monthly loan transactions, monthly consump-

[27] The survey covers 634 districts in the 2012-13 round.
[28] ICRISAT is an acronym for International Crops Research Institute for the Semi-Arid Tropics.
[29] Some of the 866 households in 2010 split, and there are 870 unique households in 2014.
[30] The state is now split into Andhra Pradesh and Telangana.
[31] Data from the year 2009 is excluded since transactions are not recorded by month, but in arbitrary chunks through

tion expenditures and monthly purchases of durables and capital assets.

In addition, I use data on informal firms (and moneylenders) from the Informal Enterprise survey rounds of the NSS. This is supplemented with data from a primary phone survey of 120 informal lenders in 30 villages in 6 districts of Telangana and an additional 20 lenders in nearby urban centers. Accompanying this is a village survey of the 30 villages, and a survey of 60 borrowers who borrow from these lenders. The survey was carried out in summer 2020, and references lending in 2019, with retrospective data from 2013 for those lenders who operated then (Telangana Survey, 2020). Data on credit from formal banks is obtained from the Reserve Bank of India's Basic Statistical Returns for the years 1998 – 2016. This dataset has information on credit outstanding, credit limits and number of accounts at the loan type × bank group level for a district.[32] Rainfall data is from the University of Delaware Global Precipitation Archive's Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series (version 5.01).

5.2 Rainfall shocks

The Willmott and Matsuura (2017) gridded dataset consists of monthly observations of rainfall from rain-gauge measurements interpolated to a 0.5° by 0.5° latitude-longitude grid. I focus on monsoon rainfall in a given year, and define that as being the total rainfall in the months of June, July, August and September. The rainfall for a given district is the rainfall in the grid cell nearest to the district's centroid. The primary rainfall shock measure I use is the deviation of a district's total monsoon precipitation in a year from its historical mean, normalized by its standard deviation (Emerick, 2018). The historical mean and standard deviation for each grid-cell (and district) are computed from the 50-year distribution (1967-2017).

5.3 Formal sector credit supply

Data from the Reserve Bank of India are at the loan-type × population-group × bank-group level for each district as on 31st March of a given year. I use the credit limit in a given year to estimate the national growth in credit for each bank-group by regressing the change in the credit

the survey year – making it impossible to assign a transaction to a month or season.

[32] This data is available on the RBI's online data warehouse which is accessible at https://dbie.rbi.org.in/ for the years 2014 onwards. Data for the years 1998 to 2014 was obtained through a Right to Information petition to the Reserve Bank of India.

limit from one year to the next on loan-type (or industry), population group, bank-group and district fixed effects (following Caldwell & Danieli, 2018):[33]

$$\Delta_{t-1}^{t} log\ C_{irjd} = g_i + g_r + g_j + g_d + \epsilon_{irjd}$$

This allows me to back out a national bank-group specific measure of growth in credit, $\hat{g}_j$, that is not driven by district-, industry- or population group- specific trends. Using this measure of bank-group growth, I construct a district specific credit-growth measure using a weighted average of national bank-group credit growth, weighted by each bank-group's share in a district in the base year.[34]

$$B_d = \sum_j s_{jd}^{t-1} \times \hat{g}_j$$

This is similar to the construction of a standard shift-share or 'Bartik' instrument.[35] However, as opposed to a leave-one-out estimate, this construction ensures that B_d is not driven by local or regional shocks (Caldwell & Danieli, 2018).

5.4 The Effect of Weather on Local Credit Market Outcomes

I define a local market as being a district, focusing on households, firms and banks in a district in order to test the impacts of weather fluctuations on local credit markets. I assume that rainfall shocks are transitory and serially uncorrelated (Emerick, 2018; Jayachandran, 2006; Kaur, 2019; Paxson, 1992; Rosenzweig & Wolpin, 1993; Santangelo, 2019; Townsend, 1995). I first estimate the following specifications using household data where a household-month is the unit of analysis. The structure of the dataset allows controlling for month-of-year, year, district, and state-year fixed effects. Pooling all months, however, does not adequately reflect possible differences in borrowing across seasons. For instance, during the monsoon season, the impact of a rainfall shock might be the direct result of increases in agricultural productivity,[36] since incomes for cultivating households are realized upon harvest (in October/November). For labor households, increased demand for labor and wages (Jayachandran, 2006; Kaur, 2019) might result in increased incomes

[33] Caldwell and Danieli (2018) use this construction of a Bartik instrument in the context of labor markets, to instrument for a shock to outside options of workers.

[34] The bank-group's share is its share of bank-accounts out of the total in a district.

[35] Used in Autor and Hanson (2013); Bartik (1991); Blanchard and Katz (1992); Caldwell and Danieli (2018); Card (2001) etc. It was used specifically as a shock to credit supply in Greenstone et al. (2019).

[36] The increase in agricultural productivity might also increase expectations of income

during the monsoon too. Following the main agricultural season, incomes are realized,[37] and responses to a rainfall shock could be thought of as a response to the resulting income shock at the district level. To test for season-specific impacts of rainfall, I estimate regressions separately for each season.[38] In (1), I control for household fixed effects, for outcomes where this is possible; and in (2), I control for household characteristics. Of interest here is β_1, which captures the reduced form impact of a rainfall shock on household borrowing.

$$Y_{idsmt} = \beta_1 Rain_{dt} + \mu_m + \psi_d + \tau_{st} + \lambda_i + \varepsilon_{idsmt} \tag{6}$$

$$Y_{idsmt} = \beta_1 Rain_{dt} + \mu_m + \psi_d + \tau_{st} + X_{it}\delta + \varepsilon_{idsmt} \tag{7}$$

For outcomes measured at the loan level, I also control for loan characteristics, and estimate the effect of rainfall shocks on loan level outcomes by season,[39] In addition, since there aren't always multiple loans taken by the same household from the same source, I estimate a regression controlling for household characteristics rather than household fixed effects as the primary specification:

$$Y_{lidsmt} = \beta_1 Rain_{dt} + \mu_m + \psi_d + \tau_{st} + L_{lit}\phi + X_{it}\delta + \varepsilon_{lidsmt} \tag{8}$$

5.5 The Effect of Weather when Formal Credit Supply Contracts

In the second part of the analysis, I test whether the availability of formal credit in a district matters for informal credit market outcomes, and how weather-induced demand shocks impact these outcomes. I introduce a formal credit supply shock term to the empirical framework described above, and estimate effects on outcomes at both the household level, and the loan level.

$$Y_{idsmt} = \delta_1 Rain_{dt} + \delta_2 \mathbb{L}_{dt} + \delta_3 Rain_{dt} \times \mathbb{L}_{dt} + \mu_m + \psi_d + \tau_{st} + \lambda_i + \varepsilon_{idsmt} \tag{9}$$

$$Y_{idsmt} = \delta_1 Rain_{dt} + \delta_2 \mathbb{L}_{dt} + \delta_3 Rain_{dt} \times \mathbb{L}_{dt} + \mu_m + \psi_d + \tau_{st} + X_{it}\delta + \varepsilon_{idsmt} \tag{10}$$

[37] This is only a part of the yearly income, if the household cultivates in the Rabi or non-rain-fed season

[38] The monsoon is June – October, and Non-monsoon is Nov – May

[39] I consider the Monsoon, and Non-monsoon seasons.

The equation below represents regressions at the loan level.

$$Y_{lidsmt} = \delta_1 Rain_{dt} + \delta_2 \mathbb{L}_{dt} + \delta_3 Rain_{dt} \times \mathbb{L}_{dt} + \mu_m + \psi_d + \tau_{st} + L_{lit}\phi + X_{it}\delta + \varepsilon_{lidsmt} \tag{11}$$

The variable, $\mathbb{L}_{dt}$ is an indicator that switches on for districts which see a decrease in credit supply in a given year.[40] Of interest here are the co-efficients, $\delta_1, \delta_2, \delta_3$, which represent the reduced form impact of the rainfall-shock, the reduction in credit supply, and the interaction of the two respectively.

6 Empirical Results and Discussion

6.1 The Effect of Weather on Local Credit Market Outcomes

Increases in rainfall increase local incomes, not just in the agricultural sector but also in the non-agricultural sector (Table 3). This is likely to be the case only following harvest in the main rainfall-dependent growing season (*Kharif*), which extends from June to October or November. To distinguish between a household's borrowing response to an income shock and household's direct borrowing response to an agricultural productivity shock, I estimate the impact of a rainfall shock on household borrowing separately for the monsoon, and non-monsoon seasons. Table 4 indicates that households borrow more from informal moneylenders in the non-agricultural season following a positive rainfall shock. There is no significant impact on household borrowing from friends and relatives. These effects hold in the sample with loans that remain outstanding at the end of the reference period (i.e., 31st June of the relevant year, in panel B), and also in the sample of all loans taken between the end of the reference period and the date of survey (panel A). So, there appears to be no differential repayment of loans due to rainfall shocks. Evidence from the ICRISAT sample (in Table A1) is similar, with a significant increase in borrowing from moneylenders outside the monsoon, following a rainfall shock. Both samples (Panel A in Table 4 and Table A1) also indicate an increase in borrowing from institutional sources. However, the absence of a similar effect in panel B of Table 4 suggests caution in interpretation, and a possible effect of rainfall on the repayment of institutional loans.

[40] The decrease is over the preceding year.

Contemporaneous with the increase in borrowing in the non-monsoon season, there is an increase in moneylender interest rates (column 4, Table 6). Figure 4 corroborates this, and demonstrates that in each month with higher demand, interest rates tend to be higher. Since moneylender interest rates are usually higher for more disadvantaged borrowers, this increase could be driven by a change in the composition of borrowers alone. However, in column 5 (Table 6), we see that the effects persist when we control for household fixed effects, indicating that the same household borrows at higher interest rates when demand increases due to a positive rainfall shock. Given that not all households take multiple loans in my sample, in column 6, I estimate whether there is a differential effect of rainfall shocks for such households – and this appears to not be the case. These results reassure us that while a compositional effect might be at play, it is not the sole driver of the increase in interest rates observed. We see no significant effects in the ICRISAT sample, however, possibly due to a lack of power on the outcome (column 7, Table A1). The increase in both household borrowing and in interest rates is consistent with an increase in demand. And indeed, almost 93% of informal moneylenders in the primary survey sample report increasing interest rates when demand goes up (Figure 5).

Prima facie, it is puzzling that households borrow more when incomes are higher. On the one hand, higher incomes might increase demand for local goods and services (as in Emerick, 2018; Santangelo, 2019), leading to more borrowing to sustain local enterprises; while on the other hand, households might view purchases of durable assets or housing as a type of savings vehicle – which, coupled with indivisibilities in such assets – could also increase borrowing. Table 8 indicates lower expenditures on non-farm businesses, consistent with a view where households take up non-farm businesses following negative income shocks to smooth income (Santangelo, 2019), while Table **??** indicates that firms do not significantly increase their borrowing from moneylenders following a positive rainfall shock.

A look at what households borrow for, in Table 7, indicates that this increase is driven by loans for housing repairs or construction, and though significant only at the 10% level, for other consumption needs. Evidence in Table 8 indicates that households do, in fact, have higher expenditures on land and buildings in the non-agricultural season following a positive rainfall shock. And in the ICRISAT sample (Table A2), we see households increase consumption expenditures as well as purchases of durable goods; and the increase in borrowing from moneylenders is driven by these (Table A3).

6.1.1 Robustness

6.2 The Relationship between Moneylenders and Formal Lenders

On the other side of these transactions are the informal moneylenders, and one might wonder how moneylenders are able to meet unanticipated increases in demand. Looking at moneylenders in the sample of informal firms in the NSS Informal Firms Surveys, I find that moneylenders themselves do borrow from both institutional and non-institutional sources. Survey data from Telangana also indicates that while most lenders rely on their wealth, savings or the lending business for lending capital, 40% of lenders borrow from institutional sources, while 51% borrow from non-institutional sources (Figure 6). In fact, almost 60% of lenders in the sample report on-lending bank loans, while 52% report that they would lend more when there is an increase in bank credit supply; and 35% of lenders explicitly state that they would borrow from banks if they faced a shortfall in lending capital (Figure 6). The demand shocks described in the previous section might thus have consequences for moneylenders, and Table 14 (column 1) shows that moneylenders themselves are more likely to borrow from formal sources during these shocks. These stylized facts suggest that there is a vertical relationship between the informal and formal financial sectors. In fact, Table 14 (column 2) also indicates that moneylenders borrow less from formal institutions when faced with a reduction in formal credit supply.

6.3 The Effect of Weather when Formal Credit Supply Contracts

As a result, contractions in the supply of formal credit through the banking system potentially impact moneylenders' ability to extend loans. Simultaneously, if borrowers view moneylender loans as substitutes for formal loans, contractions in formal credit supply might also increase the demand for informal credit, particularly following a rainfall or income shock. To distinguish between these two channels, I interact the rainfall shock from the previous section with an indicator for whether a district sees a reduction in its formal credit supply. Tables 11 and 13 indicate that positive rainfall shocks increase borrowing from moneylenders and interest rates on moneylender loans only in regions where there is ample formal credit supply. Thus, while increases in income increase household demand for informal loans in rural India, households are only able to borrow from moneylenders when the lenders themselves have the ability to meet unanticipated increases in demand by dipping into the formal credit system. Finally, when faced with this, households in districts experiencing a reduction in formal credit supply borrow instead from friends or relatives (or interest-free non-institutional loans) (column 4 in Table 11). The lack of a response in borrowing interest-free loans in districts with sufficient formal credit suggest that households prefer interest-bearing moneylender loans when available. This might be because the amount households can borrow interest-free is smaller than that they might obtain through moneylenders. Alternatively, this might be because the implicit social cost to such loans is high enough to dissuade such borrowing, particularly for larger loans.

6.3.1 Robustness

7 Welfare Implications

Mark-ups; pass-through; total increase in surplus

the two-shifts can potentially change the elasticity of both demand/supply and potentially shift both, and so identifying elasticity of demand/supply is not possible as with experimentally varying prices. However,

expansions in formal credit allow 3pp more borrowers in informal market apart form 3pp more in formal market. this is an x% increase in borrowing. However, with high mark-ups, lenders potentially gain more of the surplus than borrowers do. So, in the absence

8 Conclusion

This paper looks at household borrowing in rural India, and evaluates whether formal and informal lenders compete, or are engaged in a vertical relationship in the rural credit market. An analysis of data from various sources suggests that the latter relationship holds, particularly in instances where there is an unanticipated increase in demand for informal credit. There is no significant evidence pointing to the former relationship, but the presence of both simultaneously cannot be ruled out. Further, the analysis of household borrowing suggests that households borrow *more* when faced with positive shocks to their incomes – primarily to finance housing construction or repairs and purchases of durable assets. In addition to the services such purchases provide, the ability to sell some such assets during negative shocks might also be an alternative mechanism for households to cope with risk.

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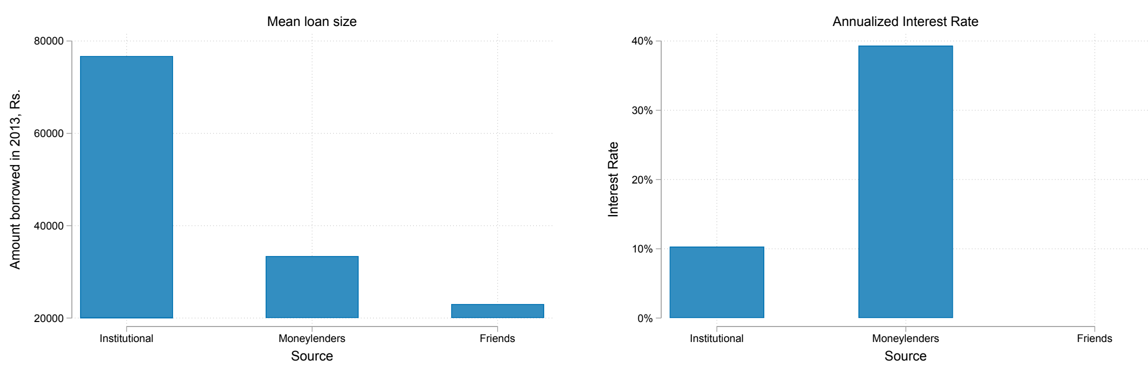
Figures

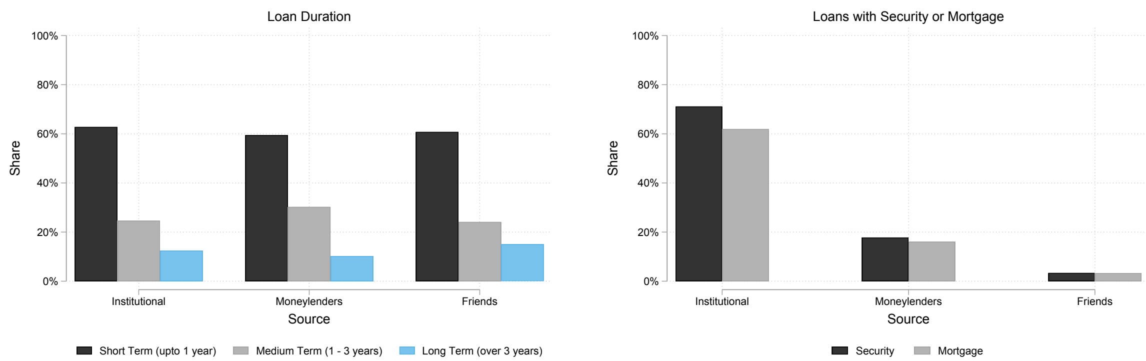
Figure 1: Monsoon Timing

Figure 2: Loan Size and Interest Rates by Lender Type



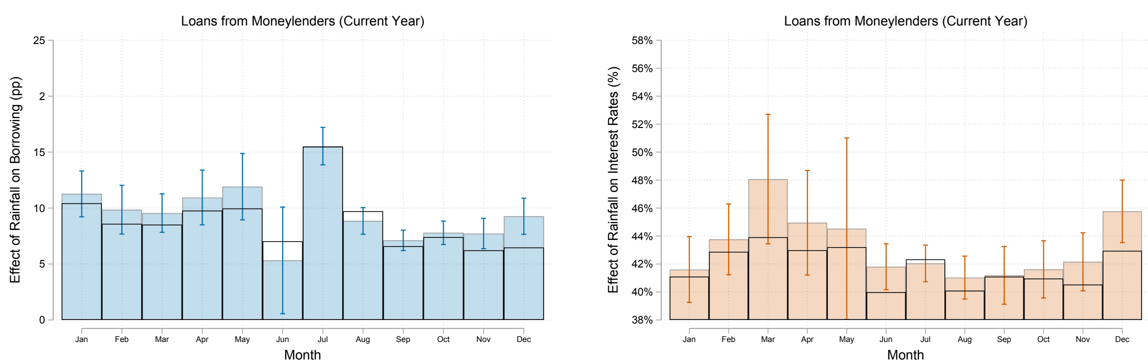
Data: NSS Debt and Investment Survey, 2013

Figure 3: Loan Terms by Lender Type



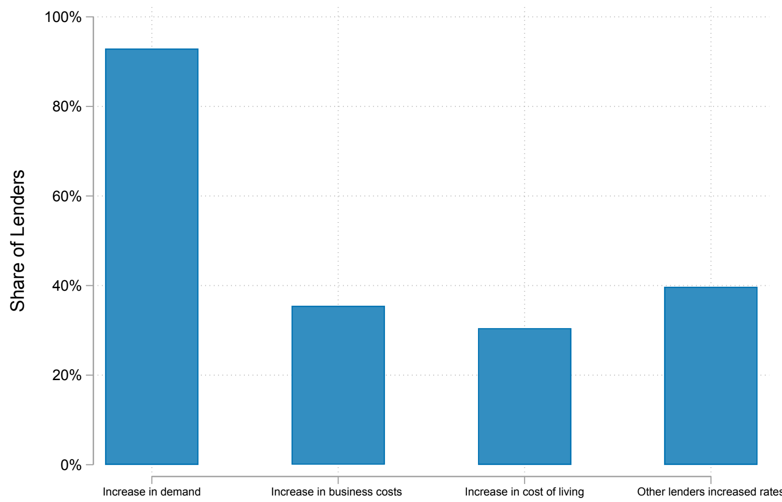
Data: NSS Debt and Investment Survey, 2013

Figure 4: Impact of Rainfall Shocks on Household Borrowing and Interest Rates (Month-wise)



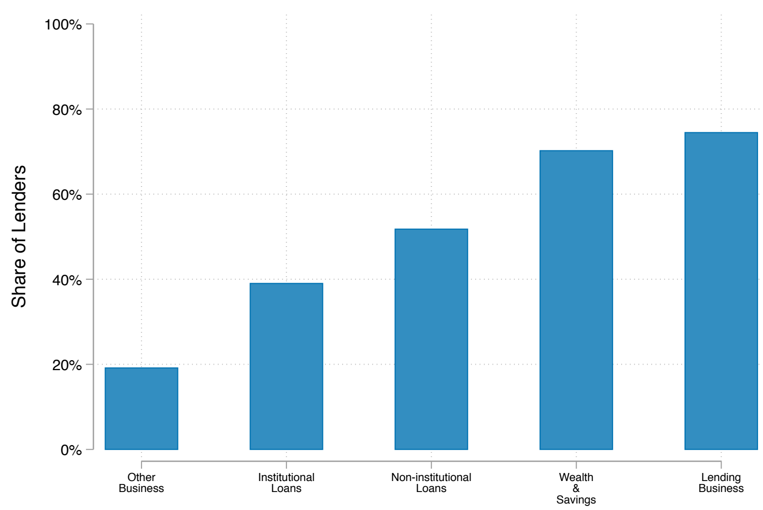
Data: NSS Debt and Investment Survey, 2001-02, 2002-03, 2011-12, 2012-13

Figure 5: Reasons for which Moneylenders increase Interest Rates



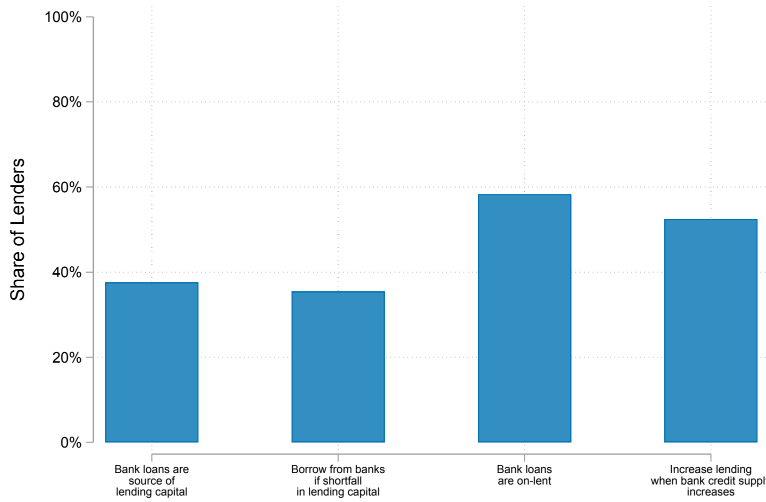
Data: Moneylender Survey (Telangana), 2020

Figure 6: Moneylenders' Source of Lending Capital



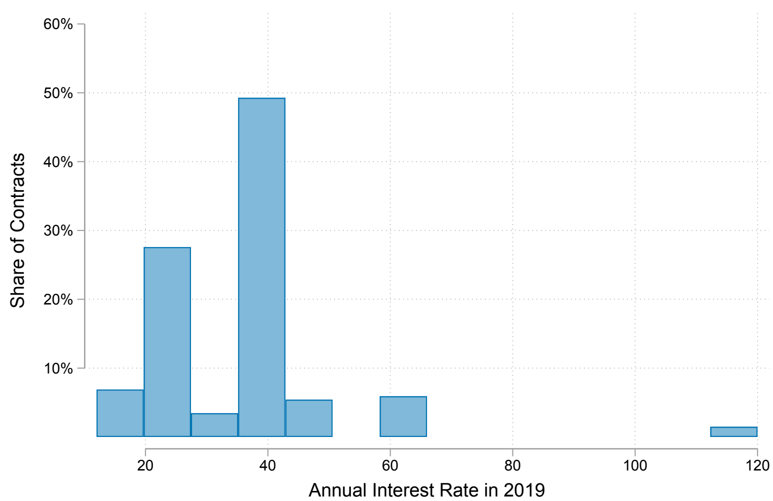
Data: Moneylender Survey (Telangana), 2020

Figure 7: Moneylenders' Bank Borrowing



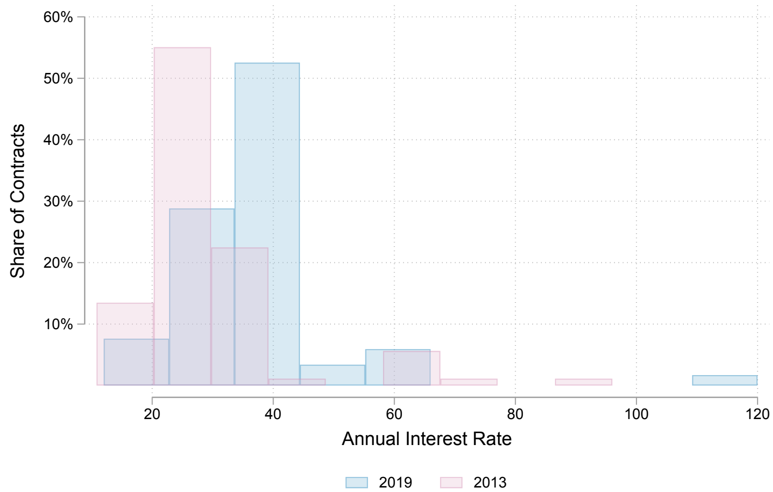
Data: Moneylender Survey (Telangana), 2020

Figure 8: Moneylender Interest Rates, 2019



Data: Moneylender Survey (Telangana), 2020

Figure 9: Moneylender Interest Rates, 2013 and 2019



Data: Moneylender Survey (Telangana), 2020

Tables

Table 1: Household Summary Statistics

	Mean	Median	SD	N
	(1)	(2)	(3)	(4)
Non-Agricultural HH	39 %			304471
Owns Land	90 %			304472
Owns Agricultural Land	26 %			304472
Scheduled Caste/Scheduled Tribe HH	36 %			304471
Any Loan?	59 %			304472
Any Loan from Moneylenders?	22 %			304472
Any Loan from Friends or Relatives?	15 %			304472
Any Loan from Institutions?	29 %			304472
Any Loan from Moneylenders (Reference period)?	9 %			304472
Any Loan from Friends or Relatives (Reference period)?	5 %			304472
Any Loan from Institutions (Reference period)?	9 %			304472
HH size	4.94	5.00	2.49	304471
No. of workers	1.94	2.00	1.24	304472

Data: NSS Debt and Investment Survey (2001-02, 2002-03, 2011-12, 2012-13)

Table 2: Summary Statistics - Household Credit

	Mean	Median	SD	N
	(1)	(2)	(3)	(4)
Outstanding Debt on the date of Survey (2001-02 ₹)				
Total	33467.63	11092.21	93969.37	173442
Moneylenders	25127.33	10120.00	52862.51	64410
Friends/Relatives	12951.82	4830.00	31241.71	42104
Institutions	38919.17	13616.23	109509.72	90228
Amount Borrowed from Moneylenders (2001-02 ₹)				
June - October	16597.06	7590.00	30572.68	8728
November - May	17506.48	6900.00	46507.01	16989
February - May	17623.61	7590.00	49384.43	11655
Amount Borrowed from Friends and Relatives (2001-02 ₹)				
June - October	12355.47	4845.00	27056.15	4644
November - May	11677.14	4600.00	26351.04	11231
February - May	11282.13	4600.00	25364.64	7843
Amount Borrowed from Institutions (2001-02 ₹)				
June - October	33652.93	12144.00	91715.59	9886
November - May	36272.72	14535.00	78040.78	20196
February - May	35279.60	14535.00	76578.52	14181
Interest Rates on Moneylender Loans (% per year)				
June - October	39.65 %	36.00	30.96	10180
November - May	40.63 %	36.00	23.03	17267
February - May	40.52 %	36.00	23.03	11772
Interest Rates on Institutional Loans (% per year)				
June - October	11.90 %	12.00	5.62	12017
November - May	10.83 %	12.00	5.70	19490
February - May	10.48 %	11.50	5.41	13477

Data: NSS Debt and Investment Survey (2001-02, 2002-03, 2011-12, 2012-13). Amounts borrowed and interest rates refer to values in the reference year.

Table 3: Rainfall and District GDP

	Agriculture		Non-Agriculture		Total	
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall Shock	0.027***	0.025***	0.006**	0.004*	0.011***	0.010***
	(0.006)	(0.006)	(0.003)	(0.002)	(0.003)	(0.002)
Obs	3925	3925	3925	3925	3925	3925
Clusters	463	463	463	463	463	463
State × Year FE	no	yes	no	yes	no	yes
Fixed Effects	District, Year					
Mean	₹74896.43		₹284699.30		₹359595.73	

Data: Planning Commission - 1999 - 2007. Means are real values in 2004.
Notes: Unit of observation is a district-year. Regressions control for log of district population in a given year. The rainfall shock is the standardized deviation of a district's June-September rainfall from its historical mean. Standard errors are clustered at the district level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: Rainfall and Amounts Borrowed by Rural Households

	Moneylender		Friends & Relatives		Institutional	
	Sample 1	Sample 2	Sample 1	Sample 2	Sample 1	Sample 2
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall Shock	0.018***	0.043**	-0.000	0.015	0.012	-0.014
	(0.007)	(0.018)	(0.005)	(0.014)	(0.009)	(0.017)
Obs	836808	302512	836808	302512	836808	302512
Clusters	578	583	578	583	578	583
Month FE	yes	no	yes	no	yes	no
HH FE	no	yes	no	yes	no	yes
Fixed Effects	District, State × Year					
Mean	₹	₹	₹	₹	₹	₹

Data: NSS Debt and Investment Survey (2001-02, 2002-03, 2011-12 and 2012-13)
Notes: The rainfall shock is the standardized deviation of a district's June-September rainfall from its historical mean. Sample 1 consists of all loans taken by a household in the survey year between October and May; the unit of observation a household × month. Sample 2 consists of all loans borrowed by a household in the reference year and that are still outstanding at the end of the reference year; the unit of observation is a household. The outcome is the inverse hyperbolic sine transformation of real amount borrowed. Standard errors are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Rainfall and Borrowing Incidence among Rural Households

	Moneylender		Friends & Relatives		Institutional	
	Sample 1	Sample 2	Sample 1	Sample 2	Sample 1	Sample 2
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall Shock	0.014***	0.004**	0.001	0.002	0.007	0.000
	(0.005)	(0.002)	(0.004)	(0.002)	(0.006)	(0.002)
Obs	836808	302512	836808	302512	836808	302512
Clusters	578	583	578	583	578	583
Month FE	yes	no	yes	no	yes	no
HH FE	no	yes	no	yes	no	yes
Fixed Effects	District, State $\times$ Year					
Mean	₹	₹	₹	₹	₹	₹

Data: NSS Debt and Investment Survey (2001-02, 2002-03, 2011-12 and 2012-13)
Notes: The rainfall shock is the standardized deviation of a district's June-September rainfall from its historical mean. Sample 1 consists of all loans taken by a household in the survey year between October and May; the unit of observation a household $\times$ month. Sample 2 consists of all loans borrowed by a household in the reference year and that are still outstanding at the end of the reference year; the unit of observation is a household. The outcome is dummy indicating any borrowing between Oct - May. Coefficients in odd columns are annualized to represent the increase in borrowing by a household between October and May. Standard errors are clustered at the district level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Rainfall and Interest Rates on Loans from Moneylenders

	Sample 1		Sample 2		
	(1)	(2)	(3)	(4)	(5)
Rainfall Shock	3.531***	4.083***	1.565**	1.631	1.602***
	(0.808)	(1.403)	(0.660)	(1.090)	(0.614)
Mult Loans					1.310***
					(0.410)
Rainfall Shock × Mult					0.000
					(0.547)
Obs	9281	8362	17088	5328	17088
Clusters	462	457	498	341	498
HH FE	no	no	no	yes	no
Fixed Effects	Month, District, State × Year				
Mean 2002	41.83%	43.52%	40.66%	40.06%	40.66%

Data: NSS Debt and Investment Survey (2001-02, 2002-03, 2011-12 and 2012-13)
Notes: The rainfall shock is the standardized deviation of a district's June-September rainfall from its historical mean. Unit of observation is a loan. All regressions control for loan characteristics, columns (1) and (4) control for household characteristics; column (4) controls for household fixed effects; column (5) includes a dummy for whether a household has multiple loans and is therefore in the sample for (4). Outcome is the annualized interest rate on a loan taken between Oct - May.
Selection Correction: Column (2) presents selection corrected results following Newey (2009), which controls for a 3rd order power series in $\Phi(p) - 1$.
Standard errors are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Rainfall and Rural Household Borrowing

	Farm	Non-Farm	Financial Investment	Consumption
	(1)	(2)	(3)	(4)
Rainfall Shock	-0.002	-0.000	0.000	0.023*
	(0.006)	(0.003)	(0.001)	(0.014)
Obs	302236	302236	302236	302236
Clusters	578	578	578	578
Fixed Effects	District, State × Year			
Mean	₹263.85	₹97.63	₹0.95	₹261.85

Data: NSS Debt and Investment Survey (2011-12, 2012-13)
Notes: Unit of observation is a household. All regressions control for household characteristics. The non-monsoon season is Nov – May. The rainfall shock is the standardized deviation of a district's June-September rainfall from its historical mean. Outcome is the inverse hyperbolic sine transformation of real amount borrowed by the household in the reference period (in the months specified). All regressions control for household characteristics and rainfall shock in the preceding year for precision. Standard errors are clustered at the district level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 8: Rainfall and Rural Household Expenditures

	Land and Buildings	Farm Business	Non-Farm Business
	(1)	(2)	(3)
Rainfall Shock	0.278**	0.051	-0.130***
	(0.133)	(0.113)	(0.049)
Obs	151247	151247	151247
Number of clusters	583	583	583
Fixed Effects	District, State × Year		
Mean	₹384.22	₹182.79	₹69.46

Data: NSS Debt and Investment Survey (2001-02 and 2011-12)
Notes: The rainfall shock is the standardized deviation of a district's June-September rainfall from its historical mean. Unit of observation is a household. All regressions control for household characteristics. This definition differs from prior tables because expenditures are only reported for July-Dec and Jan - June in the surveys. Outcome is the inverse hyperbolic sine transformation of real expenditure by the household in the reference period (Jan-June). Standard errors are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: District Total Formal Credit

	Credit Limit (ln real ₹)		Credit Amount (ln real ₹)		No. accounts (ln)	
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall Shock	0.003		0.004		-0.001	
	(0.006)		(0.005)		(0.004)	
Rainfall Shock Last Year		-0.002		0.001		-0.001
		(0.006)		(0.005)		(0.003)
Obs	10873	10873	10873	10873	10873	10873
Clusters	581	581	581	581	581	581
Fixed Effects	District, State × Year					
Mean	₹ 16.74 mil		₹ 11.30 mil		165514.9	

Data: Reserve Bank of India – Basic Statistical Returns (1998 - 2014).
Notes: The rainfall shock is the standardized deviation of a district's June-September rainfall from its historical mean. Monetary values are in 1990-91 ₹. Unit of observation is a district. Standard errors in parentheses are clustered at the district level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Formal Credit Supply and Amounts Borrowed by Rural Households

	Moneylender		Friends & Relatives		Institutional	
	Sample 1	Sample 2	Sample 1	Sample 2	Sample 1	Sample 2
	(1)	(2)	(3)	(4)	(5)	(6)
Low Supply	0.006	0.004	0.001	-0.036	-0.035***	-0.072
	(0.009)	(0.048)	(0.008)	(0.035)	(0.011)	(0.055)
Obs	836808	302236	836808	302236	836808	302236
Clusters	578	578	578	578	578	578
Month FE	yes	no	yes	no	yes	no
HH FE.	no	yes	no	yes	no	yes
Fixed Effects	District, State × Year					
Mean	₹829.10	₹1030.74	₹350.40	₹465.37	₹1834.46	₹2616.18

Data: NSS Debt and Investment Survey (2001-02, 2002-03, 2011-12 and 2012-13)
Notes: The rainfall shock is the standardized deviation of a district's June-September rainfall from its historical mean. The low supply shock is an indicator that takes a value of 1 when the 'shift-share' measure is less than 0. Sample 1 consists of all laons taken by a household in the survey year between October and May; the unit of observation is a household ×month. Sample 2 consists of all loans taken by a household in the reference year and that are still outstanding at the end of the reference year; the unit of observation is a household. The outcome is the inverse hyperbolic sine transformation of the real amount borrowed. Standard errors are clustered at the region×year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Rainfall, Formal Credit Supply and Amounts Borrowed by Rural Households

	Moneylender		Friends & Relatives		Institutional	
	Sample 1	Sample 2	Sample 1	Sample 2	Sample 1	Sample 2
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall Shock	0.026***	0.077***	-0.005	-0.010	0.027***	0.002
	(0.007)	(0.018)	(0.004)	(0.020)	(0.009)	(0.028)
Low Supply	0.003	0.010	0.002	-0.042	-0.039***	-0.070
	(0.007)	(0.054)	(0.005)	(0.034)	(0.008)	(0.057)
Rainfall Shock × Low Supply	-0.014**	-0.079***	0.009	0.060**	-0.025***	-0.031
	(0.006)	(0.028)	(0.009)	(0.029)	(0.007)	(0.034)
Obs	836808	302236	836808	302236	836808	302236
Clusters	578	578	578	578	578	578
Month FE	yes	no	yes	no	yes	no
HH FE.	no	yes	no	yes	no	yes
Fixed Effects	District, State × Year					
Mean	₹829.10	₹1030.74	₹350.40	₹465.37	₹1834.46	₹2616.18

Data: NSS Debt and Investment Survey (2001-02, 2002-03, 2011-12 and 2012-13)
Notes: The rainfall shock is the standardized deviation of a district's June-September rainfall from its historical mean. The low supply shock is an indicator that takes a value of 1 when the 'shift-share' measure is less than 0. Sample 1 consists of all laons taken by a household in the survey year between October and May; the unit of observation is a household ×month. Sample 2 consists of all loans taken by a household in the reference year and that are still outstanding at the end of the reference year; the unit of observation is a household. The outcome is the inverse hyperbolic sine transformation of the real amount borrowed. Standard errors are clustered at the region×year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: Rainfall, Formal Credit Supply and Borrowing Incidence among Rural Households

	Moneylender		Friends & Relatives		Institutional	
	Sample 1	Sample 2	Sample 1	Sample 2	Sample 1	Sample 2
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall Shock	0.023***	0.008***	-0.000	-0.001	0.020**	-0.000
	(0.005)	(0.002)	(0.004)	(0.002)	(0.007)	(0.003)
Low Supply	0.007	0.001	0.002	-0.004	-0.030***	-0.007
	(0.006)	(0.005)	(0.005)	(0.004)	(0.006)	(0.005)
Rainfall Shock $\times$ Low Supply	-0.013**	-0.009***	0.003	0.006**	-0.021**	0.003
	(0.006)	(0.003)	(0.006)	(0.003)	(0.006)	(0.004)
Obs	836808	302236	836808	302236	836808	302236
Clusters	578	578	578	578	578	578
Month FE	yes	no	yes	no	yes	no
HH FE.	no	yes	no	yes	no	yes
Fixed Effects	District, State $\times$ Year					
Mean	8.2%	6%	6.4%	5%	9.09%	14%

Data: NSS Debt and Investment Survey (2001-02, 2002-03, 2011-12 and 2012-13)
Notes: The rainfall shock is the standardized deviation of a district's June-September rainfall from its historical mean. The low supply shock is an indicator that takes a value of 1 when the 'shift-share' measure is less than 0. Sample 1 consists of all laons taken by a household in the survey year between October and May; the unit of observation is a household $\times$month. Sample 2 consists of all loans taken by a household in the reference year and that are still outstanding at the end of the reference year; the unit of observation is a household. The outcome is a dummy indicating any borrowing between Oct - May. Standard errors are clustered at the region$\times$year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 13: Rainfall, Formal Credit Supply and Interest Rates on Loans from Moneylenders

	Sample 1	Sample 2
	(1)	(2)
Rainfall Shock	5.672***	1.562**
	(1.432)	(0.652)
Low Supply	3.270*	2.431***
	(1.823)	(0.912)
Rainfall Shock × Low Supply	-3.906**	-1.861**
	(1.720)	(0.787)
Obs	8376	15264
Clusters	459	495
Fixed Effects	Month, District, State × Year	
Mean	43.51%	41.11%

Data: NSS Debt and Investment Survey (2001-02, 2002-03, 2011-12 and 2012-13)
Notes: The rainfall shock is the standardized deviation of a district's June- September rainfall from its historical mean. Unit of observation is a loan. All regressions control for loan characteristics. Outcome is the annualized interest rate on a loan taken between October-May. Standard errors are clustered at the district level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

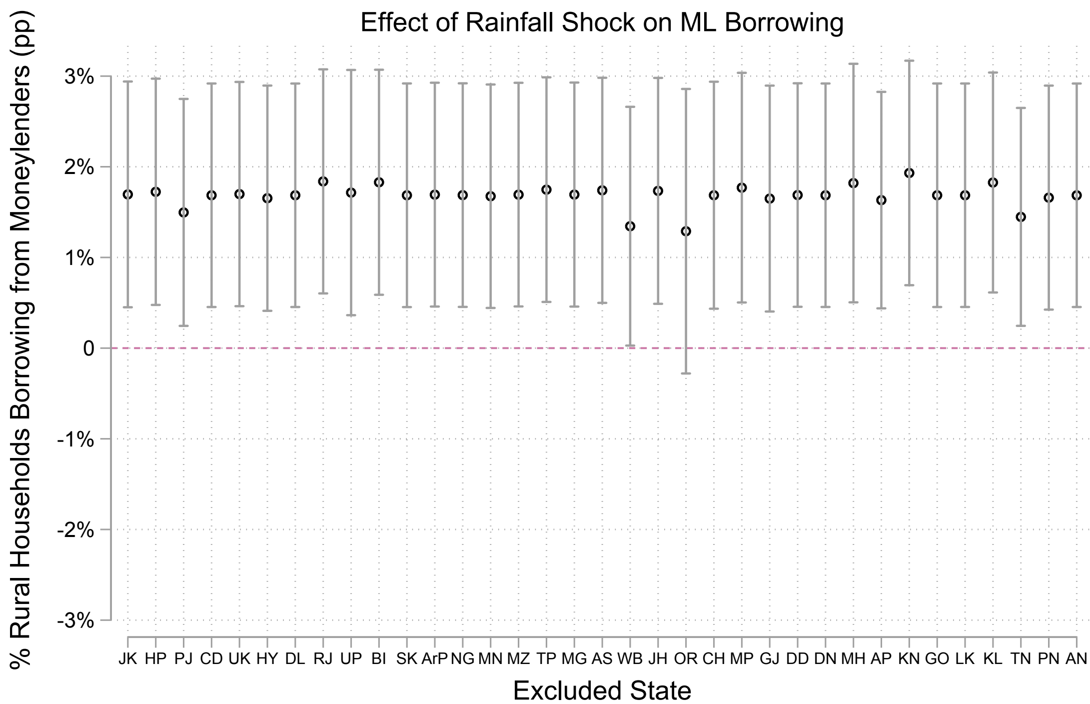
Table 14: Moneylenders' Own Borrowing from Formal Institutions

	Any Loans from Formal Sources?		Credit Access Problem
	(1)	(2)	(3)
Rainfall Shock	0.044**		
	(0.021)		
Low Supply		-0.177***	0.037*
		(0.059)	(0.022)
Obs	907	907	907
Clusters	126	126	126
Fixed Effects	Quarter, District, State × Year		
Mean	14%	14%	4%

Data: NSS Informal Enterprise Surveys (2010-11 and 2015-16)
Notes: The rainfall shock is the standardized deviation of a district's June-September rainfall from its historical mean. Low Supply is a dummy indicating that there was a decline in formal credit supply in that district. Unit of observation is a moneylender. All regressions control for firm characteristics. The outcome in columns (1) and (2) is a dummy taking the value one if the firm has any loans outstanding loans from a formal source on the date of survey. The outcome in column (3) is an indicator that takes the value 1 if a firm reports that non-availability of/or high cost of credit is a problem. Standard errors are clustered at the district level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

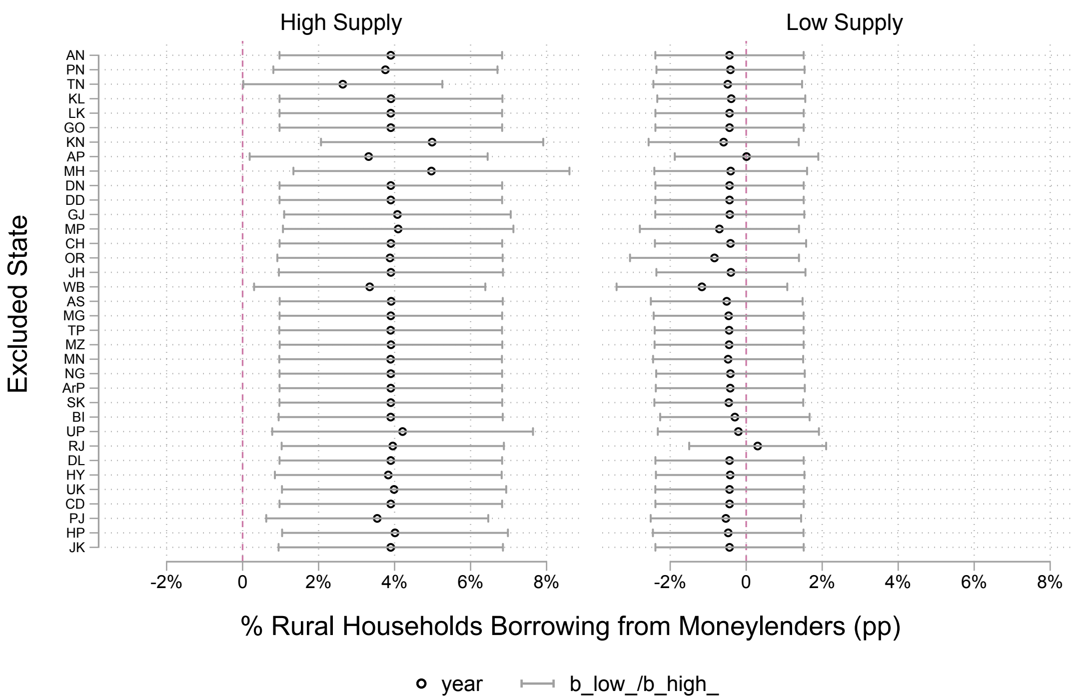
Additional Figures

Figure A1: Rural Household Borrowing from Moneylenders: Iteratively Excluding States



Data: NSS Debt and Investment Survey, 2001-02, 2002-03, 2011-12, 2012-13

Figure A2: Rural Household Borrowing from Moneylenders across High and Low Formal Credit Supply: Iteratively Excluding States



Data: NSS Debt and Investment Survey, 2001-02, 2002-03, 2011-12, 2012-13

Additional Tables: ICRISAT Sample

Table A1: Positive Rainfall Shocks and Household Borrowing

	Moneylenders		Friends & Relatives		Institutions		Moneylender Interest
	(Any, %)	Asinh real ₹	(Any, %)	Asinh real ₹	(Any, %)	Asinh real ₹	% per year
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Rainfall Shock	0.024**	0.278***	0.049	0.553	0.099***	1.055***	1.563
	(0.009)	(0.080)	(0.076)	(0.676)	(0.010)	(0.093)	(2.388)
Obs	4317	4317	4317	4317	4317	4317	1125
Clusters	9	9	9	9	9	9	9
Fixed Effects	District, State ×Year						
Mean	24.36%	₹5729.59	18.50%	₹2103.75	8.62%	₹6736.23	29.27%

Data: ICRISAT Village Dynamics Studies Dataset. Monetary values are in 2010 ₹.
Notes: The rainfall shock is the standardized deviation of a district's June-September rainfall from its historical mean. Unit of observation is a household in columns (1) - (6) while it is a loan in column (7). Regressions control for caste, landholdings and whether the household split from a parent household during the study period. Outcomes in columns (1), (3) and (5) are dummies, which take a value of 1 when the household has borrowed from the source between Oct - May in the year. The outcome in columns (2), (4) and (6) is the inverse hyperbolic sine of the amount a household borrowed between Oct - May in the year. The outcome in column (7) is the annualized interest rate on loans from moneylenders. Standard errors are clustered at the district level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A2: Effect of Positive Rainfall Shocks on Household Consumption and Purchases of Durables

	Consumption Expenditure (per capita)			Any Durables	Durables
	Total (log real ₹)	Food (log real ₹)	Non-food (log real ₹)	Purchased? (%)	Expenditure (asinh real ₹)
	(1)	(2)	(3)	(4)	(5)
Rainfall Shock	0.055*	0.024**	0.088	0.136**	1.117**
	(0.027)	(0.009)	(0.049)	(0.059)	(0.436)
Obs	4195	4195	4195	4317	4317
Clusters	9	9	9	9	9
Fixed Effects	District, State $\times$Year				
Mean	₹1533.96	₹688.08	₹845.88	36.78%	₹14100.82

Data: ICRISAT Village Dynamics Studies Dataset. Monetary values are in 2010 ₹.
Notes: The rainfall shock is the standardized deviation of a district's June-September rainfall from its historical mean. Unit of observation is a household. Regressions control for caste, landholdings and whether the household split from a parent household during the study period. The outcome in columns (1), (2), and (3) is the natural logarithm of the real value of consumption between Oct - May. The outcome in column (4) is a dummy which takes a value of 1 if the household has purchased any durables between Oct - May. The outcome in column (5) is the inverse hyperbolic sine of the real expenditure on durable goods between Oct - May. Standard errors are clustered at the district level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A3: Effect of Positive Rainfall Shocks on Household Borrowing across Households with/without Purchases of Durables

	Moneylenders	Friends & Relatives	Institutions
	(1)	(2)	(3)
Rainfall Shock	0.007	0.032	0.096^{***}
	(0.011)	(0.069)	(0.008)
Any Durables	0.037^{**}	0.061^{**}	0.019
	(0.015)	(0.025)	(0.014)
Rainfall Shock $\times$ Any Durables	0.024	0.018	0.000
	(0.014)	(0.017)	(0.008)
Obs	4317	4317	4317
Clusters	9	9	9
Fixed Effects	HH, District, State $\times$Year		
Mean (Omitted Group)	20.15%	14.62%	6.30%

Data: ICRISAT Village Dynamics Studies Dataset.
Notes: The rainfall shock is the standardized deviation of a district's June-September rainfall from its historical mean. Unit of observation is a household. Regressions control for caste, landholdings and whether the household split from a parent household during the study period. The outcome is is a dummy variable which takes a value of one when a household has borrowed. Standard errors are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Additional Tables: Heterogeneity and Robustness Checks

Table B1: Effect of Savings on Rural Household Borrowing Responses to Rainfall Shocks

	Moneylender		Friends & Relatives		Institutional	
	Sample 1	Sample 2	Sample 1	Sample 2	Sample 1	Sample 2
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall Shock	0.021***	0.060***	0.003	0.026	0.006	0.033
	(0.007)	(0.021)	(0.005)	(0.016)	(0.009)	(0.023)
Savings	-0.003		-0.004		0.086***	
	(0.003)		(0.003)		(0.005)	
Rainfall Shock $\times$ Savings	-0.005	-0.035**	-0.006**	-0.020	0.001	-0.099***
	(0.003)	(0.017)	(0.003)	(0.014)	(0.005)	(0.021)
Obs	836808	302512	836808	302512	836808	302512
Clusters	578	583	578	583	578	583
Month FE	yes	no	yes	no	yes	no
HH FE.	no	yes	no	yes	no	yes
Fixed Effects	District, State $\times$ Year					
Mean	₹829.10	₹1030.74	₹350.40	₹465.37	₹1834.46	₹2616.18

Data: NSS Debt and Investment Survey (2001-02, 2002-03, 2011-12 and 2012-13)
Notes: The rainfall shock is the standardized deviation of a district's June-September rainfall from its historical mean. 'Savings' is an indicator that takes a value of 1 when the household's savings in the first visit is above the median value for that year. This data was not collected in the second visit. So, the household fixed effects absorb the 'savings' dummy.
Sample 1 consists of all loans taken by a household in the survey year between October and May; the unit of observation is a household $\times$month. Sample 2 consists of all loans taken by a household in the reference year and that are still outstanding at the end of the reference year; the unit of observation is a household. The outcome is the inverse hyperbolic sine transformation of the real amount borrowed. Standard errors are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B2: Asymmetric Effects of Rainfall Shocks on Rural Household Borrowing

	Moneylender		Friends & Relatives		Institutional	
	Sample 1	Sample 2	Sample 1	Sample 2	Sample 1	Sample 2
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall Shock	0.017**	0.036**	-0.000	0.021	0.012	-0.037
	(0.007)	(0.018)	(0.005)	(0.016)	(0.009)	(0.027)
Drought	-0.055**	-0.042	-0.016	-0.015	0.031	-0.078
	(0.023)	(0.065)	(0.011)	(0.045)	(0.025)	(0.069)
Rainfall Shock × Drought	-0.033	-0.011	-0.011	-0.028	0.060***	0.013
	(0.020)	(0.066)	(0.011)	(0.039)	(0.023)	(0.063)
Obs	836808	302512	836808	302512	836808	302512
Clusters	578	583	578	583	578	583
Month FE	yes	no	yes	no	yes	no
HH FE.	no	yes	no	yes	no	yes
Fixed Effects	District, State × Year					
Mean	₹829.10	₹1030.74	₹350.40	₹465.37	₹1834.46	₹2616.18

Data: NSS Debt and Investment Survey (2001-02, 2002-03, 2011-12 and 2012-13)
Notes: The rainfall shock is the standardized deviation of a district's June-September rainfall from its historical mean. 'Drought' is an indicator that takes a value of 1 when monsoon rainfall is 20 or more below the 50-year mean for a district. The Indian Meteorological Department uses this definition to designate a drought. Sample 1 consists of all loans taken by a household in the survey year between October and May; the unit of observation is a household ×month. Sample 2 consists of all loans taken by a household in the reference year and that are still outstanding at the end of the reference year; the unit of observation is a household. The outcome is the inverse hyperbolic sine transformation of the real amount borrowed. Standard errors are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B3: Alternate Definitions of Rainfall Shocks: Effect on Rural Household Borrowing

	Moneylender		Friends & Relatives		Institutional	
	Sample 1	Sample 2	Sample 1	Sample 2	Sample 1	Sample 2
	(1)	(2)	(3)	(4)	(5)	(6)
Percentile Shock	0.021***	0.052**	0.002	0.019	0.009	0.007
	(0.007)	(0.021)	(0.006)	(0.018)	(0.009)	(0.024)
Fractional Deviation	0.072**	0.085*	0.007	0.051	0.063	0.036
	(0.030)	(0.051)	(0.018)	(0.041)	(0.039)	(0.066)
Non-Monsoon Rainfall	-0.005	0.033	-0.006	-0.030*	-0.025***	0.013
	(0.006)	(0.023)	(0.004)	(0.016)	(0.008)	(0.026)
Obs	836808	302512	836808	302512	836808	302512
Clusters	578	583	578	583	578	583
Month FE	yes	no	yes	no	yes	no
HH FE.	no	yes	no	yes	no	yes
Fixed Effects	District, State × Year					
Mean	₹829.10	₹1030.74	₹350.40	₹465.37	₹1834.46	₹2616.18

Data: NSS Debt and Investment Survey (2001-02, 2002-03, 2011-12 and 2012-13)
Notes: Following Jayachandran (2006), percentile shock takes values -1 when monsoon rainfall is below the 20th percentile of the district's historical rainfall distribution; 1 when rainfall is above the 80th percentile of the district's historical rainfall distribution; and 0 otherwise. Fractional deviation defines the rainfall shock as a the fractional difference between the monsoon rainfall in a given year from the district's Long Period Mean (or 50 year mean, as defined by the Indian Meteorological Department (IMD)). Non-Monsoon rainfall is the standardized deviation of the Oct - May rainfall in a given year from the district's historical mean, and is meant as a placebo test.
Sample 1 consists of all loans taken by a household in the survey year between October and May; the unit of observation is a household ×month. Sample 2 consists of all loans taken by a household in the reference year and that are still outstanding at the end of the reference year; the unit of observation is a household. The outcome is the inverse hyperbolic sine transformation of the real amount borrowed. Standard errors are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table B4: Alternate Definitions of Formal Credit Supply Shocks:
Effect of Formal Credit Supply on Household Borrowing Response to Rainfall Shocks

	Moneylender		Friends & Relatives		Institutional	
	Sample 1	Sample 2	Sample 1	Sample 2	Sample 1	Sample 2
	(1)	(2)	(3)	(4)	(5)	(6)
Alternate Definition 1: 'Shift-Share' using Outstanding Credit						
Rainfall Shock	0.027***	0.074***	-0.005	-0.002	0.021*	0.013
	(0.009)	(0.023)	(0.007)	(0.017)	(0.012)	(0.029)
Low Supply 2	0.004	-0.010	0.001	-0.042	-0.037***	-0.074
	(0.009)	(0.047)	(0.008)	(0.033)	(0.011)	(0.055)
Rainfall Shock × Low Supply 2	-0.016*	-0.070**	0.010	0.043*	-0.022*	-0.054
	(0.009)	(0.029)	(0.008)	(0.025)	(0.011)	(0.040)
Obs	836808	302236	836808	302236	836808	302236
Clusters	578	578	578	578	578	578
Month FE	yes	no	yes	no	yes	no
HH FE.	no	yes	no	yes	no	yes
Fixed Effects	District, State × Year					
Mean	₹829.10	₹1030.74	₹350.40	₹465.37	₹1834.46	₹2616.18
Alternate Definition 2: 'Shift-Share' using Number of Accounts						
Rainfall Shock	0.024**	0.071***	-0.005	-0.004	0.024*	-0.006
	(0.010)	(0.023)	(0.007)	(0.016)	(0.012)	(0.028)
Low Supply 3	-0.001	0.014	0.006	-0.031	-0.015	-0.037
	(0.010)	(0.041)	(0.008)	(0.031)	(0.012)	(0.046)
Rainfall Shock × Low Supply 3	-0.010	-0.061**	0.009	0.044**	-0.029***	-0.013
	(0.009)	(0.026)	(0.008)	(0.021)	(0.011)	(0.038)
Obs	836808	302236	836808	302236	836808	302236
Clusters	578	578	578	578	578	578
Month FE	yes	no	yes	no	yes	no
HH FE.	no	yes	no	yes	no	yes
Fixed Effects	District, State × Year					
Mean	₹829.10	₹1030.74	₹350.40	₹465.37	₹1834.46	₹2616.18

Data: NSS Debt and Investment Survey (2001-02, 2002-03, 2011-12 and 2012-13)
Notes: The rainfall shock is the standardized deviation of a district's June-September rainfall from its historical mean. 'Drought' is an indicator that takes a value of 1 when monsoon rainfall is 20 or more below the 50-year mean for a district. The Indian Meteorological Department uses this definition to designate a drought. Sample 1 consists of all loans taken by a household in the survey year between October and May; the unit of observation is a household ×month. Sample 2 consists of all loans taken by a household in the reference year and that are still outstanding at the end of the reference year; the unit of observation is a household. The outcome is the inverse hyperbolic sine transformation of the real amount borrowed. Standard errors are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$