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. While policy-makers view the formal and informal financial sectors as competing, survey data from India indicates that moneylenders use formal (bank) credit as lending capital. I explore this relationship by analyzing the impact of reductions in formal credit supply on non-agricultural informal lending to households in rural India. I find that exogenous reductions in formal credit supply by themselves drive up informal interest rates, with no significant impact on loans transacted. However, when households experience unanticipated weather-induced increases in credit demand, formal credit supply is more salient — a 10% increase in bank credit supply when demand is high results in 12% more borrowing from the informal market. However, moneylender mark-ups are large, at between 41% and 53%, implying that moneylenders accrue a larger share of the additional surplus generated in the informal credit market by formal credit expansions.

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1 Introduction

From informal moneylenders across South Asia (Aleem, 1990; Bottomley, 1963; Timberg & Aiyar, 1984, etc) to payday lenders in the United States (Allcott, Kim, Taubinsky, & Zinman, 2020; Baradaran, 2015; Morse, 2011, etc), high-interest non-bank lenders often meet the consumption-credit needs of the underbanked. In this context, concerns about usurious rates and 'over-indebtedness' have prompted regulation (Allcott et al., 2020; RBI, 2007),[1] and countries across the developing world have looked to expansions in access to formal finance to reduce the prevalence of high-interest informal debt. However, 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).

Where the two sectors co-exist — if the formal and informal credit sectors primarily compete, then short-run expansions (contractions) in formal credit supply might crowd out (in) informal credit.[2] On the other hand, if formal credit primarily serves as a source of lending capital for informal lenders, then short-run expansions (contractions) in formal credit supply might crowd in (out) informal credit.[3] While both channels might allow more households to borrow, the former might lead to a decrease in moneylender market power while the latter might consolidate it. Thus, the dominance of one over the other matters when evaluating the welfare effects of formal credit expansions on rural households. In this paper, I test what the nature of this relationship is in the context of non-agricultural lending in rural India — where demand for credit might vary with the vagaries of monsoon rainfall.[4]

I exploit quasi-random variation in a district's bank credit supply (à la Greenstone, Mas, and Nguyen (2020)), and variation in rural households' demand for credit (driven by positive rainfall shocks) to estimate the causal effect of expansions (contractions) in bank liquidity on rural household borrowing. To do this, I combine nationally representative household survey data, moneylender survey data (both from sample surveys and a primary survey I conducted), and banking

[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)

[2] As in Bell, Srinivasan, and Udry (1997); Giné (2011); Jacoby (2008); Jain (1999); Kochar (1997)

[3] As in Floro and Ray (1997); Hoff and Stiglitz (1998); Jacoby (2008)

[4] I consider loans contracted outside of the main agricultural season, *kharif*. The season coincides with the south-west or summer monsoon in India between June and September each year, and so I consider loans taken between October in a given year and May in the following year.

data from Reserve Bank of India. I begin by establishing that rural households' demand for credit in the non-agricultural season increases following a positive shock to incomes in a district, driven by an increase in monsoon rainfall. I then estimate the impact of expansions (contractions) in bank credit supply on rural household borrowing — first without explicitly considering household demand, and then when demand is higher than anticipated. Finally, I estimate the impact of these shocks on moneylenders themselves.

This paper has three main sets of findings. First, I find that when rural households experience an unanticipated increase in income following a one standard-deviation increase in monsoon rainfall, 1 percentage point or 12% more households borrow from informal moneylenders in the non-agricultural season following the shock. The increase in borrowing is accompanied by an 8% increase in the interest rates at which informal loans are contracted, indicating that there is an increase in rural household demand for non-agricultural loans. This effect is driven by an increase in consumption rather than production loans, and suggestive evidence is consistent with an increase in borrowing to purchase durable goods, when households lack savings.

Second, I find that a 10% contraction in the formal credit supply in a district drives the interest rates at which informal moneylenders lend up by 8.5%. There appears to be no significant impact on quantities borrowed due to this formal credit supply shock, on average. However, when there is also an increase in demand for credit, households in districts with lower formal credit supply are able to borrow less than their counterparts in districts with higher formal credit supply. Put differently, when credit demand is high, a 10% increase in a district's formal credit supply allows 12% more households to borrow indirectly through the informal market, apart from the additional borrowing it enables in the formal market — generating additional surplus in the informal market.

Finally, moneylenders themselves borrow significantly more from formal sources following a positive rainfall shock, and significantly less due to a contraction in formal credit supply. This suggests that moneylenders borrow from formal sources to meet unanticipated increases in demand, and are thus less able to meet demand when formal credit supply is low — resulting in the lower equilibrium borrowing. In addition, I find that the median moneylender earns a high markup of 52%-53%, and so moneylenders themselves accrue most of the additional surplus generated by the formal credit expansion.

This paper contributes to three stands of literature. First, it contributes to the body of work that examines the effects of bank credit supply on economic outcomes. Across contexts, negative bank liquidity shocks have been shown to worse the financial position of small firms (Greenstone et al., 2020; Khwaja & Mian, 2008), without necessarily worsening employment (Greenstone et al., 2020). Other negative lender liquidity shocks reduce wages, incomes and even household consumption (Breza & Kinnan, 2018). On the other hand, longer-term increases in supply through bank expansions themselves appear to have had mixed effects. In the Indian context in particular, evidence suggests such expansions increased output (Burgess & Pande, 2005; Young, 2019), decreased poverty (Burgess & Pande, 2005) but also increased consumption inequality (Kochar, 2011). This literature, however, has not often focused on the impact such shocks have on informal credit institutions, and I contribute to this literature by evaluating the impact of short-term reductions in bank liquidity on households and lenders in the informal credit market context in rural India.[5]

Second, it also contributes to the literature evaluating 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; Madestam, 2014; 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. 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, as opposed to most prior analyses, I focus on the interaction in the context of consumption rather than production borrowing. Also related is Kanz (2016) and Giné and Kanz (2018), where the authors focus on formal sector debt relief, finding that it leads to greater reliance on informal debt and increased strategic default in the formal sector.

This is one of the first papers to demonstrate that informal moneylenders in India are able to

[5]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, Emran, and Shilpi (2013); Breza and Kinnan (2018); Crépon, Devoto, Duflo, and Parienté (2015); deJanvry, McIntosh, and Sadoulet (2010); Demont (2016); Ghatak and Guinnane (1999); Hoffmann, Rao, Surendra, and Datta (in press); Karlan and Zinman (2009, 2010); Meager (2019); Tarozzi, Desai, and Johnson (2015) among many others.

arbitrage across the formal and informal sectors while earning high markups, building on Aleem (1990); Hoff and Stiglitz (1998), as well as contributing to extensive work on intermediary markups (Bergquist & Dinerstein, 2019; Mitra, Mookherjee, Torero, & Visaria, 2018, etc). In addition, recent work has focused on the impact of expansions in microfinance or self-help groups in India on informal moneylender (Berg et al., 2013; Demont, 2016; Hoffmann et al., in press; Mallick, 2011; Mookherjee & Motta, 2016) — and with its finding that informal lenders do increase interest rates when faced with increases in demand, this paper adds to this body of work.

Finally, this paper also contributes to the literature on risk-coping and consumption smoothing (Friedman, 1957; Paxson, 1992; Wolpin, 1982). In the context of rural agrarian economies, earlier literature 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). I add to this the finding that when faced with positive shocks, in a context with limited savings, household borrow to purchase durable goods and asset, which could also bolster their ability to deal with unexpected negative shocks in the future. Finally, 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; Santangelo, 2019; Wolpin, 1982).

The rest of this paper proceeds as follows – section 2 describes both the demand and supply sides of the credit market in rural India, section 3 presents the theoretical framework, section 4 describes the data and empirical strategy used in the paper, section 5 discusses the results, and section 7 concludes.

2 Background

Household Borrowing in Rural India

Around half of all rural households in India are indebted,[6] and the median indebted household owed approximately ₹40,000 to its creditors in 2012-13.[7] 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).[8,9,10] 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

[6] 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)

[7] 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

[8] 74% of all loans were for non-productive needs in 2016-17 (NAFIS, 2017)

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

[10] 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).[11,12]

Non-institutional lenders

Non-institutional lenders,[13] 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;[14] 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., in press; 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,[15] 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) re-

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

[12] 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.

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

[14] 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.

[15] 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)

porting that fewer than 25% of borrowers ever defaulted.[16] 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,[17] gold or other assets, promissory notes or a co-signer.[18] 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.[19] 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. (in press) 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.[20]

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

[16] 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.

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

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

[19] 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.

[20] 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.[21]

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.[22] Formal banks channel credit to rural populations, in particular, through the Kisan Credit Card (KCC) scheme,[23] 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;[24] and the SHG-bank linkage program,[25] 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).[26]

3 Theoretical Framework

I outline a model of a rural economy with borrowers and lenders to derive testable implications about the relationship between institutional and non-institutional credit. While households in real-world rural settings borrow for both production and consumption — I focus on agents' behavior in the non-agricultural season,[27] where loans are more likely to be for for consumption. The model draws on earlier work relating to household consumption and loan decisions (Hane-

[21]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

[22]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

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

[24]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.

[25]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., in press).

[26]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.

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

mann, 1984; Ligon & Worrall, 2020; Ngo, 2018, etc), as well as theoretical literature on informal lending (Hoff & Stiglitz, 1998; Karaivanov & Kessler, 2018, etc).

3.1 Demand for Informal Credit

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 according to the function, $F(\cdot)$ over the interval $[\theta_L, \theta_H]$. I consider a two-season horizon, where each household derives a per-season utility, $u(\cdot)$ (with $u(0) = 0$, $u'(\cdot) > 0$, and $u''(\cdot) < 0$), from the consumption of a numeraire good, c_t.[28] A household may also choose to purchase a durable good, D, at price, $p > 1$ in season 1, and in doing so, benefits from the services, d, provided by the durable over both seasons.

Household income depends on an exogenous season-specific productivity parameter, R_t.[29] In season 1, a household earns, $R_1\theta$, and expects to earn, $\mathbb{E}[R_2]\theta$ in season 2. Households may also borrow institutional loans, b_B, interest-bearing non-institutional loans (or moneylender loans), b_{ML}, or interest-free non-institutional loans, b_F. The interest rate on institutional loans is r_B, while while that on moneylender loans is r_{ML}.[30] Loans from institutional sources are assumed to be cheaper than loans from non-institutional sources, but are only available to relatively wealthier households because they require large collateral; and the poorest households are only able to borrow from friends or relatives.[31]

Assumption 1. *Households with endowments greater than a threshold, $\bar{\theta}$ borrow from institutional sources, and households with endowments below $\underline{\theta}$ borrow from interest-free non-institutional sources.*

For a household that borrows from a moneylender, its utility across the two seasons is:

$$U_{ML} = u(c_1) + d\mathbb{1}\{D = 1\} + \beta\mathbb{E}\Big[u(c_2) + d\mathbb{1}\{D = 1\}\Big]$$

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

[29] R_1 could be thought of as the monsoon realization in a given year, which impacts both agricultural and non-agricultural incomes alike (Table 4). R_2 is the income shock in the lean season prior to the next monsoon.

[30] 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). However, I do not explicitly focus on this implicit cost in the model.

[31] Interest-free loans also tend to be smaller than interest-bearing non-institutional loans, and institutional loans are much larger than non-institutional loans.

In addition, moneylenders report low default rates, and borrowers report that the penalties for default are high enough to prevent default (Telangana Survey, 2020), and so I explicitly assume this.

Assumption 2. *The cost of defaulting on moneylender 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* $U_f(repay) > U_f(default)$.

Households thus choose whether to purchase durables or not, and accordingly choose a loan size. This allows me to define $\hat{\theta}$ as the endowment at which a borrower in the moneylender market is indifferent between purchasing durables and not purchasing durables. All households with $\theta > \hat{\theta}$ choose to borrow and purchase durables. Based on these household decisions, the total demand in the local economy for interest-bearing non-institutional loans, or moneylender loans, is given by:

$$L^* = \int_{\underline{\theta}}^{\hat{\theta}} b^*_{ML} f(\theta) d\theta + \int_{\hat{\theta}}^{\bar{\theta}} b^*_{ML,d} f(\theta) d\theta \tag{1}$$

3.1.1 Supply of Informal Credit

I now restrict attention to the supply of interest-bearing informal credit (loans from informal moneylenders). Following Aleem (1990) and 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.

I assume that lenders are endowed with fixed liquid capital, $\bar{K}$, which is higher following a positive shock to R_1. Lenders may also borrow, G from banks at an interest rate, r_B. There are N_L such lenders in this rural economy, each earning zero profit in the long-run equilibrium. I consider the symmetric case with identical lenders, and so each lender lends $l = \frac{L}{N_L}$. Each lender chooses the interest rate, r_{ML} to charge, and earns:

$$\Pi = r_{ML} \frac{L}{N_L} - r_B G - \rho \bar{K} \tag{2}$$

where L is determined by the household's decisions above, and since monopolistically competitive lenders make no economic profit in the long run, $r_{ML}\frac{L}{N_L} = F(\frac{L}{N_L})$.

Proposition 1. *In the symmetric equilibrium, each lender chooses an interest rate, r^*_{ML}, that satisfies $L^* = (r_B - r^*_{ML})\frac{\partial L}{\partial r_{ML}}$.*

Proof. See Appendix. ■

3.2 Implications of the Model

In the rural Indian context, rainfall during the monsoon increases local incomes (Table 4), and an increase in monsoon rainfall could be thought of as an increase in the season-1 exogenous productivity parameter, R_1. In addition, a reduction in the formal/bank credit supply could thought of as an increase in the formal market interest rate, r_B.[32] Here, I relate the market equilibrium informal interest rate and equilibrium quantity borrowed to changes in R_1 and r_B.

Proposition 2. *An increase in the exogenous productivity parameter, R_1, increases the equilibrium informal interest rate, r^*_{ML}, i.e., $\frac{dr^*_{ML}}{dR_1} > 0$*

Proof. See Appendix. ■

Proposition 3. *An increase in the exogenous productivity parameter, R_1, increases the equilibrium amount borrowed from informal moneylenders, L^* (or $\frac{dL^*}{dR_1} > 0$) only when $\Phi > 0$.*

Proof. See Appendix. ■

The intuition behind these proposition is that an increase in R_1 increases the number of households that choose to borrow and purchase durables, and when this is sufficiently large, borrower demand increases. At the same time, the increase in R_1 increases the liquid capital that moneylenders have access to, potentially increasing moneylender supply. When the supply impacts are small, the increase in demand pushes up the equilibrium informal moneylender interest rate. The implication of this is that an observed increase in both the quantity borrowed and in interest rates suggests that the demand effect is larger, and net demand increases.

[32]Even if r_B does itself increase, if we consider a constraint on the quantity a moneylender can borrow from a bank, say, $\bar{G}$, then a reduction in $\bar{G}$ would push up the shadow price in on the constraint, $L - \bar{K} = \bar{G}$ when it binds in the optimization problem. The effect is the same as an increase in r_B when I consider the comparative statics.

Assumption 3. *An exogenous decrease in formal credit (or increase in r_B) decreases the number of borrowers who can borrow from institutional sources, i.e., $\frac{d\bar{\theta}}{dr_B} > 0$.*

Proposition 4. *An exogenous increase in r_B (contraction in formal credit supply) increases the equilibrium moneylender interest rate, r^*_{ML}, i.e., $\frac{dr^*_{ML}}{dr_B} > 0$.*

Proof. See Appendix. ■

Proposition 5. *An exogenous decrease in formal credit (or increase in r_B) has ambiguous effects on on the equilibrium amount borrowed from moneylenders.*

Proof. See Appendix. ■

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. At the same time, the contraction 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 $|\frac{d\bar{\theta}}{dr_B}|$ is large, then the net effect is an expansion in borrowing from informal moneylender; while the converse is true if $|\frac{d\bar{\theta}}{dr_B}|$ is small. However, both effects push up the informal moneylender interest rates.

Proposition 6. *An exogenous increase in the productivity parameter, R_1, has a smaller impact on the equilibrium amount borrowed when formal credit supply is low than when it is high (i.e., $\frac{d^2L^*}{dR_1 dr_B} < 0$) when $\Phi > 0$.*

Proof. See Appendix. ■

Proposition 7. *The differential impact of an exogenous increase in the productivity parameter, R_1, on the equilibrium informal rate when formal credit supply is low compared to when it is high (i.e., $\frac{d^2r^*_{ML}}{dR_1 dr_B}$) depends on the change in demand elasticity.*

Proof. See Appendix. ■

The preceding two propositions address the impact of a reduction in formal credit supply when demand for moneylender credit is high as opposed to when it is low. The intuition behind is that at low levels of formal credit (when r_B is high), moneylenders have access to lower levels of lending capital. So, an increase in demand in this low supply case would mean that moneylenders are less able to meet the increase in demand — this results in smaller increase in borrowing following an equivalent increase in demand.

4 Data and Empirical Strategy

4.1 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,[33] 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 of June 30$^{\text{th}}$ June, 2002 or 2012, and the second, as of 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[34] Village Dynamics survey, with data from 866 households[35] in 18 villages in 9 districts in the states of Andhra Pradesh,[36] Maharashtra, Karnataka, Gujarat, and Madhya Pradesh. Each household is surveyed every month between 2010 and 2014,[37] and the survey records monthly loan transactions, monthly consumption expenditures and monthly purchases of durables and capital assets.

In addition, the Informal Enterprise survey rounds of the NSS provide me with data on moneylenders themselves. I supplement 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 borrow-

[33] The survey covers 634 districts in the 2012-13 round.

[34] ICRISAT is an acronym for International Crops Research Institute for the Semi-Arid Tropics.

[35] Some of the 866 households in 2010 split, and there are 870 unique households in 2014.

[36] The state is now split into Andhra Pradesh and Telangana.

[37] Data from the year 2009 is excluded since transactions are not recorded by month, but in arbitrary chunks through the survey year – making it impossible to assign a transaction to a month or season.

ers 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 on 31st March each year at the loan type $\times$ population-group $\times$ bank group level for a district.[38] Rainfall data is from the University of Delaware Global Precipitation Archive's Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series (version 5.01), and consists of monthly observations of rainfall from rain-gauge measurements interpolated to a 0.5° by 0.5° latitude-longitude grid.

4.2 Rural household credit demand and rainfall shocks

The empirical strategy in this paper relies on plausibly exogenous variation in rural households' demand for credit, and in formal sector credit supply. For the former, I rely on increases in household income arising from positive rainfall shocks during the summer monsoon. The summer monsoon usually extends from June to September in India, and coincides with the rain-fed, *kharif*, agricultural season. *Kharif* crops are harvested in September or October, following which agricultural incomes are realized. Years with a good monsoon tend to increase both agricultural incomes and, through a multiplier effect, non-agricultural incomes in a district (Table 4). Following Emerick (2018); Jayachandran (2006); Kaur (2019); Paxson (1992); Rosenzweig and Wolpin (1993); Santangelo (2019); Townsend (1995), I assume that rainfall shocks are transitory and serially uncorrelated.

Since I am primarily interested in non-agricultural household borrowing, and since credit is fungible, I focus on household borrowing outside of the agricultural season rather than on loans by reported type. Another advantage of focusing on the non-agricultural period is that this allows me to interpret the rainfall shock as a shock to realized incomes rather than as a shock to agricultural productivity alone. I define the primary rainfall shock measure as the deviation of a district's total monsoon precipitation in a year from its historical mean, normalized by its standard deviation (Emerick, 2018). The rainfall for a given district is the rainfall in the grid cell nearest to

[38] 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.

the district's centroid. The historical mean and standard deviation for each grid-cell (and district) are computed from the 50-year distribution (1967-2017). Further discussions of the relationship between an income shock and household demand for credit are in sections 3 and 5.

4.3 Formal sector credit supply

The second component of this paper's empirical strategy is plausibly exogenous variation in a district's bank credit supply. Based on the observation, similar to that in Greenstone et al. (2020), that bank presence varies across districts, and that banks themselves vary in their lending across sectors in India — I follow their shift-share or 'Bartik' instrument-inspired approach.[39] I first estimate an equation that decomposes observed credit limits into a loan-type or industry component, a population-group component, a district component and a bank-group component.[40]

$$\Delta log\ C_{irjd} = g_i + g_r + g_j + g_d + \epsilon_{irjd}$$

Here the outcome is the credit-limit for an industry or sector, i, in a population sub-group, r, in a bank-group, j in district, d.[41] The predicted bank-group specific change in credit supply, $\hat{g}_j$, is no longer driven by district-, industry-, or population-group- specific variation in demand for credit[42]. For each pair of consecutive years, the constructed district-level credit supply shock is the inner-product of $\hat{g}_j$ and each bank-group's market-share in that district in the initial year, s_{jd}.

$$B_d = \sum_j s_{jd} \times \hat{g}_j$$

The credit-supply shock used in the analysis is an indicator for whether the district experienced a positive or a negative shock: $\mathbb{L}_{dt} = \mathbb{1}\{B_{dt} < 0\}$.

Goldsmith-Pinkham, Sorkin, and Swift (2020) argue that identification in a research design that uses a 'Bartik' instrument requires the exogeneity of the market-shares, conditional on ob-

[39] Used in Autor and Hanson (2013); Bartik (1991); Blanchard and Katz (1992); Caldwell and Danieli (2018); Card (2001) etc.

[40] While an approach using data at the bank level might be preferable, the RBI was unwilling to share data at this level. There are five bank groups — State Bank of India and its associates, nationalized banks, other public sector banks, foreign banks, private banks.

[41] A population sub-group refers to whether the credit pertains to a rural, semi-urban, urban or metropolitan area. An industry or loan-type refers to whether a loan pertains to one of agriculture, industry, transport operators, professional and other services, personal loans, trade, finance, and other.

[42] Apart from Greenstone et al. (2020), this is similar in spirit to the approach used in Khwaja and Mian (2008) where the authors control for firm specific demand to separate supply and demand response to credit shocks.

servables. In addition, a feature of the banking system in India is that in addition to bank level decisions, credit is also planned at a state level through State Level Bankers Committees at the start of each financial year (1st April). Accounting for this, the identification assumption here is that is the credit-supply shock is uncorrelated with unobserved shocks to the outcomes, conditional on state $\times$ year fixed effects (Baum-Snow & Ferreira, 2015).[43] I probe the validity of this assumption in Table **??**, which presents differences in the mean values of various district characteristics each year between districts with positive and negative formal credit supply. There are no significant differences across the groups.

4.4 The Effect of Weather on Local Credit Market Outcomes

I estimate the causal effect of a positive rainfall shock on household outcomes in the non-agricultural season using household-level, household$\times$month-level and loan-level data. When using household-level data, I control for household fixed effects, and otherwise, I control for household characteristics.[44]When outcomes pertain to a household, I estimate:

$$Y_{hdst} = \beta_1 Rain_{dt} + \psi_d + \tau_{st} + \lambda_h + \varepsilon_{hdst} \tag{3}$$

When outcomes pertain to a household in a specific month, I estimate:

$$Y_{hdsmt} = \beta_1 Rain_{dt} + \mu_m + \psi_d + \tau_{st} + X_{it}\delta + \varepsilon_{hdmst} \tag{4}$$

where μ_m denotes month-of-year fixed effects, λ_h denotes household fixed effects, ψ_d denotes district fixed effects, τ_{st} denotes state$\times$year fixed effects and X_{it} denotes a vector of household characteristics. For outcomes measured at the loan level, I control for loan characteristics and household characteristics.

$$Y_{lidmst} = \beta_1 Rain_{dt} + \mu_m + \psi_d + \tau_{st} + L_{lit}\phi + X_{it}\delta + \varepsilon_{lidsmt} \tag{5}$$

where L_{lit} is a vector of loan characteristics. Robust standard errors in all specifications are clustered at the district-level. Since loan-level outcomes, in particular, interest rates, are only observed when a loan has been transaction, the rainfall shock could potentially impact selection into bor-

[43]The state $\times$ year fixed effects control for state macroeconomic conditions in a given year, apart from State Level Bankers Committee (SBLC) decisions.

[44]I am unable to control for household fixed effects in the household$\times$month dataset since different households are surveyed in different months, and the same household is surveyed in different months each time it is surveyed.

rowing. This might be of concern in the context of interest rates since 'riskier' borrowers might only get loans at higher interest rates. To address this, I also present loan-level results that correct for selection bias using a semi-parametric two-step procedure proposed by Newey (2009) — which is also used in Botsch and Malmendier (2020); Hoffmann et al. (in press).[45]

4.5 The Effect of Reductions in Formal Credit Supply

Similar to the approach in the previous section, I estimate the causal effect of reductions in formal credit supply, $\mathbb{L}_{dt}$, on outcomes at both the household level, and the loan level. In all cases, I estimate the reduced form impact of the supply shock, as well as of the interaction between the supply shock and the rainfall shock.

$$Y_{hdst} = \gamma_1 \mathbb{L}_{dt} + \psi_d + \tau_{st} + \lambda_h + \varepsilon_{hdst} \tag{6}$$

$$Y_{hdst} = \delta_1 Rain_{dt} + \delta_2 \mathbb{L}_{dt} + \delta_3 Rain_{dt} \times \mathbb{L}_{dt} + \psi_d + \tau_{st} + \lambda_h + \varepsilon_{hdst} \tag{7}$$

$$Y_{hdmst} = \gamma_1 \mathbb{L}_{dt} + \mu_m + \psi_d + \tau_{st} + X_{ht}\delta + \varepsilon_{hdmst} \tag{8}$$

$$Y_{hdmst} = \delta_1 Rain_{dt} + \delta_2 \mathbb{L}_{dt} + \delta_3 Rain_{dt} \times \mathbb{L}_{dt} + \mu_m + \psi_d + \tau_{st} + X_{ht}\delta + \varepsilon_{hdmst} \tag{9}$$

where the fixed effects are the same as in the preceding section. The equation below represents regressions at the loan level.

$$Y_{lhdmst} = \delta_1 Rain_{dt} + \delta_2 \mathbb{L}_{dt} + \delta_3 Rain_{dt} \times \mathbb{L}_{dt} + \mu_m + \psi_d + \tau_{st} + L_{lht}\phi + X_{ht}\delta + \varepsilon_{lhdmst} \tag{10}$$

5 Empirical Results and Discussion

5.1 The Effect of Weather on Local Credit Market Outcomes

I first focus on rural household demand before turning to the impact of formal credit supply shocks. As the model in section 3 indicates, a positive income shock for rural households might increase their demand for informal credit in the non-agricultural season if a sufficiently

[45] I use a third-order power series control function of the probability of selection, which is computed in the first-stage using a probit model that includes the same set of controls as in the household specification. Importantly, identification here relies on an instrument for selection in the first stage — and I use the incidence of births in the household in the last year. Standard errors are bootstrapped with 5000 repetitions.

large number of borrowers increase their borrowing for consumer durables, weddings, festivals or other similar consumption needs that require large outlays. Tables 9 and 10 indicate that households borrow more from informal moneylenders in the non-agricultural season following a positive rainfall shock (columns 1 and 2). A one standard deviation increase in the rainfall shock or a 1% increase in a district's per capita GDP (Table 4) results in 1 percentage point more households borrowing from moneylenders (column 1, Table 10) — this is a 12% increase in the number of borrowers, and a 4% increase in the amount borrowed by households over the non-agricultural season in a year (columns 2 and 1 in Table 9).[46] However, there are no significant effects on either interest-free loans from friends or relatives (which tend to be smaller in size) or on loans from institutions (which may not readily lend to rural households for non-agricultural purposes). These results are robust to alternative defintions of the rainfall shock (Table B3).[47] Iteratively dropping one state from the sample at a time also yields similar results (Figure A1), and reassuringly, a placebo test uses a standardized measure of the non-monsoon rainfall shock does not have similar results (row 3, Table B3).[48] Evidence from the ICRISAT sample (in Table A1) is similar, with a significant increase in borrowing from moneylenders in the non-agricultural season.

Contemporaneous with this increase in borrowing from moneylenders in the non-agricultural season, is 3.5% increase in annualized moneylender interest rates (or an 8% increase over the mean of 41.83% per year) (Table 11). 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. Column 2 in Table 11 presents Newey (2009) selection corrected results, and reassuringly, the effect is similar. There is no significant effect on the interest rate in the ICRISAT sample, though the point estimate is positive (column 7, Table A1). As described in the model, a positive income shock could not only impact household borrowing, but also increase lending capital that moneylenders have access to.[49] However, the increase in both

[46] Column 1 in Table 9 represents a monthly rather than yearly increase

[47] The percentile shock follows the definition in Jayachandran (2006), where the 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. The 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)).

[48] 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.

[49] This might be through improved repayment following a rainfall shock, or through increased returns to a secondary

household borrowing *and* in interest rates is consistent with a net increase in demand. Indeed, almost 93% of informal moneylenders in the Telangana Survey (2020) report increasing interest rates when demand goes up (Figure 5). The average borrowing household in the NSS sample borrowed ₹13431.56 (in 2000-01 prices) in the non-agricultural season, with loans accruing an additional ₹5,910 in interest due at the end of a year. This implies that an average household that borrows will owe xx times the average rural agricultural income in the following year.

A look at what households borrow for, in Table 12, indicates that this increase is indeed driven by loans reported as being for consumption (though significant only at the 10% level); and Table 13 indicates that households have higher expenditures on land and buildings in the non-agricultural season following a positive rainfall shock. Similarly, results from the ICRISAT sample (Table A2) indicate that households increase consumption expenditures as well as purchases of durable goods following a positive rainfall shock. Further, Table A3 suggests that the increase in borrowing from moneylenders in the non-agricultural season following a positive rainfall shock is driven by households which also purchase durables in the same period. These results are consistent with the model, which suggests that any increase in household borrowing that might arise following an positive shock to incomes arises due to an increase in borrowing for large consumption expenses, such as purchases of durables, improvements to land or housing etc.

An alternative explanation might be that a positive rainfall shock increases borrowing for non-agricultural production if the increases in district incomes increase demand for non-tradable goods or services, leading to an increase in demand for credit.[50] However, Table 13 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). Yet another explanation might be that the positive rainfall shock increases demand for loans for agricultural expenses in the non-rain-fed *Rabi* season (which extends from October to January, and is entirely irrigated). However, the main household results hold when restricting the sample entirely to the lean season (February to May).

It is still puzzling that households borrow more following positive rainfall shocks at interest rates that average around 40% per year rather than saving to make these purchases. However,

business or agriculture.

[50]This is similar to the aggregate demand channel that the authors propose in Breza and Kinnan (2018).

results in Table B1 suggest that it is households without access to any meaningful savings that increase their borrowing. Also counter-intuitive is the implication that households might be borrowing far less in the non-agricultural season following a drought. The model suggests that it might also be possible for household informal borrowing to increase following a drought if the increase in the amount each borrower borrows increases, particularly among relatively poorer borrowers. I test whether the household informal borrowing responds symmetrically to both a positive and a negative rainfall shock in Table B2. Though the effect is not significant, the interaction term in columns 1 and 2 suggest that the effect could be asymmetric with possible increases in moneylender borrowing following droughts too — from lower levels of overall borrowing.

5.2 The Effect of Formal Credit Supply Contractions on Local Credit Market Outcomes

Having established how household demand for moneylender loans might increase following positive rainfall shocks, I next estimate the effect of a reduction in credit supply on household borrowing in the non-agricultural season. As one might expect, Table 7 demonstrates that the reduction in credit supply at the district level significantly reduced institutional loans borrowed by rural households (column 5). When it comes to borrowing from informal sources (loans from moneylenders interest-bearing informal loans, while loans from friends and relatives are interest-free loans), the model indicates that there are two possible opposing effects. First, a reduction in formal supply could increase demand for informal loans, driving up informal loan interest rates. In the survey of moneylenders (Telangana Survey, 2020), 40% of lenders indicate that they rely on formal loans for their lending capital (Figure 6). And so, a reduction in formal supply could decrease the informal credit supply. This would also lead to an increase in the informal market interest rates. Table 8 indicates that a reduction in formal credit supply does indeed increase interest rates on informal loans by 3.83 percent per year4 (column 2). Thus, a 10% decrease (implied by the difference in the average shock in low and high supply districts) in formal credit supply results in an 8.8% increase in informal market interest rates. However, there is no significant impact on household borrowing from either moneylenders or friends and relatives. This leaves us unable distinguish between the two channels when rural household credit demand is at expected levels.

5.3 The Effect of Formal Credit Supply Contractions on Local Credit Market Responses to Weather

Given moneylenders' reliance on formal credit for lending capital, reduced access to formal credit could be more salient when the demand for informal credit is also high, reducing moneylenders' ability to extend additional loans following an unanticipated increase in demand. As a result, the increase in loans transacted following a demand shock would be lower when there is lower formal supply. If, however, reduced formal credit primarily increases demand for moneylender credit, then borrowing would be even higher following an unanticipated increase in demand accompanying and reduction in formal credit. To distinguish between the two, I interact the positive rainfall shock with the low formal supply indicator to estimate the differential effects of the supply shock across environments with low and high household demand.

Tables 14 and 15 demonstrate that the increase in borrowing following a positive rainfall shock is smaller when a district simultaneously experiences a reduction in formal credit supply than when there is an expansion in formal credit supply (columns 1 and 2). Following a one standard deviation increase in rainfall (or a 1% increase in district per capita incomes), an additional 1 percentage point or 12% more households borrow from informal moneylenders when formal supply is high than when formal supply is 10% lower. These results persist when iteratively dropping one state from the sample at a time (Figure A2), and when I define the same formal supply shock measure using credit outstanding or the number of loan accounts rather than the credit limit (Table B4).

Column 5 also indicates that households borrow more from institutional sources following a positive rainfall shock, only when the formal credit supply in the district also expands. While column 4 indicates that household possibly cope with this reduction in both formal and moneylender credit supply by increasing interest-free borrowing from friends or relatives, the magnitude of the same estimate in column 3 is far smaller, and not statistically significant, suggesting caution in interpreting this result. An increase in loans from friends/relatives still outstanding at the end of the reference year but not in loans borrowed could also result from reduced repayment of these loans. These results point to the the supply effect as being the dominant channel through which contractions in formal credit impact informal borrowers rather than an additional increase in demand.

Finally, Table 16 indicates that the increase in moneylender loan interest rates is also smaller following a positive rainfall shock when formal credit supply is low when compared to a situation where formal supply is high. While the heterogeneous effect on borrowing quantity and incidence sheds light on the nature of the interaction between the formal and informal credit markets, the differential effect on interest rates does not by itself do so. This is because the predicted sign on the the interaction term in this setting depends on the demand elasticity, and the change in demand elasticity due to the rainfall shock.

5.3.1 The Relationship between Moneylenders and Formal Lenders

The above results suggest that while increases in incomes 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. Data from the Telangana Survey (2020) provides suggestive evidence to support this — 35% of moneylenders surveyed report that they have borrowed from banks when they faced shortfalls in lending capital, while over 50% report that they would lend more if they were able to borrow from banks more easily (Figure 7). Turning to data from moneylenders that form part of the sample in the NSS Informal Firms survey — a one standard deviation increase in the rainfall shock (or a 1% increase in district per capita income) results in a 4 percentage point or 28% increase in the number of lenders who have outstanding loans from formal institutions (column 1, Table 17). In addition, a 1% decline in formal credit supply results in a 1.7 percentage point or a 12% decline in outstanding loans from formal institutions (column 2, Table 17). Column 3 in Table 17 further indicates that the decline in formal credit supply also leads to an increase in lenders reporting having trouble with credit access (i.e., they report the high cost or unavailability of credit as being a problem).

6 Welfare Implications

In this section, I analyze a cross-section of cost and lending data from 396 private moneylenders across India to help contextualize what the previous results imply for consumer welfare.[51] The median annual interest rate implied by lenders interest receipts and loan advances is 36% (Table 18), the same as the median from the household data (Table 2) — though the mean interest rate from the lender data is much higher than that in the household data. Similarly, the median formal interest rate in both household and lender datasets are 12% per year. The median monthly costs per hundred rupees lent is 18%, while the mean is 53%. Thus, a lower bound on the marginal cost of lending is the formal sector interest rate that moneylenders face, while an upper bound is the average cost of lending. Taking these two cases and computing the implied mark-up for each moneylender suggests that the median mark-up is between 52% and 53% while the mean mark-up is between 41% and 48% — which point to high mark-ups.

This suggests that moneylenders are able to arbitrage across the sectors and profit; and second, that though formal sector expansions allow additional borrowing by rural households in the informal sector, with high mark-ups, moneylenders accrue most of the additional surplus generated.

7 Conclusion

This paper focuses on informal non-agricultural household borrowing in rural India, and presents findings on demand, supply and the interaction of the informal market with the formal credit market. I first find that positive rainfall shocks increase rural household borrowing, due to an increase in demand for durable goods. This is possibly driven by limited household savings. Second, I evaluate whether formal credit institutions and informal moneylenders primarily compete, or whether they are primarily engaged in a vertical relationship in the market for non-agricultural lending in rural India. While this analysis does not rule out the competition channel, it does highlight that the latter relationship is particularly relevant when there is an unanticipated increase in rural household demand for informal credit. This is because one of the mechanisms for moneylenders to expand supply is to increase lending from formal sources, and when one such

[51] Available only in the 73rd Round of the NSS Informal Firms Survey, 2015-16

source is constrained, the effect spills over into the informal credit market. In addition, this paper contributes evidence on the extent on mark-ups moneylenders earn — suggesting that moneylenders successfully arbitrage across sectors and earn a larger share of the surplus in the informal market than consumers do.

These results further indicate that despite increased access in rural India to agricultural credit, other needs keep households transacting with informal moneylenders. This is possibly because moneylenders offer greater flexibility to borrowers than formal institutions do, or because access to formal credit remains difficult. Apart from collateral requires, red tape might also prevent increased use of formal credit (**?**). While this does suggest that moneylenders provide a service borrowers value, high mark-ups and coercive enforcement mechanisms (Telangana Survey, 2020) also suggest that there remains the potential to make rural households better off by improving the availability of non-agricultural credit.

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Figures

Figure 1: Monsoon Timing

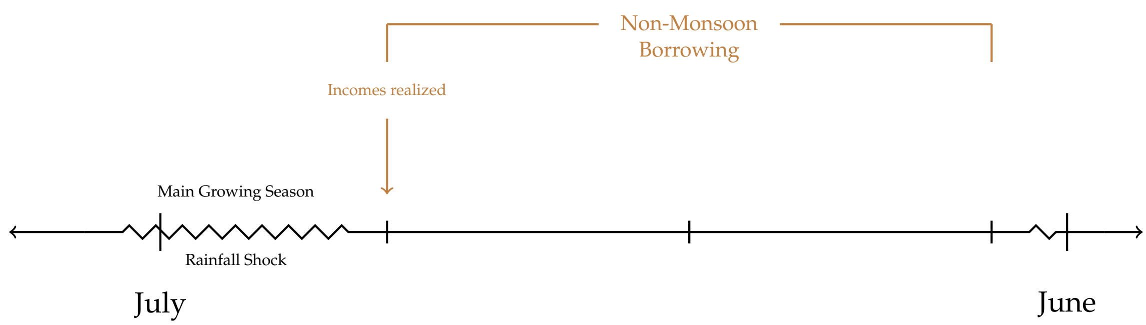
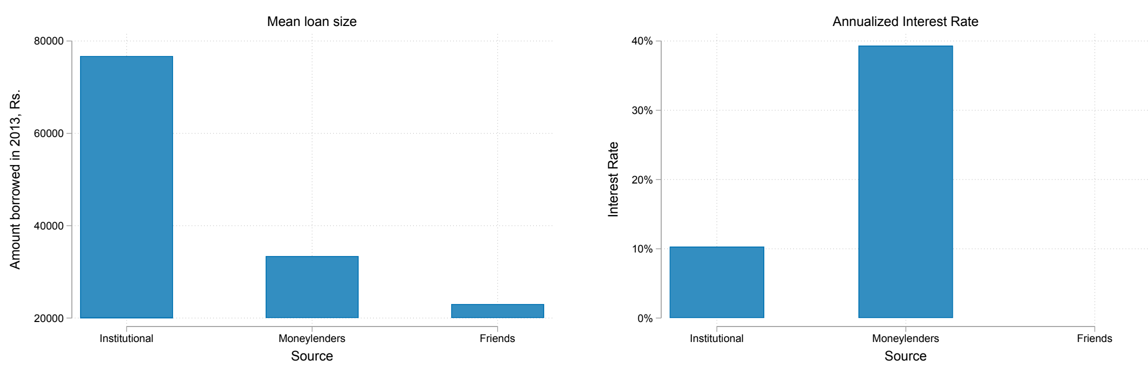
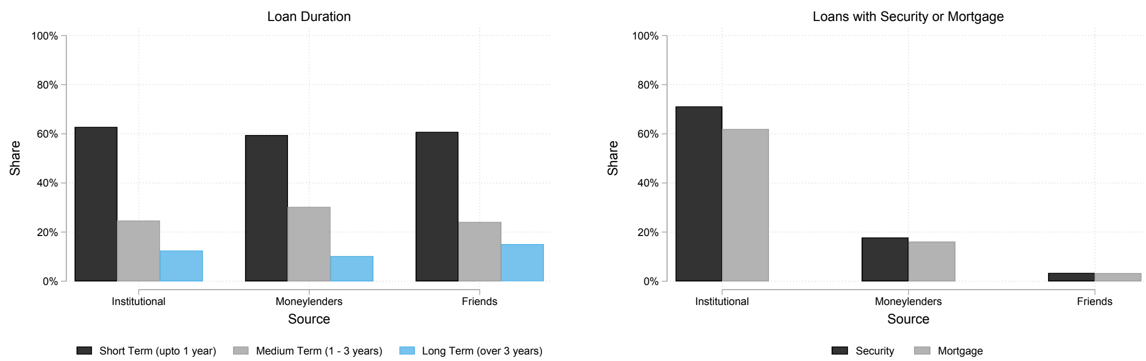


Figure 2: Loan Size and Interest Rates by Lender Type



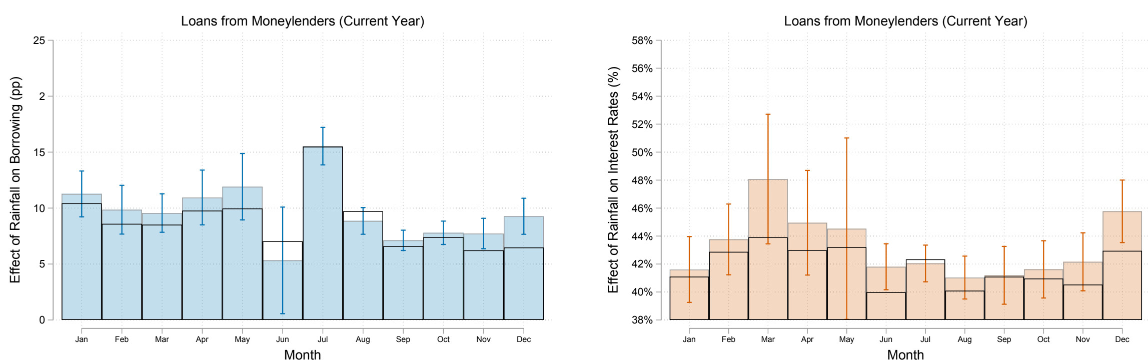
Data: NSS Debt and Investment Survey, 2013

Figure 3: Loan Terms by Lender Type



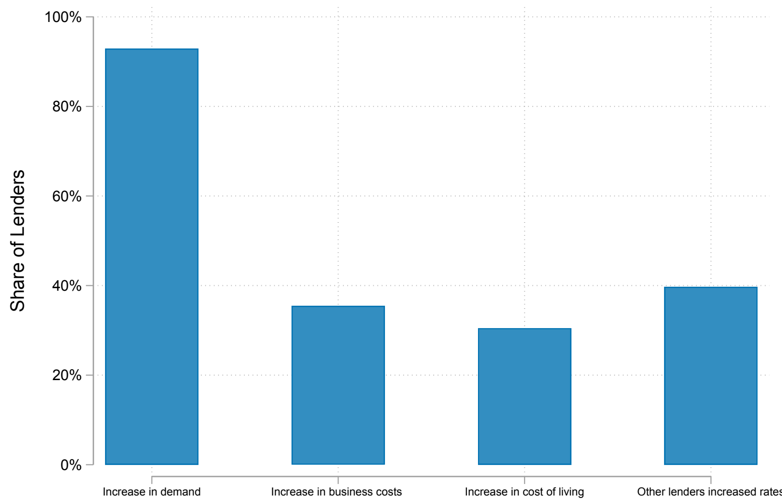
Data: NSS Debt and Investment Survey, 2013

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



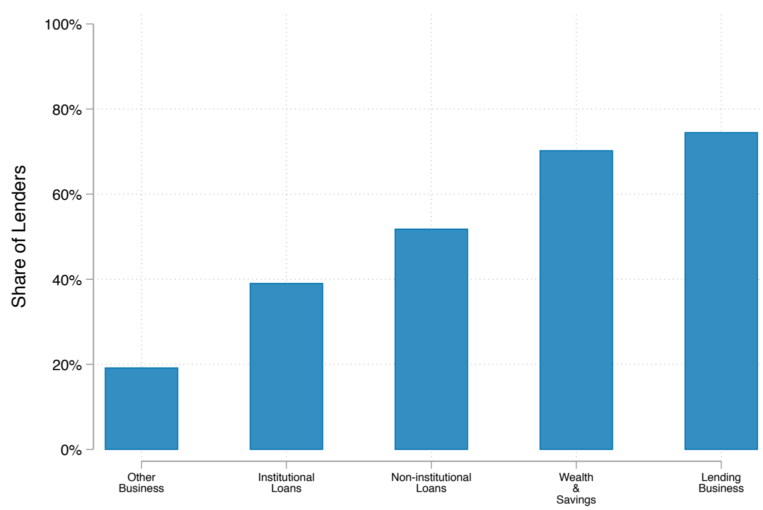
Data: NSS Debt and Investment Survey, 2001-02, 2002-03, 2011-12, 2012-13

Figure 5: Reasons for which Moneylenders increase Interest Rates



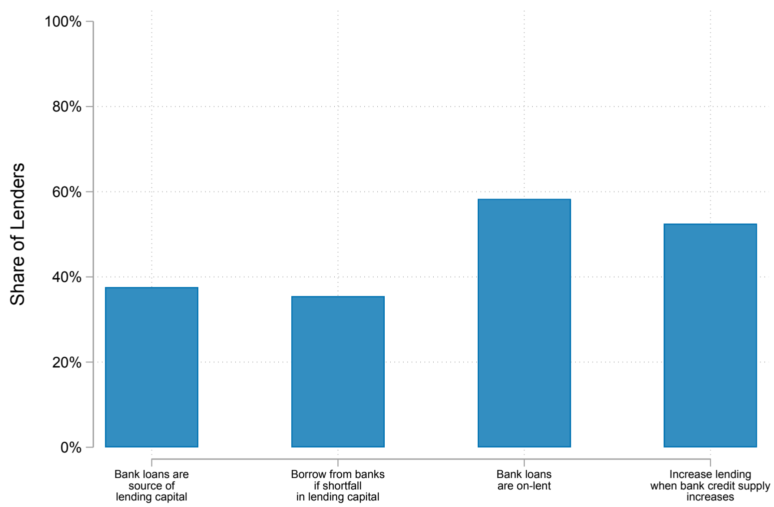
Data: Moneylender Survey (Telangana), 2020

Figure 6: Moneylenders' Source of Lending Capital



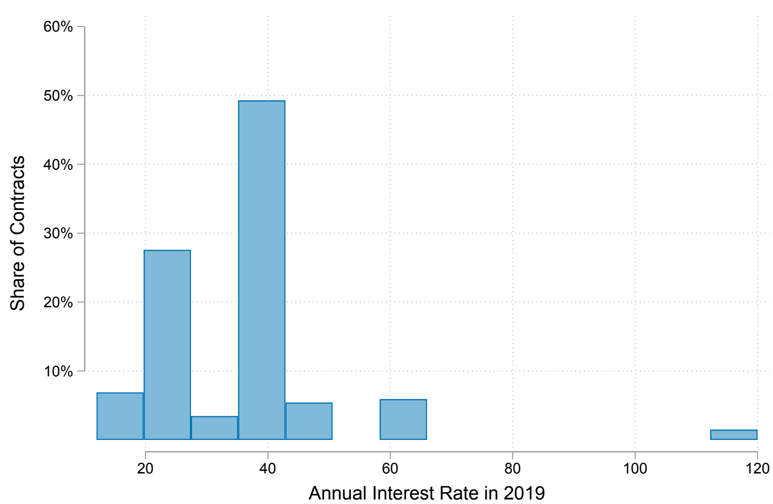
Data: Moneylender Survey (Telangana), 2020

Figure 7: Moneylenders' Bank Borrowing



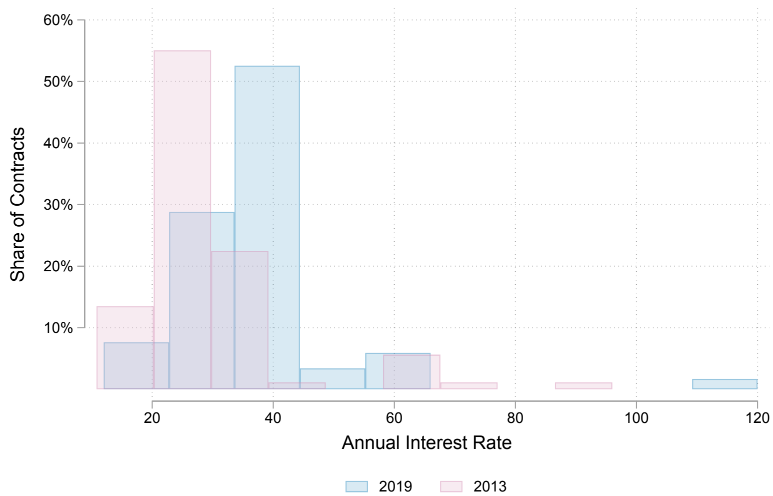
Data: Moneylender Survey (Telangana), 2020

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: 'Shift-Share' Credit Supply and District Total Formal Credit

	Credit Limit (ln real ₹)		Credit Amount (ln real ₹)		No. accounts (ln)	
	(1)	(2)	(3)	(4)	(5)	(6)
Credit Shock	0.401***		0.276**		0.321***	
	(0.118)		(0.109)		(0.087)	
High Supply		0.034***		0.024**		0.045***
		(0.012)		(0.011)		(0.007)
Obs	10344	10344	10344	10344	10344	10344
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). Monetary values are in 1990-91 ₹
Notes: The credit shock is a fractional change in the 'shift-share' measure of exogenous changes in credit supply. Coefficients represent the % change in the outcome due to a 100% exogenous change in the credit supply shock. The High Supply variable is an indicator that takes a value of 1when the credit shock is greater than 0. Coefficients represent the % change in the outcome due to a 11% exogenous change in the credit supply shock. Unit of observation is a district. Standard errors are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 4: 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 5: Rainfall and District Total Formal Credit

	Credit Limit (ln real ₹)		Credit Amount (ln real ₹)		No. accounts (ln)		Credit Shock (shift-share)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rainfall Shock	0.003		0.004		-0.001		-0.000	
	(0.006)		(0.005)		(0.004)		(0.000)	
Rainfall Shock Last Year		-0.002		0.001		-0.001		-0.000
		(0.006)		(0.005)		(0.003)		(0.001)
Obs	10873	10873	10873	10873	10873	10873	10458	10458
Clusters	581	581	581	581	581	581	581	581
Fixed Effects	District, State × Year							
Mean	₹ 16.74 mil		₹ 11.30 mil		165514.9		0.001	

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 are clustered at the district level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: 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 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 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 region×year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: 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)
Low Supply	0.010	0.000	0.002	-0.004	-0.026***	-0.008
	(0.008)	(0.005)	(0.008)	(0.004)	(0.009)	(0.005)
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	0.08	0.06	0.06	0.04	0.09	0.07

Data: NSS Debt and Investment Survey (2001-02, 2002-03, 2011-12 and 2012-13)
Notes: 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 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 8: Formal Credit Supply Shock and Interest Rates on Loans from Moneylenders

	Sample 1		Sample 2
	(1)	(2)	(3)
Low Supply	3.728*	3.828*	2.358**
	(1.908)	(2.125)	(0.929)
Obs	8376	8362	15375
Clusters	459	457	495
Fixed Effects	Month, District, State × Year		
Mean	43.51%	43.52%	41.11%

Data: NSS Debt and Investment Survey (2001-02, 2002-03, 2011-12 and 2012-13)
Notes: The low supply shock is an indicator that takes a value of 1 when the 'shift-share' measure is less than 0. Unit of observation is a loan. All regressions control for loan characteristics, and household characteristics. 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 $2\Phi(x\beta) - 1$.
Standard errors are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 9: 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 10: 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 11: Rainfall and Interest Rates on Loans from Moneylenders

	Sample 1		Sample 2
	(1)	(2)	(3)
Rainfall Shock	3.531^{***}	4.083^{***}	1.565^{**}
	(0.808)	(1.403)	(0.660)
Obs	9281	8362	17088
Clusters	462	457	498
HH FE	no	no	no
Fixed Effects	Month, District, State $\times$ Year		
Mean	41.83%	43.52%	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, and household characteristics. 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 $2\Phi(x\beta) - 1$.
Standard errors are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 12: 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 13: 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 14: 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 15: 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 × 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 × 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 ×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×year level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 16: 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 $\times$ Low Supply	-3.906**	-1.861**
	(1.720)	(0.787)
Obs	8376	15264
Clusters	459	495
Fixed Effects	Month, District, State $\times$ 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 17: 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.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

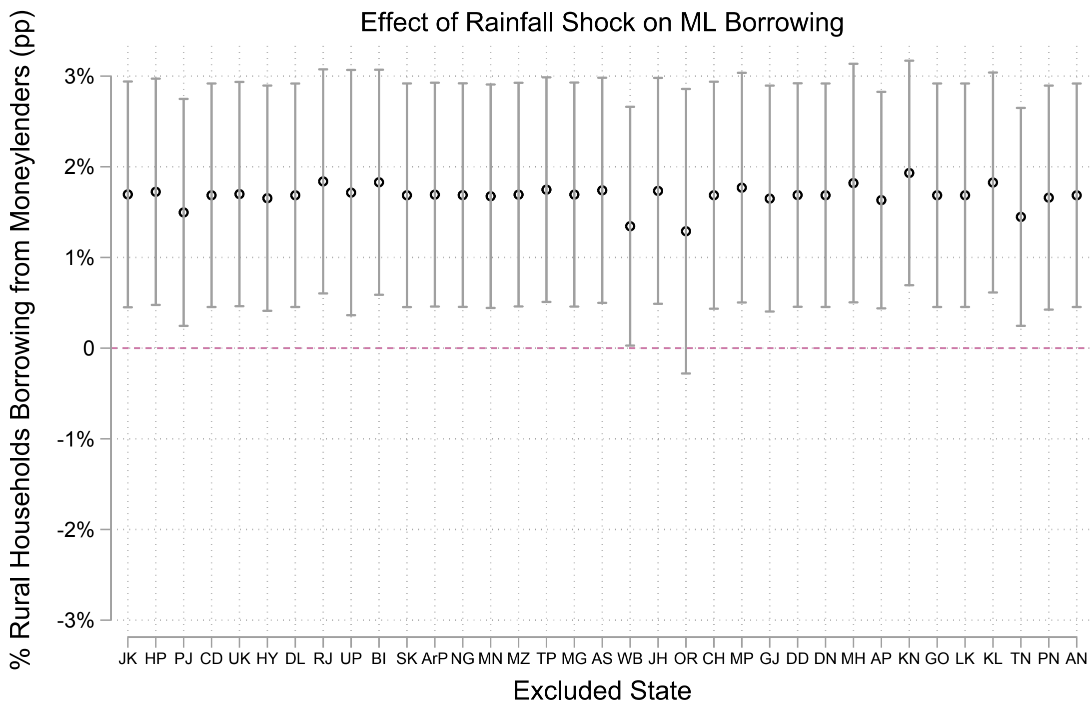
Table 18: Lender Statistics

	Mean	Median	SD	N
	(1)	(2)	(3)	(4)
Total Amount Outstanding ('000 ₹)	597.16	281.96	1349.32	396
Share Lent to HHs	81.92%	100%	26.96%	342
Lending Rate (% per year)	92	36	199	387
Average Cost (% per year)	53	18	159	395
Interest on all Outstanding Debt (% per year)	14	12	6	94
Interest on Outstanding Formal Debt (% per year)	13	12	4	72
Margin over Avg. Cost	0.41	0.52	0.62	387
Mark-up	0.48	0.53	0.39	60

Data: Private Moneylenders from NSS Informal Firms Survey (2015-16)
₹ values are in real 2000-01 INR

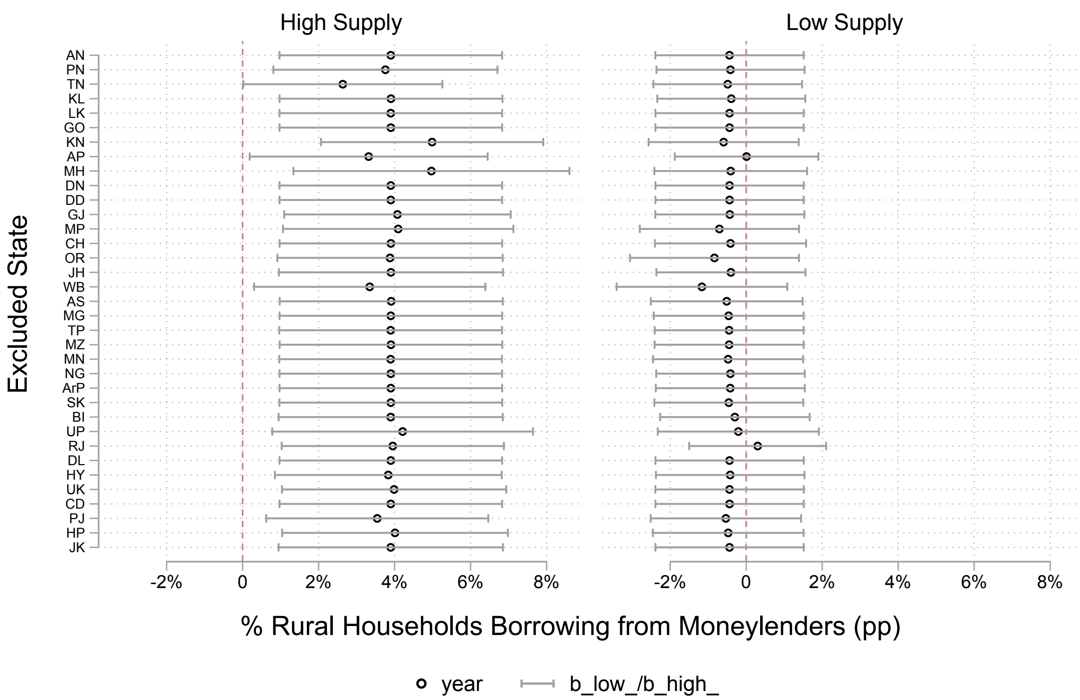
Additional Figures

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 ×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	0.017	0.06	0.109***
	(0.046)	(0.063)	(0.027)
Any Durables	0.036*	0.060**	0.019
	(0.015)	(0.025)	(0.015)
Rainfall Shock × Any Durables	0.023*	0.016	-0.000
	(0.012)	(0.016)	(0.007)
Obs	4317	4317	4317
Clusters	9	9	9
Fixed Effects	HH, District, State ×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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Mathematical Appendix