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

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Abstract

Most borrowers in developing countries rely on informal lenders. Using exogenous weather-induced credit demand shocks and variation in bank credit supply, this paper shows that informal moneylenders in rural India rely on formal credit to ease lending-capital constraints. Moneylenders borrow more from banks when household credit demand rises, and household borrowing from moneylenders increases more in districts with expanding bank credit supply — driven by changes in moneylender supply rather than in household demand for credit overall. These results help explain the persistence of informal credit since they indicate that, rather than competing with informal moneylenders, banks effectively collaborate with them.

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1 Introduction

High-interest non-institutional lenders continue to meet a large share of global consumer credit needs — with over three-quarters of borrowers worldwide having obtained credit from a non-institutional source in 2021 (World Bank, 2022).[1] Although decades of expansions in formal financial sectors have improved financial access (Demirguc-Kunt et al., 2022; Burgess and Pande, 2005), frictions related to the usability and suitability of formal credit persist. Banks and regulated institutions often require documentation, collateral, and procedures that exclude large segments of the population (Kanz, 2016; Allen et al., 2016). In contrast, informal lenders offer immediacy, local knowledge, and relational flexibility, filling a gap that formal systems have yet to close.

This persistent reliance on informal credit raises a central question: How do formal and informal lenders interact and what are the implications for credit policy? Existing work typically frames the relationship as either as a horizontal interaction, where the sectors compete (Jacoby, 2008; Bell et al., 1997; Kochar, 1997; Jain, 1999; Giné, 2011); or a vertical one, where informal lenders on-lend formal credit (Jacoby, 2008; Hoff and Stiglitz, 1998; Floro and Ray, 1997). Despite this rich literature, empirical evidence on informal lenders' own credit supply, particularly their links to banks, remains scarce, largely due to a paucity of data. I revisit this question using data from rural India, where borrowing from both formal and informal sources has more than doubled over the past three decades (NSSO, 2013b; NAFIS, 2017), making it an ideal setting to study how these two sectors interact.

I begin by documenting new descriptive evidence on India's informal moneylending market that draws on nationally representative sample survey data from 925 moneylenders and a novel survey of 140 moneylenders in Telangana. I find that moneylenders rely on formal

[1] Here, I use the term institutional lender to refer to refer to lenders which are regulated financial institutions such as commercial banks, cooperative banks, and non-bank financial companies (NBFCs)—including both deposit-taking and non-deposit-taking entities; and non-institutional lenders to refer to informal lenders such as moneylenders, traders, shopkeepers, and input suppliers who provide credit outside formal financial channels.

credit for lending capital; that many report using formal loans to meet capital shortfalls; and that, among those who borrow, the median moneylender sources 45% of the credit they advance from formal institutions. While the median moneylender earns margins above both marginal and average costs,[2], some operate below average cost — suggesting potential supply constraints.

Unanticipated demand shocks provide a natural setting to test whether access to formal credit helps ease such constraints. I exploit weather-induced shocks to household credit demand and district-year level variation in predicted bank credit supply growth, using matched household and moneylender survey data to study how the formal and informal credit sectors interact. I find that when household credit demand rises, moneylenders borrow more from banks, lend more to households, and charge higher interest rates. Moreover, household borrowing from moneylenders increases significantly more in district-years experiencing expanding formal credit supply than in those with contracting supply, following an equivalent demand shock. These patterns suggest that formal credit availability enables informal lenders to expand supply when demand increases.

This paper's identification strategy relies on the well-established link between monsoon rainfall and rural incomes in India — increases in monsoon rainfall increase incomes through higher agricultural output (Paxson, 1992; Jacoby and Skoufias, 1998; Wolpin, 1982; Jayachandran, 2006; Kaur, 2019; Santangelo, 2019; Emerick, 2018), which in turn impacts household credit demand. Intuitively, one might expect a decrease in incomes following a drought to increase rural household borrowing. However, I find that while household borrowing does go up following a negative rainfall shock, it goes up substantially more following a *positive* rainfall shock. I focus on this response to positive shocks, as they are both empirically stronger and conceptually distinct, being associated with greater liquidity and borrowing for lumpy expenditures by households lacking savings.

[2]Details on calculations are in Section 3.

This increase in household demand for informal credit is accompanied by a contemporaneous rise in moneylenders' borrowing from banks — a one standard deviation increase in monsoon rainfall in non-drought years increases household borrowing from moneylenders by 19% and increases moneylender borrowing from banks by 31%. Moneylenders also lend more to households, and charge higher interest rates, consistent with observed household borrowing impacts following these shocks. These effects are not driven by changes in the composition of borrowing households. The observed increase in moneylenders' own bank borrowing undermines the alternative explanation that higher incomes for lenders increases their credit supply, pointing to a need to supplement internal capital to meet demand. We also see that rainfall shocks do not increase total bank lending in a district, suggesting that the observed effects reflect lender-specific demand rather than a broader supply expansion.

To test whether limited access to bank credit constrains moneylenders' lending capacity, I compare the effects of credit demand shocks across district-years with different levels of predicted bank credit supply growth. I first construct predicted bank credit supply growth as a 'shift-share', following Greenstone et al. (2020), based on district-level credit data disaggregated by bank-group,[3] loan-type,[4] and population classification.[5]. The 'shift' is the resultant growth in credit for a particular bank-group, orthogonal to local district demand-drivers, and sector or industry specific-drivers, while the 'share' is a particular bank-group's pre-period market share. The 'shift-share' for credit in a district-year is the inner-product of the national-shifts and local pre-period shares in that year, allowing for a measure of change in credit supply at the district-year level. I then classify each district-year as having 'expanding' or 'contracting' supply based on whether the predicted change in credit supply, purged of local demand shocks, is positive or negative in a given year. On average, predicted bank credit supply increased by 10% more in 'expanding'-supply than in 'contracting'-supply dis-

[3]A bank-group, as the name suggests, is a group of banks. There are five bank groups — State Bank of India and its associates, nationalized banks, other public sector banks, foreign banks, private banks.

[4]This indicates the loan purpose for personal loans, and the industry otherwise.

[5]Population groups are urban, rural, semi-urban, metropolitan.

tricts, and this translates into 23% more borrowing from moneylenders after a one standard deviation increase in monsoon rainfall in non-drought years, consistent with formal credit easing informal lenders' capital constraints.

Identification comes from the interaction between the exogenous rainfall shock and the indicator for contracting bank credit supply. The strategy compares plausibly similar districts exposed to common credit demand shocks. Key here is that a district-year's classification as expanding or contracting in credit supply is not systematically correlated with unobserved shocks to outcomes. I assess this by comparing observable household and district characteristics that might determine credit demand across expanding- and contracting-supply district $\times$ years, and find no systematic differences. The main results are also robust to extensive controls and household fixed effects. Moreover, because the empirical focus is on the interaction with rainfall shocks, level differences are absorbed by the supply indicator, as in a standard difference-in-differences design (Frison and Pocock, 1992).

Another concern might be that an increase in formal credit supply directly increases informal credit demand, either through complementarity or general equilibrium effects. I provide the following pieces of evidence to rule this out. First, this effect is unlikely to be driven by complementarity between formal and informal credit since most borrowers in the sample borrow from just one source in a given year. Complementarity arising from loans in a previous period is still consistent with the supply channel rather than the demand channel. Second, though districts with 'contracting' formal credit supply see lower borrowing from informal moneylenders following a positive rainfall shock than districts with 'expanding' formal credit supply; at the same time, districts with 'contracting' formal credit supply see *higher* interest-free borrowing from friends or relatives following a positive rainfall shock than districts with 'expanding' formal credit supply. This suggests that it is moneylender credit supply rather than household demand that drives this result. Third, when a district has 'contracting' formal credit supply, it also has higher informal market interest rates, suggesting that the effect is driven by a decline in supply rather than an increase in demand.

A key contribution of this paper is its use of nationally representative data on informal moneylenders and a new phone survey to directly observe moneylender behavior, including their borrowing from formal banks. This allows an analysis of supply-side dynamics within the informal credit market, an understudied aspect of financial intermediation. The paper's findings that access to bank credit helps informal lenders ease lending capital constraints indicates that despite being outside the formal regulatory perimeter, moneylenders may operate analogously to shadow banks, using bank credit to finance downstream lending (Bhardwaj and Javadekar, 2024; Acharya et al., 2024, 2013), and echo findings from developed economies that shadow banks may draw down credit lines with banks during times of stress (Acharya et al., 2025). These results build on foundational studies on moneylenders in South Asia such as Aleem (1990) and Irfan et al. (1999), corroborate earlier theoretical models of vertical ties between informal lenders and banks (Hoff and Stiglitz, 1998; Floro and Ray, 1997; Madestam, 2014), and contribute to a broader understanding of the structure of financial intermediation (Buchak et al., 2024).

The finding that bank credit crowds-in moneylender credit through a supply side channel also points to a consolidation of moneylender market power. This helps reconcile existing evidence on the impact of bank expansions in India. While Burgess and Pande (2005) and Young (2019) find that bank expansions in India increased output and growth, evidence on its distributional impacts is mixed. Studies suggest that bank expansions led to a decrease in poverty (Burgess and Pande, 2005) as well as an increase in inequality (Kochar, 2011; Ligon, 2005), with formal credit benefiting only certain households due to transaction costs (Sharma, 2010; Ghate, 1992), collateral requirements (Ghosh et al., 1999; Ghate, 1992) or poor enforcement mechanisms (Giné, 2011).

Finally, this study also contributes to the literature on household borrowing responses to income shocks by documenting that households in rural India increase borrowing following positive shocks, and to a smaller extent, following negative shocks. The increase in borrowing following positive shocks to finance lumpy spending appears to be driven by households that do not have savings; and this complements findings across contexts that when households gain access to credit, they borrow more for spending that has a durable component (Banerjee et al., 2015; Kaboski and Townsend, 2012; Ruiz, 2013). The results in this paper also document that households are less likely to have old outstanding loans following positive shocks, and thus increased new borrowing might also reflect a desire to improve standards of living (González, 2017) in a context where income might go towards repaying old loans, requiring or enabling new loans for purchases.

Taken together, the results show that informal lenders can act as capital-constrained intermediaries, and that expanding formal credit supply may increase, rather than displace, informal lending through a supply-side channel. These findings have broader macroeconomic implications, suggesting that rather than the informal sector dampening monetary policy transmission or formal sector shocks, it could potentially amplify them.

2 Background on Rural Credit in India

Around half of all rural households in India are indebted,[6] with the median indebted household owing approximately ₹40,000 to its creditors in 2012–13 (equivalent to ₹56,381 or about $796 USD in 2019–20 prices). Borrowing is common across all levels of wealth (NAFIS, 2017; Banerjee, 2003) and spans a diverse array of sources, ranging along a continuum from informal to formal, with banks at the most formal or regulated end. Bank loans are usually larger than less formal loans but tend to carry lower interest rates than interest-bearing informal credit (Figure 1).

Despite dramatic improvements in financial inclusion with 79% of individuals in rural India having a bank account by 2017, only 17% of borrowers obtained credit from an institutional

[6] 53% in 2012–13 (NSSO, 2013b); 47.4% in 2016–17 (NAFIS, 2017); up from 43% in 1993.

source that year (World Bank, 2019). Most formal lending takes place through commercial banks under the Reserve Bank of India's Priority Sector Lending (PSL) mandate, which requires 40% of adjusted net bank credit to be lent to sectors like agriculture, micro and small enterprises, and disadvantaged social groups.[7] While aggregate targets are typically met, banks tend to concentrate lending among better-documented and larger borrowers within eligible categories, often bypassing more marginal clients making access uneven. Banks typically require land or gold as collateral, along with documentation that many rural borrowers lack (Mowl, 2017). Moreover, the administrative costs of small loans are high, incentivizing banks to lend to fewer, larger borrowers, even within the PSL category (Banerjee and Duflo, 2014). In fact, in 2016, agricultural loans worth INR 59,000 crore or USD 8.8 billion from public sector banks went to just 615 accounts according to news reports.[8]

Semi-formal sources like microfinance institutions (MFIs) and bank-linked self-help groups (SHGs) offer alternatives. MFIs, which are often regulated Non-Banking Financial Companies (NBFCs), lend directly to individual clients or through joint-liability group structures (RBI, 2018). SHGs, typically composed of 10–15 women, pool savings and borrow collectively—sometimes accessing PSL-linked bank loans (Hoffmann et al., 2021). Yet, such channels remained limited in the period considered in this study (which ends in 2017): in 2012–13, SHG and MFI loans accounted for just 9% of rural loans and 3% of total borrowed amount (NSSO, 2013b), rising to 20% and 10%, respectively, by 2017 (NAFIS, 2017).

Informal credit still plays a dominant role. These loans can be interest-bearing or interest-free. Professional moneylenders, pawnbrokers, input traders (who provide seeds, fertilizers, feed, etc on credit), landlords, and shopkeepers typically offer the former; friends, relatives, and patrons provide the latter (Dréze et al., 1998; ICRISAT, 2014). While interest-free loans are nominally costless, they often carry implicit obligations including social reciprocity or

[7] E.g., small and marginal farmers, SC/ST households, women, and self-help groups.

[8] "Agricultural Loans Worth Rs 59,000 Crore Went to 615 Accounts in One Year," by Dheeraj Mishra, *The Wire*. Accessed on 11/12/2019 at: https://thewire.in/agriculture/modi-govt-gave-agricultural-loans-worth-rs-59000-crore-to-615-accounts-in-one-year

status-based expectations, that make them less neutral than they appear (Ligon, 2005; Udry, 1994; Hayashi et al., 1996; Ambrus et al., 2014; Ligon and Schechter, 2012).

In 2013, 31% of all loans were interest-bearing non-institutional loans, while 20% were interest-free (NSSO, 2013b). Borrowers match sources to purposes: bank and SHG loans are typically used for production; informal loans often finance consumption, medical needs, or ceremonial expenses (NSSO, 2013a). Even among informal lenders, specialization varies: pawnbrokers help smooth income; moneylenders and traders offer lump sums for lifecycle events or emergencies; and "mobile lenders" specialize in short-term, urgent credit (Guérin et al., 2012). In Tamil Nadu, for instance, mobile lenders differ from established village lenders in both reputation and repayment dynamics, and similar distinctions appear in qualitative work from Bihar.[9]

These diverse borrowing patterns and the coexistence of formal and informal lenders underscore the importance of understanding how these sectors interact. In particular, the extent to which informal lenders depend on bank credit remains underexplored—an empirical gap that this paper addresses.

3 A Description of the Moneylender Market

This section presents new descriptive evidence on the structure and behavior of informal moneylenders (non-institutional lenders who lend locally at high interest rates) in rural India using two complementary sources — (1) data on 925 moneylenders across India from two rounds of the National Sample Survey's Informal Enterprise rounds (2010-11, 2015-16); and (2) a primary phone survey of 140 moneylenders lending across thirty villages in Telangana conducted in 2020. To my knowledge, this is one of the few recent studies that directly surveys moneylenders about their operations, lending behavior, and constraints. Telangana,

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

which has the highest rural indebtedness rate in India (NAFIS, 2017), offers a particularly relevant context for understanding informal lending practices.

Multiple moneylenders operate in each of the thirty villages surveyed in Telangana, with residents on average borrowing from eight different lenders inside and two lenders outside the village. Each moneylender serves a clientele of 12 to 14 borrowers. Entry appears relatively free, with 41% of surveyed lenders having started lending in the past five years. Yet, client screening remains stringent. Half of all lenders only lend to new clients vouched for by someone they trust; another third rely on independent background checks; and 5% refuse new clients altogether. This network-based screening makes one lender an imperfect substitute for another (Hoff and Stiglitz, 1998); and also indicates that these markets are segmented across the same caste and class lines that individuals' networks are (Mookherjee and Motta, 2016; Khanna and Majumdar, 2020). Together, these features suggest a market best characterized as monopolistically competitive (Aleem, 1990; Hoff and Stiglitz, 1990, 1998).

Informal moneylenders charge high interest rates (NSSO, 2013b; ICRISAT, 2014; TNSMS, 2009; RBI, 2012; Hoffmann et al., 2021) — annualized rates in Telangana were between 12 and 120 percent in 2019 (Figure 3).[10] Lenders report raising interest rates when demand increases, when business costs increase or when other lenders increase their rates (Figure 5); and might decrease interest rates if demand decreases substantially or if there is an increase in the number of competing lenders. Moneylenders are able to price-discriminate by quantity, charging lower interest rates for larger loans (also observed in Banerjee, 2003; Dasgupta et al., 1989), and borrower type (based on their relationship with the borrower, borrower's occupation, or wealth). Lenders also offer some flexibility, adjusting repayment terms when necessary (also in Guérin et al., 2012). This often takes the form of higher interest rates

[10] While the NSS firms survey did not collect data on interest rates charged, it enables backing out an implied rate based on interest payments received and total amount advanced — which indicates a median of 36% per year, but a much higher mean of 78% a year (Table 2), possibly due to instances of delayed payments or penalties.

when loans exceed their normal duration, and indicates that lenders effectively offer state-contingent contracts.

Enforcement mechanisms vary across lenders, with default being dissuaded through social or physical collateral. In the Telangana survey, 58% of lenders report requiring some form of collateral — land or property documents, gold or other assets, promissory notes, or a co-signor.[11] In cases where lenders fear default, apart from charging additional interest or taking possession of collateral, lenders also report resorting to coercion or social pressure through the *Panchayat* or co-signer.[12]

Moneylenders fund their operations through retained profits, personal wealth, and loans from both institutional and non-institutional sources for lending capital (Figure 6). To estimate margins that moneylenders earn, I combine data on interest receipts, total loan advances, cost of own and employee time, cost of capital and other explicit costs from the NSS sample with an estimate of an upper bound on default rates from the Telangana survey. This exercise suggests that the median moneylender earns margins of between 16% and 58% over their marginal cost.[13] Despite these high margins on average, a notable share of moneylenders are also estimated to earn interest or prices below their average costs (Figure 9). This might arise from short-term demand shocks, impending market exit, or capacity constraints due to limited lending capital or other inputs.

Evidence from the Telangana survey suggests that capital constraints may be binding. Among lenders surveyed, 35% report borrowing more from banks during capital shortfalls, and over 50% say that they would lend more if bank borrowing were easier (Figure 8). These findings underscore the relevance of the central hypothesis explored in the remainder of the

[11] The co-signer is referred to as a 'witness' by lenders in the survey, and might be called on to repay the loan upon default.

[12] A few lenders report seizing durables from borrowers' homes, and one lender reported potentially sending goons after the borrower.

[13] This is comparable with estimates for traders in developing country contexts. Bergquist and Dinerstein (2019) observe markups of 40% among agricultural traders in Kenya, while Mitra et al. (2018) find 64% - 83% margins over farm-gate prices for agricultural middlemen in Eastern India.

paper: that informal moneylenders rely on upstream access to bank credit to ease lending capital constraints when faced with downstream demand shocks.

4 Theoretical Framework

This section presents a stylized model of informal rural credit markets that features optimizing moneylenders and heterogeneous borrowers. Moneylenders maximize profits by choosing interest rates, using a mix of internal capital and borrowed funds from banks. Borrowers differ by wealth and face constraints that determine whether they borrow from banks, informal moneylenders, or interest-free sources such as family or friends.

The framework captures two key features observed in the data: (i) informal lenders face capital constraints and sometimes borrow from banks, as described in the preceding section; and (ii) informal interest rates and loans increase with household income shocks, an empirical pattern analyzed in later sections, where I examine how income shocks affect informal credit terms and how these effects vary with moneylenders' access to formal credit. By deriving equilibrium interest rates and lending quantities, the model provides a structure to evaluate how shifts in bank credit availability influence informal credit supply and household borrowing under different credit supply environments.

Motivated by the descriptive evidence in Section 3, the model draws on the theoretical literature on informal lending (e.g., Karaivanov and Kessler, 2018; Hoff and Stiglitz, 1998) and household consumption and loan decisions (e.g., Ligon and Worrall, 2020; Ngo, 2018; Hanemann, 1984). I assume a vertically linked structure in which moneylenders can borrow from banks, and households may borrow either directly from banks or from informal lenders. I then examine comparative statics in response to exogenous income shocks, such as changes in agricultural productivity driven by monsoon rainfall.

4.1 Moneylenders' Credit Supply

I consider informal moneylenders who supply interest-bearing informal credit in a rural economy. Motivated by Aleem (1990), Hoff and Stiglitz (1998), and evidence from the Telangana Survey (2020), I assume that the informal moneylending market is monopolistically competitive. I abstract away from the possibility that lenders offer a menu of prices, and assume that each lender offers loans at a single interest rate which could be thought of as the average rate.

Set-up

Each moneylender is endowed with liquid capital, K, that incurs opportunity cost, ρ, per unit.[14] They may also borrow, $G \leq \bar{G}$, from banks at an exogenous interest rate, r_B, to supplement their stock of lending capital, where $\bar{G}$ represents the local supply of bank credit in a given year. There are N_L such lenders in a monopolistically competitive market, with each earning zero profit in the long-run equilibrium. I consider the symmetric case with identical lenders, where each lender chooses the moneylending market interest rate, r_{ML}, that maximizes their profit. Each lender lends $l = \frac{L}{N_L}$, where L is total demand for moneylender credit at r_{ML}. A moneylender's profit is thus:

$$\Pi = r_{ML}\frac{L}{N_L} - r_B G - \rho K \tag{1}$$

The zero-profit condition implies, $r_{ML}\frac{L}{N_L} = B(\frac{L}{N_L})$ in the long run, where $B(\frac{L}{N_L})$ is the moneylender's outside option.

Proposition 1. *In the symmetric equilibrium, where lenders borrow from banks, each lender*

[14] I assume that $K(R_1)$ is increasing in R_1, an exogenous income parameter. However, in this section, I assume that moneylenders lend more than K and so I consider a case where the marginal rupee that a moneylender lends is from a bank. So, the relationship between K and R_1 does not appear in the comparative statics in the present case.

chooses an interest rate, r^*_{ML}, that satisfies:

$$L^* = (r'_B - r^*_{ML})\frac{\partial L}{\partial r_{ML}} \tag{2}$$

where $r'_B = r_B + \lambda$ is the effective bank interest rate that moneylenders face including the shadow price when the bank supply constraint binds.

Proof. See Appendix. $\square$

4.2 Household Demand for Moneylender Credit

Set-up

I consider a continuum of borrowing households, indexed by an exogenous 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 $[\theta_L, \theta_H]$. Households make decisions pertaining to a two-season horizon, where each household derives a per-season utility, $u(\cdot)$ (with $u'(\cdot) > 0$, and $u''(\cdot) < 0$) from the consumption of a numeraire good, c_t.[15] A household may also choose to purchase a durable good or asset, D, at price, $p > 1$ in season 1, and in doing so, benefits from the services, d, provided by D over both seasons.[16] Household income depends on an exogenous season-specific productivity parameter, R_t.[17] In season 1, a household earns, $R_1\theta$, and expects to earn, $\mathbb{E}[R_2]\theta$ in season 2.

I assume households can borrow from three types of sources: (1) institutional (bank) loans at interest rate, r_B, (2) informal moneylender loans at rate, r_{ML}, and (3) interest-free informal loans from family or friends.

Access is segmented by wealth:

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

[16] This durable component could also be a production asset, in which case, d is interpreted as the additional income generated by the asset.

[17] R_1 could be thought of as the monsoon realization in a given year, which impacts both agricultural and non-agricultural incomes alike (Table 3). R_2 is the income shock in the non-monsoon season.

Assumption 1. *Households with endowments greater than a threshold,* $\bar{\theta}(\bar{G})$ *borrow from institutional sources, and households with endowments below* $\underline{\theta}$ *borrow from interest-free non-institutional sources (friends and relatives). Only those with* $\theta \in [\underline{\theta}, \bar{\theta}]$ *borrow from moneylenders.*

Assumption 2. *An exogenous decrease in bank credit decreases the number of borrowers that can borrow from banks, i.e.,* $\frac{d\bar{\theta}}{d\bar{G}} < 0$.

Households that borrow from moneylenders have utility:

$$U_{ML} = u(c_1) + d\mathbb{1}\{D = 1\} + \beta\mathbb{E}\Big[u(c_2) + d\mathbb{1}\{D = 1\}\Big] \tag{3}$$

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 3. *The cost of defaulting on moneylender loans is high enough to prevent default for all loan sizes, so* $\forall\ \theta,\ U_{ML}(repay) > U_{ML}(default)$.

Households decide 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. As a result, when $\underline{\theta} \leq \theta \leq \hat{\theta}$, households choose to borrow, b^*_{ML}; and when $\hat{\theta} < \theta \leq \bar{\theta}$, households choose to borrow, $b^*_{ML,d}$.

Proposition 2. *In equilibrium, households choose their borrowing,* b^*_{ML} *or* $b^*_{ML,d}$*, and the total household demand for moneylender credit is given by:* $L^* = \int_{\underline{\theta}}^{\hat{\theta}} b^*_{ML} f(\theta) d\theta + \int_{\hat{\theta}}^{\bar{\theta}} b^*_{ML,d} f(\theta) d\theta$

Proof. See Appendix. □

The market equilibrium interest rate is the rate at which quantity demanded ($\int_{\underline{\theta}}^{\hat{\theta}} b^*_{ML} f(\theta) d\theta +$

$\int_{\hat{\theta}}^{\bar{\theta}} b^*_{ML,d} f(\theta) d\theta$) equals quantity supplied ($(r'_B - r^*_{ML})\frac{\partial L}{\partial r_{ML}}$), and so:

$$\int_{\underline{\theta}}^{\hat{\theta}} b^*_{ML} f(\theta) d\theta + \int_{\hat{\theta}}^{\bar{\theta}} b^*_{ML,d} f(\theta) d\theta = (r'_B - r^*_{ML}) \frac{\partial}{\partial r_{ML}} \left[\int_{\underline{\theta}}^{\hat{\theta}} b^*_{ML} f(\theta) d\theta + \int_{\hat{\theta}}^{\bar{\theta}} b^*_{ML,d} f(\theta) d\theta \right] \quad (4)$$

4.3 Implications of the Model

In the rural Indian context, rainfall during the monsoon increases local incomes (Table 3), and an increase in monsoon rainfall could be thought of as an increase in the season-1 exogenous income parameter, R_1. I relate the market equilibrium moneylender interest rate and equilibrium quantity borrowed to changes in R_1. Here, $L^* = \int_{\underline{\theta}}^{\hat{\theta}} b^*_{ML} f(\theta) d\theta + \int_{\hat{\theta}}^{\bar{\theta}} b^*_{ML,d} f(\theta) d\theta$.

In practice, a reduction in the supply of bank credit (i.e., a lower $\bar{G}$) raises the shadow price of borrowing for moneylenders when the constraint binds. This increase in the effective marginal cost is equivalent, in comparative statics terms, to an increase in the formal sector interest rate r_B.[18]

Proposition 3. *An exogenous increase in the productivity parameter, R_1, increases the equilibrium informal interest rate, r^*_{ML}, i.e., $\frac{dr^*_{ML}}{dR_1} > 0$; and increases the equilibrium amount borrowed from informal moneylenders, L^*, i.e., $\frac{dL^*}{dR_1} > 0$ when $\Phi_1 > \Phi_2$.*

Proof. See Appendix. □

where, $\Phi_1 = |[b^*_{ML}(\hat{\theta}) - b^*_{ML,d}(\hat{\theta})] f(\hat{\theta}) \frac{\partial \hat{\theta}}{\partial R_1} - b^*_{ML}(\underline{\theta}) f(\underline{\theta}) \frac{\partial \underline{\theta}}{\partial R_1}|$ and $\Phi_2 = |\int_{\underline{\theta}}^{\hat{\theta}} \frac{\partial b^*_{ML}}{\partial R_1} f(\theta) d\theta + \int_{\hat{\theta}}^{\bar{\theta}} \frac{\partial b^*_{ML,d}}{\partial R_1} f(\theta) d\theta|$, and both are further described in the appendix.

The intuition behind this proposition is that an increase in R_1 increases the number of

[18] Formally, when the bank borrowing constraint $G \leq \bar{G}$ binds, the shadow price λ enters the lender's effective cost of capital as $r'_B = r_B + \lambda$. Thus, a decline in $\bar{G}$ increases r'_B, even if r_B itself remains constant.

households that choose to borrow and purchase durables, and when this is sufficiently large, borrower demand increases. Since the marginal rupee lent by the moneylender is borrowed from a bank, R_1 does not impact the marginal cost of capital. As a result, equilibrium lending and interest rates increase.

Proposition 4. *When the bank credit supply constraint does not bind, an exogenous increase in the productivity parameter, R_1, increases the equilibrium amount moneylenders borrow from banks, G^* if $\frac{dL}{dR_1} > \frac{dK}{dR_1}$, and weakly decreases it otherwise.*

Proof. See Appendix. □

Following an income shock, a moneylender increases borrowing from banks only if the increase in a moneylender's own capital exceeds the increase in equilibrium lending, the lender decreases bank borrowing if the increase in a moneylender's own capital is lower than the increase in equilibrium lending, and bank borrowing stays the same if both change by an equal amount.

Proposition 5. *An exogenous increase in the productivity parameter, R_1, has a smaller impact on the equilibrium amount borrowed when the bank supply constraint binds than otherwise.*

Proof. See Appendix. □

A binding bank credit supply constraint represents a situation where a moneylender cannot supplement their lending capital by borrowing from banks anymore. As a result, when household demand for moneylender loans increases, moneylenders are unable to meet the demand because they are effectively unable to reach their unconstrained profit maximizing levels of lending.

5 Data and Descriptive Statistics

This paper combines multiple datasets to study the interaction between rural households, informal moneylenders, and formal banks in India. I use household-level surveys, firm-level data on moneylenders, district-level rainfall, and banking sector credit data to study how income shocks affect borrowing behavior and informal credit supply.

Household Data. The primary household data come from four rounds of the National Sample Survey Office's (NSSO) Debt and Investment Surveys (2001–02, 2002–03, 2011–12, 2012–13), which are nationally representative across 584 districts (based on 2001 census boundaries).[19] These surveys record household borrowing, outstanding debt, credit terms, and six-month recall-based expenditures, allowing me to construct both household-year and household-month panels.

Summary statistics from the NSS data (Table 1) underscore both the prevalence of rural indebtedness and the segmentation of credit sources: 59% of households report outstanding debt, with borrowing spread across moneylenders (22%), formal institutions (29%), and informal networks such as friends or relatives (15%). The average moneylender loan is around ₹25,000, with a median annualized interest rate of 36%. Institutional loans, by contrast, average over ₹38,000 at rates below 12%. Land ownership is widespread (90%), though only 26% report owning agricultural land. On average, households consist of five members and two workers; 36% identify as Scheduled Caste or Scheduled Tribe.

Figure 1 illustrates the segmentation across lender types. Institutional loans are larger and cheaper, while moneylender loans are smaller and much more expensive. Interest-free credit from friends and relatives is the smallest on average and often carries implicit social obligations.

I supplement the NSS data with household panel data from the ICRISAT Village Dynamics

[19] The 2012–13 round covers 634 districts.

survey (2010–2014), which tracks 866 households across 18 villages in five Indian states. The ICRISAT dataset records monthly loan transactions, consumption, and asset purchases. While not nationally representative, these high-frequency data provide an independent check on the robustness of patterns observed in the NSS, particularly with respect to informal borrowing and expenditure responses following income shocks.

Moneylender-Level Data. To examine the supply side of informal credit, I use firm-level data on 925 private moneylenders from the NSSO's Unincorporated Non-Agricultural Enterprises Surveys (2010–11 and 2015–16). These surveys span 143 districts in 22 Indian states and include information on loan advances, interest receipts, and borrowing by moneylenders themselves. Lenders are identified via five-digit industrial codes, and I include both rural and urban lenders, as rural households often borrow from lenders in nearby towns (Telangana Survey, 2020).

Table 2 summarizes key patterns. On average, moneylenders lend nearly ₹600,000 annually (in 2000-01 INR), nearly 82% of which goes to households, and charge high average interest rates (mean: 92%, median: 36%). Lenders frequently finance operations by borrowing: 14% report formal debt, and 8% report informal liabilities. Among those with formal loans, the average outstanding amount exceeds ₹350,000 (in 2000-01 INR). Additional evidence from a 2019 survey in Telangana (Panel C) suggests that rural lenders typically serve 15–16 borrowers, with fewer operating entirely within a single village. These patterns motivate the vertically linked credit structure in Section 4.

Rainfall and Bank Credit Data. Rainfall data are from the University of Delaware's Terrestrial Precipitation dataset (version 5.01), which interpolates monthly gauge data onto a $0.5° \times 0.5°$ grid. (Willmott and Matsuura, 2018). I assign each district the rainfall in the grid cell closest to its centroid.

Bank credit data are drawn from the Reserve Bank of India (RBI)'s Basic Statistical Returns

(1998–2016). These data report district-level credit (no. of accounts, outstanding credit, and credit limits) by loan type (e.g., personal, agriculture), population group (e.g., rural, urban), and bank group (e.g., nationalized, private, regional rural banks). Bank credit data from 2010 onward are publicly available through the Reserve Bank of India's online data warehouse. For earlier years (1998–2009), I obtained credit data through a Right to Information (RTI) request filed with the RBI.

6 Empirical Strategy

This section outlines the empirical strategy used to estimate the causal effect of income shocks on household credit outcomes and moneylender behavior, and how this interaction depends on local access to formal bank credit.

Rainfall shocks as exogenous shocks to household credit demand. The empirical strategy in this paper relies on plausibly exogenous variation in rural households' demand for credit. I argue that variation in realized monsoon rainfall constitutes such a shock. The rainfall shock is defined as the deviation of monsoon-season (June–September) rainfall from the district-specific (50-year) historical mean, normalized by the standard deviation over 1967–2017 (Emerick, 2018).

Monsoon rainfall in India extends from June to September. This coincides with the rain-fed, *kharif*, agricultural season whose harvest occurs in October and November, following which incomes are realized. A good monsoon increases both agricultural incomes and, through a multiplier effect, non-agricultural incomes in a district (see, for e.g., Paxson, 1992; Rosenzweig and Wolpin, 1993; Townsend, 1995; Jayachandran, 2006; Kaur, 2019; Santangelo, 2019; Emerick, 2018). The identification strategy relies on the assumption that variation in monsoon rainfall serves as an exogenous income shock. Conceptually, rainfall determines agricultural productivity in rain-fed regions, which in turn drives income fluctuations. Empirically, I confirm this link by showing that positive rainfall deviations are strongly associated with increases in district-level per capita GDP in non-drought years (Table 3). This reinforces the interpretation of rainfall variation as a transitory and plausibly exogenous shock to local economic conditions.

Intuitively, one might expect that household demand for credit, particularly, informal credit from moneylenders, goes up following a drought. As seen in Figure 9, while informal moneylender borrowing does see a modest increase in a drought year, informal borrowing sees a substantially larger increase following a positive rainfall shock.[20] This also reflects the predictions in Section 4, which demonstrate that household responses to an income shock can be asymmetric. I focus on household responses to this positive shock in the rest of this paper. In addition, in order to be able to interpret the positive rainfall shock as a positive income shock, I focus on household transactions following the monsoon, i.e., from November to the following May, after incomes have been realized (Figure 10). Finally, I also demonstrate that these results are robust to restricting focus to the months of February - May alone, suggesting that they indeed occur after incomes are realized.

Baseline Empirical Specification. I estimate the causal effect of a positive rainfall shock on household outcomes using household-level, household×month-level and loan-level data, using the following main specifications:

$$Y_{hdsmt} = \beta_1 Rain_{dt} + \mathbb{1}\{Drought\}_{dt} + \beta_2 \mathbb{1}\{Drought\}_{dt} \times Rain_{dt} + \mu_m + \psi_d + \tau_{st} + X_{it}\delta + \varepsilon_{hdmst} \tag{5}$$

$$Y_{hdst} = \beta_1 Rain_{dt} + \mathbb{1}\{Drought\}_{dt} + \beta_2 \mathbb{1}\{Drought\}_{dt} \times Rain_{dt} + \psi_d + \tau_{st} + \lambda_h + \varepsilon_{hdst} \tag{6}$$

$$Y_{lhdmst} = \beta_1 Rain_{dt} + \mathbb{1}\{Drought\}_{dt} + \beta_2 \mathbb{1}\{Drought\}_{dt} \times Rain_{dt} + \mu_m + \psi_d + \tau_{st} + L_{lht}\phi + X_{ht}\delta + \varepsilon_{lhdmst} \tag{7}$$

[20] Figure 9 presents a graph of smoothed values from a kernel-weighted local polynomial regression of the incidence of borrowing from moneylenders on the rainfall shock variable.

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, X_{ht} denotes a vector of household characteristics, and L_{lht} is a vector of loan characteristics. In addition, I estimate the causal effect of a positive rainfall shock on moneylender outcomes using moneylender-level data, using the following specification:

$$Y_{ML,dst} = \beta_1 Rain_{dt} + \mathbb{1}\{Drought\}_{dt} + \beta_2 \mathbb{1}\{Drought\}_{dt} \times Rain_{dt} + \psi_d + \tau_{st} + M_{ML,t}\omega + \varepsilon_{ML,dst} \tag{8}$$

where ψ_d denotes district fixed effects, τ_{st} denotes state$\times$year fixed effects, and $M_{ML,t}$ denotes a vector of moneylender characteristics.

The co-efficient of interest in each case is β_1, which represents the impact of a one standard deviation increase in rainfall during non-drought years on the relevant outcome.[21] All specifications also control for rainfall shocks in drought years, district fixed effects and state$\times$year fixed effects. The state$\times$year fixed effects account for state-level macroeconomic conditions or policies in a given year. Equation (5) represents a specification where the outcome is measured at the household$\times$month level (e.g., any borrowing in that month), and so also controls for month-of-year fixed effects, and household characteristics. Equation (6) represents a specification where the outcome is measured at the household$\times$year level, and where possible controls for household fixed effects. Equation (6) represents a specification where the outcome is measured at the loan level, and so also controls for month of year, household characteristics and loan characteristics. Finally, equation (7) represents a specification at the moneylender$\times$year level, and controls for moneylender 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 transacted, the rainfall shock could potentially impact selection into borrowing. This

[21] A drought is defined according to the Indian Meteorological Department's definition; and so takes a value of one when the rainfall deviation is below 60% of the IMD defined long-period mean for a district.

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), discussed further in the appendix.

Predicting Bank Credit Supply Growth. To further my argument that household borrowing behavior is shaped not just by income shocks but also by constraints in the local financial system, I estimate how variation in the availability of formal credit across districts affects informal borrowing outcomes. Since observed bank lending in a district-year is an equilibrium quantity reflecting both demand and supply, I construct a measure of predicted credit supply growth that isolates the *supply-driven* component.

This approach builds on the logic of a 'shift-share' instrument (as used in the context of banking by Greenstone et al., 2020), and draws on institutional features of the Indian banking system. While branch penetration varies across districts, banks in India can reallocate liquidity across branches in response to internal targets, funding shocks, or regulatory mandates (Acharya and Kulkarni, 2019). These forces generate national-level, bank-group-specific shocks to lending that are not driven by district-level demand. I exploit this to construct a predicted supply measure that captures credit expansion or contraction driven by banks' balance sheet conditions, purged of local demand factors.

The measure is constructed using Reserve Bank of India (RBI) data on the total amount of sanctioned credit, rather than credit outstanding in a district-year. The credit limit reflects banks' forward-looking willingness to lend, making it a cleaner proxy for supply-side variation. By contrast, credit outstanding is a stock variable shaped by past disbursements and repayment patterns, and may further confound borrower-side liquidity or demand shocks.

The data are disaggregated by district $\times$ loan type $\times$ population group $\times$ bank group for the years 1998–2016. Loan types include agriculture, personal loans, and industry-specific categories; population groups distinguish rural, semi-urban, urban, and metropolitan areas;

and bank groups include Nationalized Banks, the State Bank of India and its associates, Private Banks, Regional Rural Banks, and Foreign Banks.[22]

To purge local demand, I regress the growth in credit for each cell (loan type i, population group r, bank group j, district d) on fixed effects:

$$\Delta_{t-1}^{t} \log C_{irjd} = g_i + g_r + g_j + g_d + \epsilon_{irjd} \tag{9}$$

The residual variation in $\hat{g}_t^j$ reflects the national-level credit supply shocks for each bank group. These shocks may arise from capital adequacy constraints, deposit growth, or regulatory changes, and are orthogonal to any district-specific demand conditions. By interacting this with the lagged market share of each bank group in a district, I construct a predicted district-year credit supply growth measure:

$$\hat{B}_{dt} = \sum_j s_{t-1}^{jd} \times \hat{g}_t^j \tag{10}$$

where s_{t-1}^{jd} is the lagged share of credit in district d issued by bank group j. This shift-share structure has clear economic logic: the extent to which a district is exposed to national bank-group-level credit supply shocks depends on the pre-existing composition of banks serving it. In other words, predicted credit supply growth at the district level reflects how national banking conditions propagate locally through the district's pre-period bank exposure.

While this measure is continuous, I discretize it to aid interpretation. Specifically, I construct a binary indicator at the district-year level:

$$\text{Contracting Supply}_{dt} = \mathcal{C}_{dt} = \mathbb{1}\{\hat{B}dt < 0\} \tag{11}$$

This indicator equals one if predicted credit supply growth is negative (indicating a con-

[22]There are a total of 50 banks in India—19 nationalized banks, 22 private sector banks, 7 foreign banks, and the State Bank of India (with five associate banks).

traction), and zero otherwise (indicating expansion). This binary form simplifies interpretation and emphasizes qualitative shifts in credit availability. It avoids assumptions about functional form, and focuses the analysis on whether the formal sector is locally credit-constrained.

Importantly, the predicted credit supply measure is not interpreted as a standalone determinant of household outcomes. Instead, it is used solely in interaction with the exogenous rainfall shock. This interaction captures how informal borrowing responds to a common positive demand shock under different formal credit supply conditions. Thus, the identifying variation in the heterogeneity analysis comes entirely from this interaction term, and allows us to test whether moneylenders' ability to meet borrower demand is mediated by the tightness of local formal credit markets.

Heterogeneity Empirical Specification. To examine whether the informal credit response to a positive income shock depends on local access to formal finance, I estimate heterogeneous treatment effects based on district-year-level credit supply conditions. Specifically, I compare household borrowing outcomes in district-year cells where predicted bank credit supply is expanding versus contracting, as captured by the binary indicator $\mathcal{C}_{dt}$ defined above.

The following specifications are estimated at the household-level, household×month-level, and loan-level:

$$Y_{hdmst} = \delta_1 Rain_{dt} + \delta_2 \mathcal{C}_{dt} + \delta_3 Rain_{dt} \times \mathcal{C}_{dt} + \mu_m + \psi_d + \tau_{st} + X_{ht}\delta + \varepsilon_{hdmst} \quad (12)$$

$$Y_{hdst} = \delta_1 Rain_{dt} + \delta_2 \mathcal{C}_{dt} + \delta_3 Rain_{dt} \times \mathcal{C}_{dt} + \psi_d + \tau_{st} + \lambda_h + \varepsilon_{hdst} \quad (13)$$

$$Y_{lhdmst} = \delta_1 Rain_{dt} + \delta_2 \mathcal{C}_{dt} + \delta_3 Rain_{dt} \times \mathcal{C}_{dt} + \mu_m + \psi_d + \tau_{st} + L_{lht}\phi + X_{ht}\delta + \varepsilon_{lhdmst} \quad (14)$$

As before, μ_m are month-of-year fixed effects, λ_h are household fixed effects, ψ_d are district fixed effects, and τ_{st} are state×year fixed effects. The vector X_{ht} includes household controls, and L_{lht} includes loan characteristics when the outcome is at the loan level. Standard errors are clustered at the district level.

The coefficients of interest are δ_1, which captures the effect of a rainfall shock in expanding-credit districts ($\mathcal{C}_{dt} = 0$), and δ_3, which captures the differential effect in contracting-credit districts ($\mathcal{C}_{dt} = 1$). Together, these allow testing whether the same exogenous income shock generates different borrowing outcomes depending on the tightness of formal credit conditions.

This specification relies on the assumption that variation in predicted credit supply, captured by $\mathcal{C}_{dt}$, is uncorrelated with unobserved shocks to outcomes, conditional on the included controls. Specifically, district×year variation in $\mathcal{C}_{dt}$ is mechanically derived from lagged bank-group exposure and national bank-group-level credit growth. In the context of a standard shift-share design, identification requires that the pre-period shares used for weighting are exogenous to potential outcomes (Goldsmith-Pinkham et al., 2020), or at least orthogonal to residual shocks after controlling for fixed effects and observables (Baum-Snow and Ferreira, 2015). However, in this setting, I treat the shift-share construct not as an instrument but as a treatment effect modifier, used solely in interaction with an exogenous rainfall shock. This strategy is more akin to a difference-in-differences design, where identification comes from comparing responses to the same shock across units with differing exposure to an external constraint. Any direct relationship between pre-period shares and the outcome is absorbed by the main effect of $\mathcal{C}_{dt}$, allowing clean identification from the interaction term (Frison and Pocock, 1992).

To assess the plausibility of this assumption, Table 4 presents a balance check comparing district-years classified as credit-expanding versus credit-contracting. Column 4 reports normalized differences in baseline covariates (Imbens and Rubin, 2015), estimated from regressions with district and state×year fixed effects and standard errors clustered at the district level (as in Hoffmann et al., 2021). None of the normalized differences exceed the 0.25 threshold above which linear regression estimates may become sensitive to specification choices (Imbens and Wooldridge, 2009). Moreover, because standard balance tests may lack power in samples with limited higher-level variation, I also report p-values from randomization inference. These are generated by reassigning the contraction indicator across district-years under placebo and re-estimating the balance statistics. The resulting RI p-values are uniformly large, reinforcing the conclusion that predicted credit supply variation is not systematically related to observable district characteristics.

7 Empirical Results and Discussion

7.1 The Effect of Rainfall Shocks on Rural Household Borrowing

Results and Robustness

This section shows that a positive rainfall shock in a non-drought year leads to an increase in both the likelihood of borrowing from moneylenders and the interest rates on those loans. Motivated by the model in Section 4 and income evidence in Section 6, I focus throughout on *positive* rainfall shocks in non-drought years, periods when rural incomes are more likely to rise.

Table 5 and Table 6 show that a one standard deviation increase in rainfall (or equivalently, a 1% increase in district per capita GDP) raises the probability of borrowing from moneylenders by 1.4 percentage points (Table 6, col 1). This represents a 19% increase in the share of households borrowing, and a 4% increase in borrowing amounts over the seven-month post-monsoon period (Table 5, cols 1–2).[23] By contrast, there is no significant effect on borrowing from friends or relatives (which typically involves smaller, interest-free loans) or from formal institutions (which may be less accessible for non-agricultural purposes).

[23]Column 1 in Table 5 presents monthly changes, that are annualized.

These results are robust to alternative definitions of the rainfall shock (Table A7), including percentile-based thresholds (Jayachandran, 2006) and fractional deviations from the Indian Meteorological Department's Long Period Mean.[24] They also hold under iterative leave-one-state-out checks (Figure A1), and are echoed in high-frequency ICRISAT data (Table A1). A placebo test using non-monsoon rainfall shows no comparable change in borrowing (Table A7, row 3), further supporting the identification strategy.[25]

Alongside this increase in borrowing is a significant rise in interest rates — moneylender rates increase by 3.5 percentage points, or roughly 8% relative to the mean of 41.83% annually (Table 7). Figure 11 shows that months with higher borrowing consistently exhibit higher average interest rates. While the ICRISAT sample does not show a statistically significant price effect, the point estimate is positive (Table A1, col 7).

One potential concern is selection into borrowing, with moneylenders charging higher rates not because of increased demand directly, but because more disadvantaged (i.e., higher-risk) borrowers enter the market during income shocks. To address this, I apply a selection correction following Newey (2009) (Table 7, col 2), and the effect remains robust.

A second concern is that positive income shocks may increase not just demand, but also moneylenders' supply of capital, e.g., by enabling greater household loan repayment or an increase in incomes in other businesses. Indeed, Table A4 shows a decline in the likelihood of households holding old, outstanding moneylender loans following a positive rainfall shock. While this points to improved repayment capacity, the simultaneous increase in both new borrowing and *interest rates* suggests that the demand effect dominates. This is further discussed in the following section, with evidence on moneylenders' own borrowing. This interpretation is reinforced by qualitative evidence: 93% of moneylenders surveyed in Telangana Survey (2020) report raising interest rates for all clients when demand increases

[24] The percentile shock takes values of -1 (below 20th percentile), 0 (between 20th and 80th), or 1 (above 80th percentile); the fractional deviation is calculated relative to the 50-year district-level mean.

[25] The placebo uses rainfall from October to May, standardized by district historical means.

(Figure 5).

Overall, the evidence indicates that rainfall-induced income gains trigger higher demand for informal credit, especially from moneylenders, and that this demand is met at higher interest rates, consistent with limited supply elasticity.

Interpretation and Alternative Mechanisms

What do households borrow for following a positive rainfall shock? Evidence from Table 8 suggests that the increase in borrowing is largely driven by loans reported as being for consumption, though this result is marginally significant (10% level). Table 9 provides more direct evidence, indicating that households increase spending on land and building improvements after positive rainfall shocks. This pattern is mirrored in the ICRISAT panel (Table A2), where households increase both consumption expenditures and durable goods purchases.

Further, Table A3 shows that the rise in moneylender borrowing is concentrated among households that also purchase durables in the same period. These findings align with the predictions of the model in Section 4, which shows that exogenous income increases can spur borrowing to finance lumpy expenditures, such as asset purchases or housing improvements. This mechanism echoes results from credit access experiments, where increases in credit supply similarly lead to increases in durable or investment-oriented spending (Banerjee et al., 2015; Kaboski and Townsend, 2012; Ruiz, 2013).

An alternative explanation is that higher incomes raise local demand for non-tradable goods or services, increasing credit demand for operating non-agricultural businesses.[26] However, Table 9 shows that expenditures on non-farm business are lower following rainfall shocks, not higher. Another possibility is that households borrow more for expenses in the non-monsoon *Rabi* season (October–January), which is less dependent on rainfall. But results remain

[26]This reflects the aggregate demand mechanism proposed by Breza and Kinnan (2020).

robust even when restricting the sample to the post-*Rabi*, lean season (February–May). Taken together, these patterns suggest that increased borrowing primarily finances lumpy household expenditures, and not general business needs or seasonal input costs.

Overall, since money and credit are fungible, this gives us an understanding of the proximate purpose for credit rather than the ultimate driver. Regardless of the precise motivations, other reasons for borrowing do not change the broader argument advanced in this paper, which primarily concerns the impact of an increase in household borrowing on a moneylender's business.

Finally, Table A4 shows that households are less likely to have outstanding moneylender loans from previous years after positive rainfall shocks. This may reflect increased repayment, which could free up borrowing capacity for new expenditures. Alternatively, it may represent a reduction in debt overhang, potentially improving households' willingness or ability to take on new loans.[27]

Importantly, Table A5 shows that the increase in borrowing is concentrated among households that lack savings. This suggests that even when incomes rise, households may still rely on credit to finance durables or improvements, especially when seeking to raise living standards (González, 2017) or respond to social aspirations (Guérin et al., 2011). That households do not self-finance such expenditures may reflect limited access to convenient or safe savings tools, a lack of commitment devices (e.g., Ashraf et al., 2006), or behavioral constraints such as present bias (Banerjee and Mullainathan, 2010). The current data do not allow for distinguishing among these mechanisms, but they reinforce the idea that even transitory income gains can trigger meaningful shifts in credit behavior.

[27] Kanz (2016) finds that formal debt relief in India did not increase subsequent borrowing, but that setting involved a government program with different incentive effects.

7.2 The Effect of Rainfall Shocks on the Informal Moneylending Business

Results and Robustness

This section shows that an increase in rural household credit demand, triggered by a positive rainfall shock, leads to an increase in moneylenders' own borrowing from banks. Table 10 shows that a one standard deviation increase in monsoon rainfall (in a non-drought year), or a 1% increase in district-level per capita GDP (Table 3), is associated with a 4.4 percentage point increase in the likelihood that moneylenders borrow from banks (column 1). This represents a 31% increase relative to the baseline, and mirrors the 19% increase in the number of households borrowing from moneylenders over the same period.

Cross-sectional data further support this relationship. Moneylenders report lending 12% more to clients (column 2) and earning 19% higher interest receipts (column 3) during these high-demand periods, patterns consistent with the household-level results on loan volumes and rates.

This is plausibly a result of capital constraints: when household borrowing increases unexpectedly, moneylenders may lack sufficient liquidity and therefore turn to formal financial institutions to meet demand. Qualitative evidence supports this interpretation. In the survey of moneylenders from Telangana, over 35% of moneylenders report borrowing from banks to meet lending capital shortfalls (Figure 8), often through agricultural, gold, or personal loan channels (Telangana Survey, 2020).[28]

Interpretation and Alternative Explanations

In the preceding section, I point out that increase in incomes due to a positive rainfall shock could also increase moneylenders' capital, particularly since repayment is also seen to

[28] As one lender explained, "I borrow from the bank because if I refuse a client, they won't believe I don't have the money."

increase. If an increase in supply is all that occurs, moneylenders are unlikely to borrow more from banks. So, the results are consistent with a net increase in demand over and above any possible increases in supply.

Another possibility is that banks themselves are more willing to lend following a positive rainfall shock. However, Table 11 shows that total district-level bank credit does not increase significantly with rainfall, suggesting no systematic loosening of credit constraints at the aggregate level. While this does not rule out targeted lending to moneylenders in good rainfall years, such behavior seems unlikely given the diverse channels through which moneylenders report borrowing (e.g., agricultural loans, gold loans, personal loans, reported in Telangana Survey (2020)). Moreover, since most moneylenders borrow under schemes not explicitly designed for them, broad-based targeting by banks seems improbable.

Together, these results support the view that when household borrowing rises unexpectedly, moneylenders are often unable to meet this demand from internal capital alone and instead turn to the formal banking sector for liquidity.

7.3 Heterogeneity in Rural Household Borrowing Responses to Rainfall Shocks

Results and Robustness

Having established that increased household demand for credit raises both borrowing from moneylenders and the interest rates charged, I now ask whether this response varies with the availability of formal credit. I do so by examining heterogeneity in borrowing responses to a positive rainfall shock across district×year cells with differing predicted credit supply conditions. District-years are classified as experiencing contracting credit supply if predicted bank credit growth, $\hat{B}_{dt}$, falls below zero, as described in Section 6.

Table 12 and Table 13 show that the same positive rainfall shock yields sharply different household borrowing responses across credit supply environment. In districts where predicted credit supply is contracting, a one standard deviation increase in rainfall (or a 1% increase in district per capita income, per Table 3) leads to a 1 percentage point increase in borrowing from moneylenders. In contrast, the same shock leads to nearly a 3 percentage point increase in districts with expanding credit supply. In relative terms, higher bank credit supply enables 1.8 percentage points or about 12% more informal borrowing during periods of heightened credit demand.

This heterogeneity extends to loan terms as well. Table 14 shows that interest rates on moneylender loans rise significantly in response to a rainfall shock, but the increase is substantially muted in contracting-credit districts. In Sample 1, interest rates increase by 5.7 percentage points in expanding-supply districts, compared to only 1.8 percentage points in contracting ones. The interaction term is negative and statistically significant across both samples, indicating a more muted price response when formal credit supply is tight.

Importantly, interest rates are already significantly higher in contracting-credit districts, even absent a rainfall shock. This baseline difference (captured by the main effect of the contracting supply indicator) reflects tighter liquidity and higher marginal costs of capital. Thus, the net price increase in contracting supply districts is higher than in expanding supply districts. In addition, marginal borrowers in contracting districts are either priced out or substitute toward other segments, such as interest-free loans. As a result, the observed change in rates understates the underlying pressure on informal lenders. In this sense, the interaction term likely captures only the residual price response conditional on already high borrowing costs for borrowers who remain in the moneylender market. Borrowing responses from friends and relatives support this claim, and are discussed below.

In contrast to moneylender borrowing, columns 3 and 4 of Tables 12 and 13 show that borrowing from friends and relatives does not respond significantly to rainfall in expanding-credit districts, but increases in contracting-supply districts. This substitution is consistent with households turning to social networks when moneylenders are less able to meet demand. Finally, columns 5 and 6 confirm that borrowing from institutions does not increase in contracting-supply areas following rainfall shocks, suggesting that banks are not directly absorbing the additional demand either.

Taken together, Table 12, Table 13 and 14 show that formal credit supply plays a critical role in shaping both the volume and pricing of informal credit. When bank liquidity is high, moneylenders are better able to accommodate borrower demand through both expanded lending and interest rate adjustments. When liquidity is constrained, moneylenders appear to be unable to meet demand fully, resulting in both smaller increases in borrowing and shifts to borrowing from friends and relatives.

Interpretation, Concerns, and Alternative Explanations

The evidence presented above suggests that variation in bank credit supply shapes informal credit outcomes through a supply-side channel, specifically, by constraining moneylenders' ability to expand lending or adjust prices in response to an unanticipated increase in household demand. However, alternative interpretations ought to be considered.

One possibility is a borrower-side demand channel, where bank and moneylender credit function as complements (from the borrower's perspective). In this view, limited access to formal loans reduces the overall demand for credit, including from moneylenders. For this to explain the observed heterogeneity, the same borrowers would need to use both formal and informal credit, and their borrowing from moneylenders would need to rise when formal credit supply is more abundant. However, only 4% of borrowing households (0.05% of all households) borrow from both sources in a given year, including during agricultural seasons. Moreover, there is no significant interaction between rainfall shocks and contracting bank credit supply in predicting joint borrowing.[29][30]

[29] Using the same specification as in this section, and regressing an indicator for whether a household has borrowed from both sources indicates that borrowing from both does not increase following a positive rainfall shock, and the interaction with low bank supply is negligible and not significant.

[30] Conversely, one might expect greater dual borrowing under constrained formal credit if bank loans are

A second possibility is a general equilibrium demand effect, where tighter bank credit dampens local economic activity, thereby muting informal credit demand in affected districts (see, e.g., Young, 2019; Breza and Kinnan, 2020; Burgess and Pande, 2005). However, the pattern of substitution to interest-free borrowing suggests otherwise. Columns 3 and 4 of Table 12 and Table 13 show that, following a positive rainfall shock, households in contracting-supply districts increase borrowing from friends and relatives, while such borrowing is flat in expanding-supply districts. If demand were uniformly weaker, substitution across credit types would be less pronounced.

Table 14 further supports a supply-side interpretation where interest rates are higher in contracting-supply districts (independent of the rainfall shock), consistent with tighter liquidity. Yet following the shock, interest rates increase less in these same areas. This suggests that moneylenders in credit-constrained settings face capital limits that prevent them from expanding lending or adjusting prices fully. Together, these findings rule out pure demand-side stories and indicate that tighter bank credit supply constrains the informal market's capacity to absorb demand shocks.

7.4 Welfare Implications

These results indicate that, due to the vertical interaction between moneylenders and banks, bank credit supply shapes informal credit access as well. A 10% higher growth in bank credit supply enables approximately 23% more loans in the moneylender market following a one standard deviation rainfall shock in non-drought years. Households, however, are not entirely without alternatives when formal liquidity is tight — they partially substitute interest-bearing loans from moneylenders with interest-free loans from friends or relatives. This substitution, however, is incomplete: only 40% of the decline in moneylender borrowing is offset by increased borrowing from social networks. From the household's perspective,

rationed and moneylender loans are used as a supplement. But again, given the small fraction of overlapping borrowers, this cannot explain the average treatment heterogeneity.

this implies that a 10% increase in bank credit supply growth allows for 14% more borrowing in the informal market overall (combining interest-bearing and interest-free borrowing) following a positive rainfall shock in non-drought years.

Since this substitution occurs precisely when moneylender loans are more expensive, it underscores that "interest-free" loans carry implicit costs (Ligon, 2005; Udry, 1994; Hayashi et al., 1996; Ambrus et al., 2014; Ligon and Schechter, 2012). These may include social obligations or reputational consequences. Indeed, borrowers do not increase use of interest-free loans when formal credit supply is expanding. Using values from Table 13 and Table 14, back-of-the-envelope calculations suggest that the marginal borrower who switches to interest-free credit when formal liquidity is tight implicitly values its cost at approximately 49.42% per year. This does not account for complex social dynamics, such as dignity or autonomy, which also shape credit decisions (Mowl, 2017).

Beyond these static margins, constrained access to credit during periods of high liquidity demand may have dynamic welfare consequences. Households may delay or forgo lumpy investments in durables, land improvements, or health-related expenditures, potentially lowering future income and welfare. Moreover, households without strong social networks face the greatest constraints, amplifying inequalities in access to consumption smoothing or investment opportunities.

Taken together, the evidence suggests that even marginal expansions in formal credit supply may generate relatively larger welfare benefits, by easing household liquidity constraints directly and indirectly through informal institution.

More broadly, these findings have implications for the transmission of monetary policy in vertically interacting credit markets. When bank liquidity improves, through looser monetary policy, deposit inflows, or regulatory easing, these effects can propagate through informal credit channels too, generating a multiplier effect in the informal sector. Conversely, informal markets may not serve as a buffer to formal sector shocks.

8 Conclusion

In this paper, I focus on the interaction between banks and moneylenders in rural India and find that it is best characterized as a vertical relationship where moneylenders borrow from banks and on-lend these loans to their clients. As a result, when faced with unanticipated increases in demand for credit, moneylenders rely on bank loans to ease lending capital constraints. This analysis also establishes that increases in bank-credit supply enable additional informal borrowing. However, moneylenders wield considerable market power, as indicated by their 16% - 58% margins over marginal cost in Section 3 — suggesting that they accrue most of the surplus generated by the additional loans transacted. Moneylenders are thus able to successfully arbitrage across the formal and informal credit sectors.

In this context, continued household engagement with moneylenders is possibly because moneylenders offer greater flexibility to borrowers than formal institutions do, or because access to formal credit remains a challenge for some. 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 in particular.

These findings also speak to policy design. Past approaches have often framed formal and informal credit as substitutes, aiming to crowd out the latter. But the evidence here suggests a more complex complementarity. When banks lend more, moneylenders lend more, rather than less, and informal borrowers benefit through improved access, albeit at high cost. Expanding bank-linked self-help groups and well-capitalized microfinance institutions, particularly those targeting excluded borrowers, may ease these constraints. Recent evidence suggests such programs can lower moneylender interest rates and reduce reliance on informal credit (Hoffmann et al., 2021).

More broadly, this paper has implications for monetary policy transmission. Loosening or tightening bank liquidity can propagate downstream, amplifying formal sector shocks via vertical linkages, rather than buffering against them. It is worth noting though that the analysis here extends to 2017, and the primary phone survey was conducted in 2020. As a result, this study does not fully capture the rapid rise of digital credit and fintech lending in India over the past few years. These newer channels may be altering the structure of informal credit markets, expanding access while also introducing new risks related to privacy, repayment enforcement, and data use. Understanding how these emerging intermediaries interact with both traditional informal lenders and formal banks remains an important area for future research.

Overall, this study highlights the importance of viewing informal lenders not as isolated actors, but as integrated parts of a broader credit ecosystem, alongside banks and shadow banks. Improving household welfare may require not just increasing credit access, but re-thinking how formal liquidity flows through informal institutions, and how that flow can be made more competitive, inclusive, and welfare-enhancing.

References

Acharya, Viral and Nirupama Kulkarni (2019). “Government Guarantees and Bank Vulnerability During a Crisis: Evidence from an Emerging Market,” *NBER Working Paper 26564*.

Acharya, Viral V., Nicola Cetorelli, and Bruce Tuckman (2024). “Where do banks end and nbfis begin?” NBER Working Paper 32316, National Bureau of Economic Research, jEL No. G01, G20, G21, G22, G23, G24, G28, G29.

Acharya, Viral V., Manasa Gopal, Maximilian Jager, and Sascha Steffen (2025). “Shadow always touches the feet: Implications of bank credit lines to non-bank financial intermediaries,” Working Paper 33590, National Bureau of Economic Research, nBER Working Paper No. 33590.

Acharya, Viral V., Hemal Khandwala, and T. Sabri Öncü (2013). “The growth of a shadow banking system in emerging markets: Evidence from india,” *Journal of International Money and Finance*, 39: 207–230.

Aleem, I. (1990). “Imperfect Information, Screening, and the Costs of Informal Lending: A Study of a Rural Credit Market in Pakistan,” *The World Bank Economic Review*, 4(3): 329–349.

Allen, Franklin, Asli Demirguc-Kunt, Leora Klapper, and Maria Soledad Martinez Peria (2016). “The foundations of financial inclusion: Understanding ownership and use of formal accounts,” *Journal of Financial Intermediation*, 27: 1–30.

Ambrus, Attila, Markus Mobius, and Adam Szeidl (2014). “Consumption Risk-sharing in Social Networks,” *American Economic Review*, 104(1): 149–182.

Ashraf, Nava, Dean Karlan, and Wesley Yin (2006). “Tying Odysseus to the Mast: Evidence from a Commitment Savings Product in the Philippines,” *The Quarterly Journal of Economics*, 121: 635–672.

Banerjee, Abhijit (2003). “Contracting Constraints, Credit Markets, and Economic Development,” in Mathias Dewatripont, Lars Peter Hansen, and Stephen J. Turnovsky (eds.), “Advances in Economics and Econometrics Theory and Applications, Eighth World Congress,” Cambridge University Press, pp. 1–46.

Banerjee, Abhijit and Esther Duflo (2014). “Do Firms Want to Borrow More? Testing Credit Constraints Using a Directed Lending Program,” *Review of Economic Studies*, 81: 572–607.

Banerjee, Abhijit, Esther Duflo, Rachel Glennerster, and Cynthia Kinnan (2015). “The Miracle of Microfinance? Evidence from a Randomized Evaluation,” *American Economic Journal: Applied Economics*, 7(1): 22–53.

Banerjee, Abhijit and Sendhil Mullainathan (2010). “The Shape of Temptation: Implications for the Economic Lives of the Poor,” *National Bureau of Economic Research Working Paper: 15973*.

Baum-Snow, Nathaniel and Fernando Ferreira (2015). “Causal Inference in Urban and Regional Economics,” in Gilles Duranton, J. Vernon Henderson, and William C. Strange (eds.), “Handbook of Reegional and Urban Economics,” Amsterdam: Elsevier, pp. 3–68.

Bell, Clive, T Srinivasan, and Christopher Udry (1997). “Rationing, Spillover and Interlinking in Credit Markets: The Case of Rural Punjab,” *Oxford Economic Papers*, 49: 557 – 587.

Bergquist, Lauren Falco and Michael Dinerstein (2019). “Competition and Entry in Agricultural

Markets: Experimental Evidence from Kenya," *Working Paper*.

Bhardwaj, Abhishek and Apoorva Javadekar (2024). "How does bank lending to non-banks affect credit allocation and systemic risk," Working paper, SSRN, available at SSRN: https://ssrn.com/abstract=4946216.

Botsch, Mattheww J. and Ulrike Malmendier (2020). "The Long Shadhows of the Great Inflation: Evidence from Residential Mortgages," *Working Paper*.

Breza, Emily and Cynthia Kinnan (2020). "Measuring the Equilibrium Impacts of Credit: Evidence from the Indian Microfinance Crisis," *Working Paper*.

Buchak, Greg, Gregor Matvos, Tomasz Piskorski, and Amit Seru (2024). "Beyond the balance sheet model of banking: Implications for bank regulation and monetary policy," *Journal of Political Economy*, 132(2): 616–693.

Burgess, Robin and Rohini Pande (2005). "Do Rural Banks Matter? Evidence from the Indian Social Banking Experiment," *American Economic Review*, 95(3): 780–795.

Dasgupta, A., C.P.S Nayar, and Associates (1989). *Urban Informal Credit Markets in India*, New Delhi.

Demirguc-Kunt, Asli, Leora Klapper, Dorothe Singer, and Saniya Ansar (2022). *The Global Findex Database 2021: Financial Inclusion, Digital Payments, and Resilience in the Age of COVID-19 - Executive Summary*, Washington, D.C.: World Bank Group, accessed May 2025.

Dréze, Jean, Peter Lanjouw, and Naresh Sharma (1998). "Credit," in "Economic Development in Palanpur over Five Decades," Oxford University Press.

Emerick, Kyle (2018). "Agricultural productivity and the sectoral reallocation of labor in rural India," *Journal of Development Economics*, 135: 488–503.

Floro, Maria Sagrario and Debraj Ray (1997). "Vertical Links Between Formal and Informal Financial Institutions," *Review of Development Economics*, 1(1): 34–56.

Frison, Lars and Stuart J Pocock (1992). "Repeated Measures in Clinical Trials: Analysis Using Mean Summary Statistics and its Implications for Design," *Statistics in Medicine*, II: 1685 – 1704.

Ghate, P.B. (1992). "Interaction between the Formal and Informal Financial Sectors: The Asian Experience," *World Development*, 20(6): 859–872.

Ghosh, Parikshit, Dilip Mookherjee, and Debraj Ray (1999). "Credit Rationing in Developing Countries: An Overview of the Theory," *Working Paper*.

Giné, Xavier (2011). "Access to Capital in Rural Thailand: An Estimated Model of Formal vs. Informal Credit," *Journal of Development Economics*, 96: 16 – 29.

Goldsmith-Pinkham, Paul, Isaac Sorkin, and Henry Swift (2020). "Bartik Instruments: What, When, Why and How," *American Economic Review*, 110: 2586–2624.

González, Felipe (2017). "Privatized Keynesiansim or conspicuous consumption? Status anxiety and the financialization of consumption in Chile," *MPIfG Discussion Paper No. 17/3*.

Greenstone, Michael, Alexandre Mas, and Hoai-Luu Nguyen (2020). "Do Credit Market Shocks affect the Real Economy? Quasi-Experimental Evidence from the Great Recession and 'Normal' Economic Times," *American Economic Journal: Economic Policy*, 12(1).

Guérin, Isabelle, Marc Roesch, Govindan Venkatasubramanian, and Bert D'espalliers (2012). "Credit from Whom and for What? The Diversity of Borrowing Sources and Uses in Rural Southern India," *Journal of International Development*, 24: S122–S137.

Guérin, Isabelle, Marc Roesch, Govindan Venkatasubramanian, and Santosh Kumar (2011). "The Social Meaning of Over-Indebtedness and Creditworthiness in the Context of Poor Rural South Indian Households (Tamil Nadu)," *Rural Microfinance and Employment (RuMe) Working Paper, 2011-1.*

Hanemann, Michael W (1984). "Discrete/Continuous Models of Consumer Demand," *Econometrica*, 52(3): 541–561.

Hayashi, Fumio, Joseph Altonji, and Laurence Kotlikoff (1996). "Risk-Sharing Between and Within Families," *Econometrica*, 64(2): 261–294.

Hoff, Karla and Joseph E. Stiglitz (1990). "Introduction: Imperfect Information and Rural Credit Markets: Puzzles and Policy Perspectives," *The World Bank Economic Review*, 4(3): 235–250.

Hoff, Karla and Joseph E. Stiglitz (1998). "Moneylenders and Bankers: Price-Increasing Subsidies in a Monopolistically Competitive Market," *Journal of Development Economics*, 55: 485–518.

Hoffmann, Vivian, Vijayendra Rao, Vaishnavi Surendra, and Upamanyu Datta (2021). "Relief from Usury: Impact of a Self-Help Group Lending Program in Rural India," *Journal of Development Economics*.

ICRISAT (2014). "ICRISAT Village Dynamics Study Dataset (2009-2014)," .

Imbens, Guido W. and Donald B. Rubin (2015). *Causal Inference in Statistics and the Social Sciences*, Cambridge and New York: Cambridge University Press.

Imbens, Guido W. and Jeffrey M. Wooldridge (2009). "Recent Developments in the Econometrics of Program Evaluation," *Journal of Economic Literature*, 47(1): 5–86.

Irfan, M., G.M. Arif, Syed Mubashir, and Hina Nazli (1999). *The Structure of Informal Credit Market in Pakistan*, Research Report No. 168.

Jacoby, Hanan G. (2008). "Moneylenders in Developing Countries," in Steven N. Durlauf and Lawrence E. Blume (eds.), "The New Palgrave Dictionary of Economics," Palgrave Macmillan, 2 edition.

Jacoby, Hanan G. and Emmanuel Skoufias (1998). "Testing Theories of Consumption Behavior using Information on Aggregate Shocks: Income Seasonality and Rainfall in Rural India," *American Journal of Agricultural Economics*, 80(1): 1–14.

Jain, Sanjay (1999). "Symbiosis vs. crowding-out: the interaction of formal and informal credit markets in developing countries," *Journal of Development Economics*, 59: 419 – 444.

Jayachandran, Seema (2006). "Selling Labor Low: Wage Responses to Productivity Shocks in Developing Countries," *Journal of Political Economy*, 114(3): 538–575.

Kaboski, Joseph P. and Robert Townsend (2012). "The Impact of Credit on Village Economies," *American Economic Journal: Applied Economics*, 4(2): 98–133.

Kanz, Martin (2016). "What Does Debt Relief Do for Development? Evidencee from India's Bailout for Rural Households," *American Economic Journal: Applied Economics*, (4).

Karaivanov, Alexander and Anke Kessler (2018). "(Dis)advantages of informal loans – Theory and evidence," *European Economic Review*, 102: 100–128.

Kaur, Supreet (2019). "Nominal Wage Rigidity in Village Labor Markets," *American Economic Review*, 109(10): 3585–3616.

Khanna, Madhulika and Shruti Majumdar (2020). "Caste-ing Wider Nets of Credit: A Mixed Methods Analysis of Informal Moneylending and Caste Relations in Bihar," *World Development Perspectives*, 20.

Kochar, Anjini (1997). "An Empirical Investigation of Rationing Constraints in Rural Credit Markets in India," *Journal of Development Economics*, 53(2): 339–371.

Kochar, Anjini (2011). "The Distributive Consequences of Social Banking: A Microempirical Analysis of the Indian Experience," *Economic Development and Cultural Change*, 59(2): 251–280.

Ligon, Ethan (2005). "Formal Markets and Informal Insurance," *International Review of Law and Economics*, 25(1): 75–88.

Ligon, Ethan and Laura Schechter (2012). "Motives for Sharing in Social Networks," *Journal of Development Economics*, 99: 13–26.

Ligon, Ethan and Timothy Worrall (2020). "Optimal Roscas," *Working Paper*.

Madestam, Andreas (2014). "Informal Finance: A Theory of Moneylenders," *Journal of Development Economics*, 107: 157 – 174.

Mitra, Sandip, Dilip Mookherjee, Maximo Torero, and Sujata Visaria (2018). "Asymmetric Information and Middleman Margins: An Experiment with Indian Potato Farmers," *The Review of Economics and Statistics*, (1).

Mookherjee, D. and A. Motta (2016). "A Theory of Interactions between MFIs and Informal Lenders," *Journal of Development Economics*, 121: 191 – 200.

Mowl, Amy Jensen (2017). "The Technology of Lending: Informal Credit Contracts," *NSE-IFMR Finance Foundation Financial Deepening and Household Finance Research Initiative Working Paper*.

NAFIS (2017). "NABARD All India Rural Financial Inclusion Survey 2016-17," Technical report, National Bank for Agriculture and Rural Development.

Newey, W.K. (2009). "Two-step Series Estimation of Sample Selection Models," *Econometrics Journal*, 12: S217–S229.

Ngo, Diana K. L. (2018). "A Theory-Based Living Standards Index for Measuring Poverty in Developing Countries," *Journal of Development Economics*, 130: 190–202.

NSSO (2013a). "Key Indicators of Debt and Investment in India: NSS 70th Round (January - December, 2013)," Technical report, National Sample Survey Organization.

NSSO (2013b). "National Sample Survey Office Socio-Economic Survey: Debt and Investment Schedule 18.2 (1990-91, 1991-92, 2001-2002, 2002-2003, 2011-12, 2012-13)," .

Paxson, Christina H. (1992). "Using Weather Variability to Estimate the Response of Savings to Transitory Income inThailand," *American Economic Review*, 82(1): 15–33.

RBI (2012). "Report on Trend and Progress of banking in India 2011-12," Technical report, Reserve Bank of India.

RBI (2018). "Co-origination of loans by Banks and NBFCs for lending to priority sector," Technical report, Reserve Bank of India.

Rosenzweig, Mark R. and Kenneth I. Wolpin (1993). "Credit Market Constraints, Consumption Smoothing, and the Accumulation of DurableProduction Assets in Low-Income Countries: Investments in Bullocks in India," *Journal of Political Economy*, 101(2): 223–244.

Ruiz, Claudia (2013). "From Pawn Shops to Banks: The Impact of Formal Credit on Informal Households," *World Bank Policy Research Working Paper. 6634*.

Santangelo, Gabriella (2019). "Firms and Farms: The Local Effects of Farm Income on Firms' Demand," *Working Paper*.

Sharma, Naresh Kumar (2010). "Indigenous Institutions, Benevolent Intervention and Justicec: The Ccase of Rural Credit Markets in India," *Contemporary Issues and Ideas in Social Science*.

Telangana Survey (2020). "Telangana Moneylenders Survey Dataset," .

TNSMS (2009). "Tamil Nadu Socio-Economic Mobility Survey," .

Townsend, Robert (1995). "Financial Systems in Northern Thai Villages," *The Quarterly Journal of Economics*, 110(4): 1011–1046.

Udry, Christopher (1994). "Risk and Insurance in a Rural Credit Market: An Empirical Investigation in Northern Nigeria," *The Review of Economic Studies*, 61(3): 495–526.

Willmott, Cort J. and Kenji Matsuura (2018). "Terrestrial Air Temperature and Precipitation: Monthly and Annual Time Series (1950 - 2017)," .

Wolpin, Kenneth I. (1982). "A New Test of the Permanent Income Hypothesis: The Impact of Weather on the Incomeand Consumption of Farm Households in India," *International Economic Review*, 23(3): 583–594.

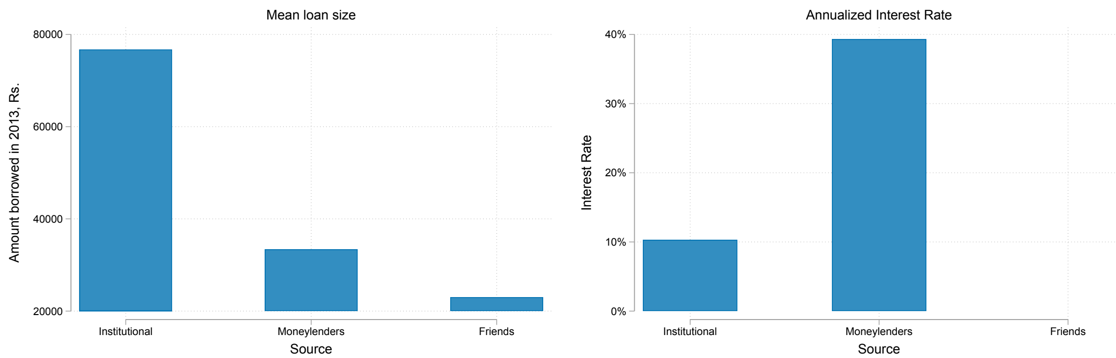
World Bank (2019). Data retrieved from The Global FINDEX Database, https://globalfindex.worldbank.org/.

World Bank (2022). Data retrieved from The Global FINDEX Database, https://globalfindex.worldbank.org/.

Young, Nathaniel (2019). "Banking and Growth: Evidence from a Regression Discontinuity Analysis," *Working Paper*.

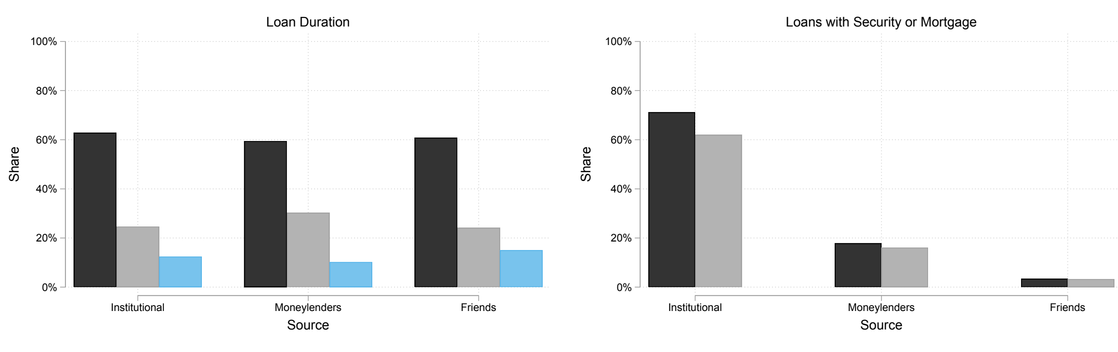
Figures

Figure 1: Loan Size and Interest Rates by Lender Type



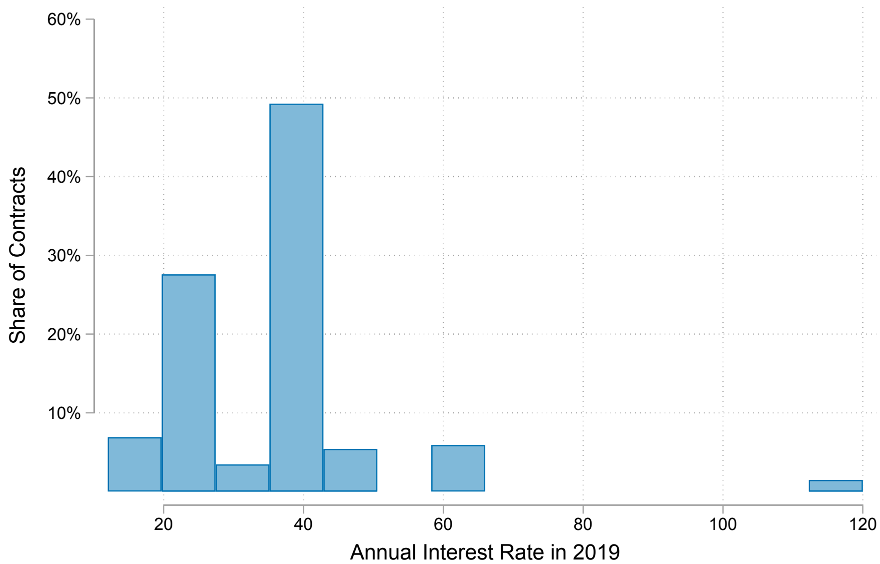
Data: NSS Debt and Investment Survey, 2013
Alt text: Two graphs, the first graph depicts mean loan size across lender types, and the second presents annualized interest rates across lender types

Figure 2: Loan Terms by Lender Type



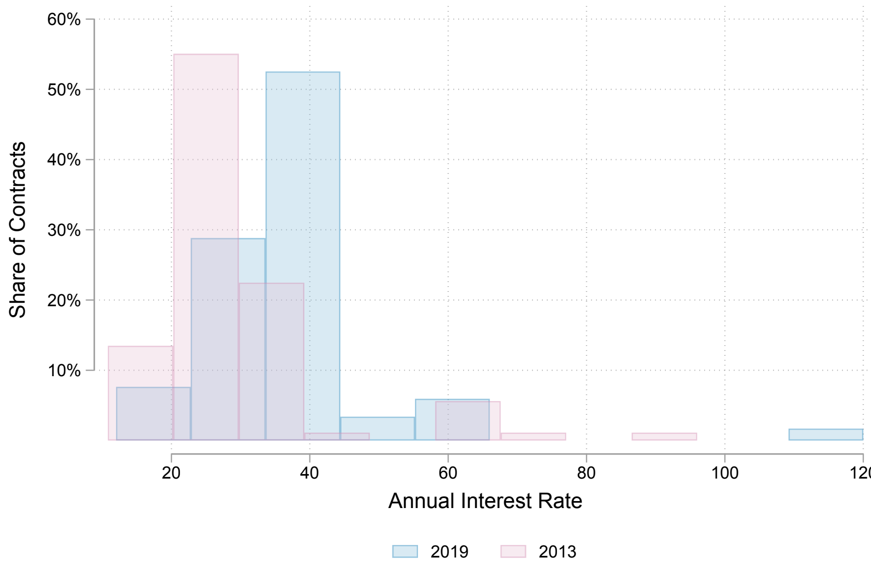
Data: NSS Debt and Investment Survey, 2013
Alt text: Two graphs, the first graph depicts mean loan duration lender types, and the second presents the share of loans requiring security or mortgage across lender types

Figure 3: Moneylender Interest Rates, 2019



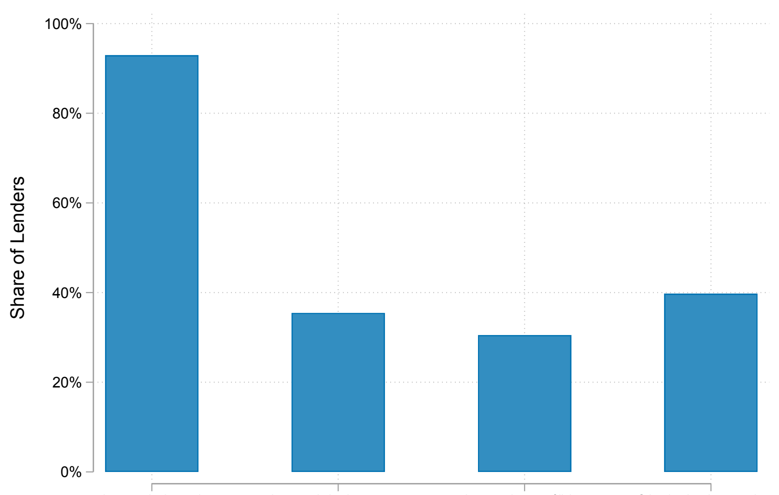
Data: Moneylender Survey (Telangana), 2020
Alt text: A bar graph presenting the distribution of annual interest rates in 2019 from the moneylender survey in Telangana

Figure 4: Moneylender Interest Rates, 2013 and 2019



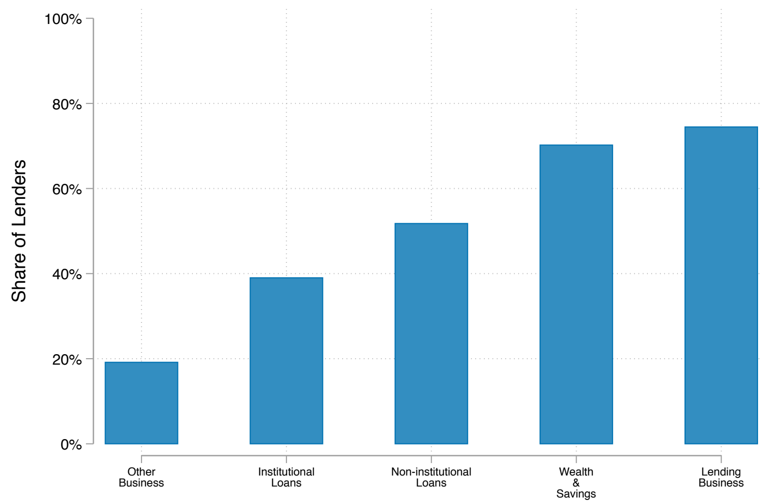
Data: Moneylender Survey (Telangana), 2020
Alt text: A bar graph presenting the distribution of annual interest rates in 2019, overlaid on the distribution of annual interest rates in 2013 from the moneylender survey in Telangana

Figure 5: Reasons for which Moneylenders increase Interest Rates



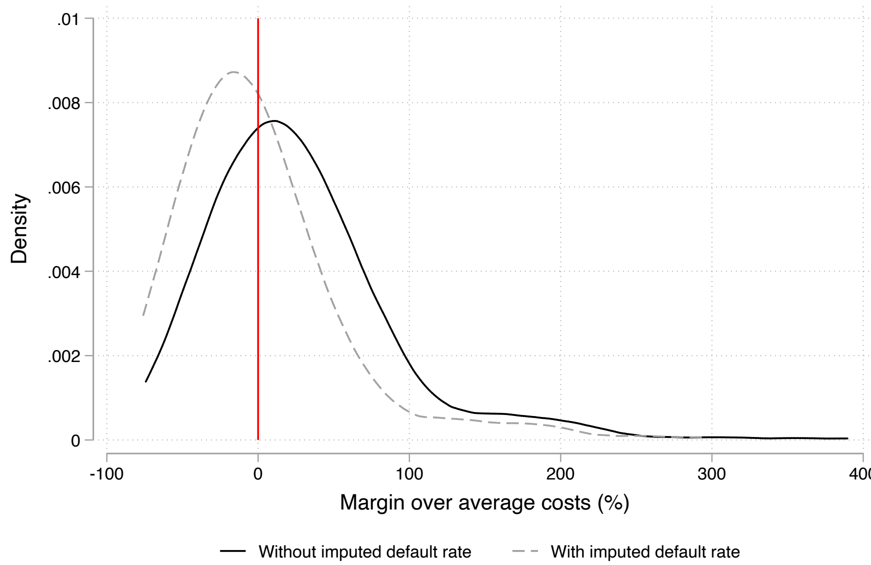
Data: Moneylender Survey (Telangana), 2020
Alt text: A bar graph presenting the reasons for which moneylenders report increasing interest rates in the Telangana moneylender survey

Figure 6: Moneylenders' Source of Lending Capital



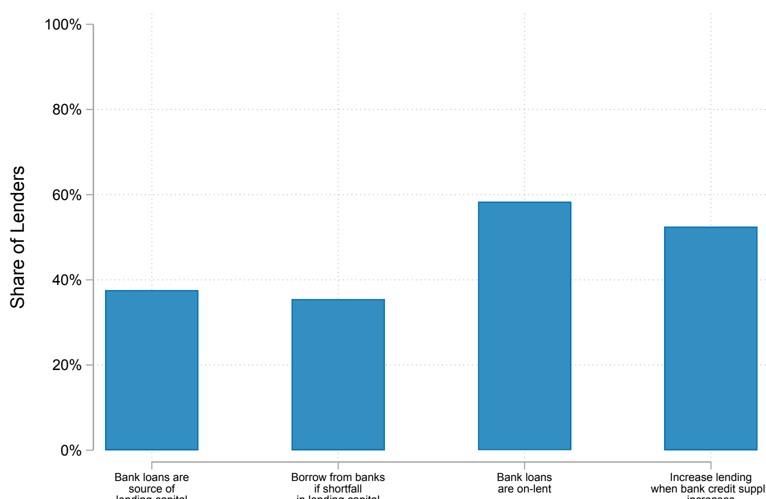
Data: Moneylender Survey (Telangana), 2020
Alt text: A bar graph presenting the sources of moneylenders' lending capital reported in the Telangana moneylender survey

Figure 7: Moneylender Margins over Average Costs



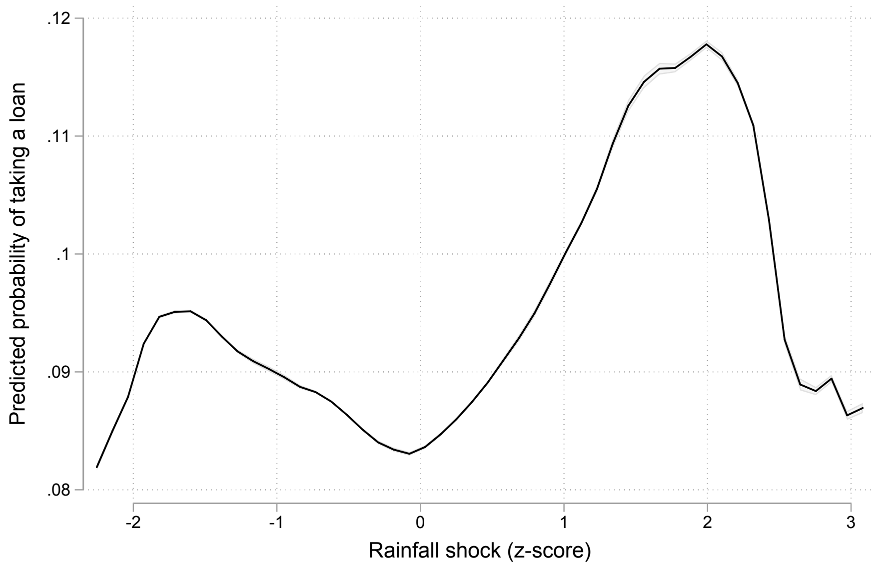
Data: NSS Informal Firms Survey, 2015-16
Alt text: A density graph of moneylenders' margins over average costs from the NSS informal firms survey (2015-16)

Figure 8: Moneylenders' Bank Borrowing



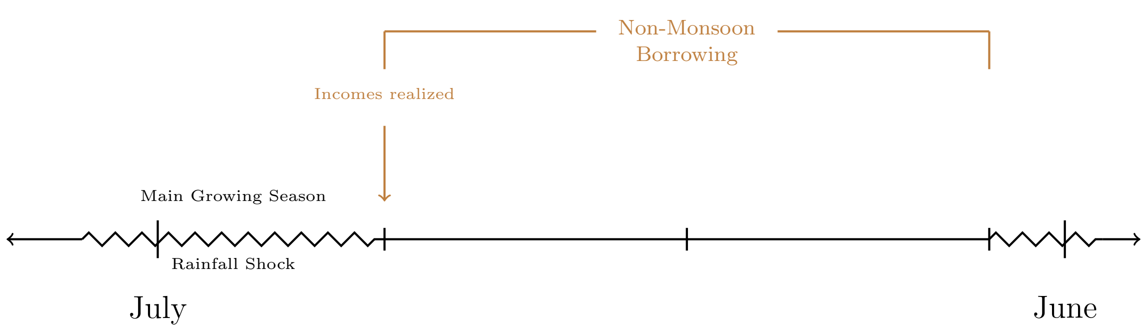
Data: Moneylender Survey (Telangana), 2020
Alt text: A bar graph presenting moneylenders' lending or borrowing actions relating to bank loans

Figure 9: Asymmetric Effect of Rainfall Shocks on Rural Household Borrowing



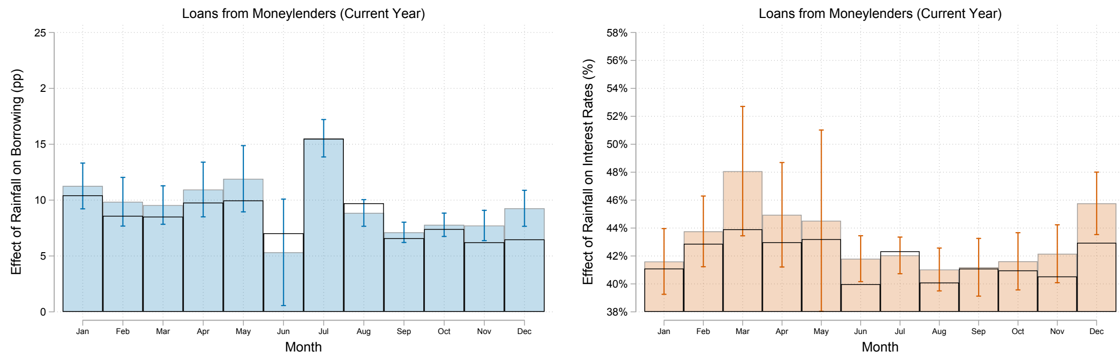
Data: NSS Debt and Investment Survey, 2001-02, 2002-03, 2011-12, 2012-13
Alt text: A density graph of the continuous rainfall shock measure

Figure 10: Monsoon Timing



Alt text: A chart depicting the timing of monsoon rainfall and income realization

Figure 11: 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

Alt text: Two graphs. The first depicts treatment effects of rainfall shocks on household borrowing from moneylenders month-wise. The second depicts treatment effects of rainfall shocks on moneylender loan interest rates month-wise.

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: Moneylender Summary Statistics

	Mean	Median	SD	N
	(1)	(2)	(3)	(4)
A: Moneylender Lending and Costs				
Total Amount Lent ('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
B: Moneylender Borrowing				
Any Formal Loans Outstanding (%)	14.05%		0.348	925
Any Informal Loans Outstanding (%)	8.43%		0.278	925
Formal Debt ('000 ₹)	356.29	153.55	655.202	130
Informal Debt ('000 ₹)	262.38	107.52	492.76	78
C: Moneylender Market				
No. of borrowers (rural lenders)	15.64	12.5	11.25	120
No. of borrowers (urban lenders)	24.38	20	12.93	21
No. of lenders (inside village)	8.67	8	5.19	30
No. of lenders (outside village)	2.17	2	3.73	30

Data: Panel A uses data on private moneylenders from NSS Informal Firms Survey (2015-16). Panel B uses data on private moneylenders from an additional round – NSS Informal Firms Surveys (2015-16; 2010-11). Panel C uses data on from a primary survey of 140 moneylenders and 30 village heads in Telangana (2019) ₹values are in real 2000-01 INR

Table 3: Rainfall and District GDP

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

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

Table 4: District characteristics across expanding and contracting predicted bank credit supply

	Means			Normalized Differences (Low - High)	p-value (Randomization Inference)
	Obs	Above median (High)	Below median (Low)		
	(1)	(2)	(13	(4)	(5)
Rainfall (z-score)	2280	-0.344	0.131	-0.018	0.812
Irrigated Land (Area irrigated/ Area cultivated)	1091	33.6%	33.6%	0.005	0.884
Landless Households	2280	39.8%	39.2%	0.003	0.420
SC/ST Households	2280	36.5%	39.5%	0.018	0.583
Non-Agricultural Households	2280	39.5%	37.5%	0.035	0.592
Population per bank branch	6435	12848.6	14484.1	0.002	0.685
Private bank branch share	6237	11.9%	7.5%	-0.008	0.112

Notes: Imbens and Rubin (2015) define the normalized difference as $\hat{\Delta}_{HL} = \frac{\overline{x}_L - \overline{x}_H}{\sqrt{(s_L^2 + s_H^2)/2}}$, where $\overline{x}_i$ is the sub-sample mean and s_i^2 is the sub-sample standard deviation, for expanding-credit and contracting-credit group. This is a scale-free measure of differences in covariate values, and the difference in means is estimated through a linear regression with controls for district and state $\times$ year fixed effects. Observations used to estimate differences in rainfall, landlessness, caste status and occupation come from the district $\times$ years in the NSS sample - 2002, 2003, 2012, 2013. Irrigated land is a subset of these observations where data on irrigation is available. Population per bank branch and share of private banks is from the Reserve Bank of India's data for the years 2006 - 2016. Data for earlier years is not publicly available.

Table 5: 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	₹170.01	₹976.53	₹79.83	₹431.25	₹484.86	₹2407.37
Mean (conditional on borrowing)	₹13,431.56	₹17,482.10	₹9456.32	₹11,660.56	₹35,004.39	₹36,238.4

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 6: 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 × Year					
Mean	0.073	0.056	0.053	0.037	0.083	0.066

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 dummy indicating any borrowing between Nov - 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 7: 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 Nov - 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 8: Rainfall and Rural Household Borrowing Purpose

	Farm	Non-Farm	Cons
	(1)	(2)	(3)
Rainfall Shock	-0.002	-0.000	0.023*
	(0.006)	(0.003)	(0.014)
Obs	302236	302236	302236
Clusters	578	578	578
Fixed Effects	District, State × Year		
Mean	₹287.88	₹110.26	₹425.27
Mean (Conditional on borrowing)	₹27,552.43	₹40,072.17	₹20,039.62

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

Table 9: 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	₹1279.23	₹640.16	₹225.93
Mean (Conditional on borrowing)	₹5733.53	₹2679.14	₹3522.18

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 10: Moneylenders' Own Borrowing and Lending

	Any Loans from Formal Sources?	Amount Lent to Households (asinh '000 real ₹)	Interest Rate
	(1)	(2)	(3)
Rainfall Shock	0.044**	0.121**	15.180*
	(0.021)	(0.031)	(5.928)
Obs	907	341	380
Clusters	126	4	4
District FE	Yes	No	No
Fixed Effects	Quarter, State × Year		
Mean	0.14	₹465.72	77.27%

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. Unit of observation is a moneylender. All regressions control for firm characteristics. The outcome in column (1) 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 (2) is the inverse hyperbolic sine of the real amount lent to households. The outcome in column (3) is the effective annualized interest rate based on interest payments received. Regressions in columns (2) and (3) use cross-sectional data, with additional district controls. Standard errors are clustered at the district level in column (1), and at the state level in columns (2) and (3). * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 11: Rainfall and District Total Formal Credit

	Credit Limit	Credit Amount	No. Accounts	Predicted Credit Supply
	(ln real ₹)	(ln real ₹)	(ln)	(shift-share, %)
	(1)	(2)	(3)	(4)
Rainfall Shock	0.003	0.004	-0.00	-0.000
	(0.006)	(0.005)	(0.004)	(0.000)
Obs	10873	10873	10873	10458
Clusters	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 12: 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	0.029***	0.086***	-0.005	-0.003	0.027**	0.004
	(0.009)	(0.025)	(0.006)	(0.020)	(0.012)	(0.028)
Contracting Supply	-0.001	-0.006	0.004	-0.028	-0.036***	-0.087
	(0.009)	(0.047)	(0.008)	(0.035)	(0.010)	(0.057)
Rainfall Shock × Contracting Supply	-0.018**	-0.071**	0.010	0.064**	-0.025**	-0.027
	(0.009)	(0.028)	(0.009)	(0.025)	(0.010)	(0.042)
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	₹170.01	₹976.53	₹79.83	₹431.25	₹484.86	₹2407.37
Mean (conditional on borrowing)	₹13,431.56	₹17,482.10	₹9456.32	₹11,660.56	₹35,004.39	₹36,238.4

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. Contracting supply is an indicator that takes a value of 1 when the predicted bank credit supply is negative. 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 13: 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	0.026***	0.010***	-0.001	0.000	0.020**	-0.000
	(0.008)	(0.003)	(0.006)	(0.002)	(0.009)	(0.003)
Contracting Supply	0.003	-0.001	0.005	-0.003	-0.027***	-0.009
	(0.007)	(0.005)	(0.008)	(0.004)	(0.008)	(0.005)
Rainfall Shock × Contracting Supply	-0.017**	-0.008***	0.004	0.007**	-0.021**	-0.002
	(0.008)	(0.003)	(0.008)	(0.003)	(0.008)	(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	0.073	0.056	0.053	0.037	0.083	0.066

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. Contracting supply is an indicator that takes a value of 1 when the predicted bank credit supply is negative. Sample 1 consists of all loans taken by a household in the survey year between November 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 Nov - May. Standard errors are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

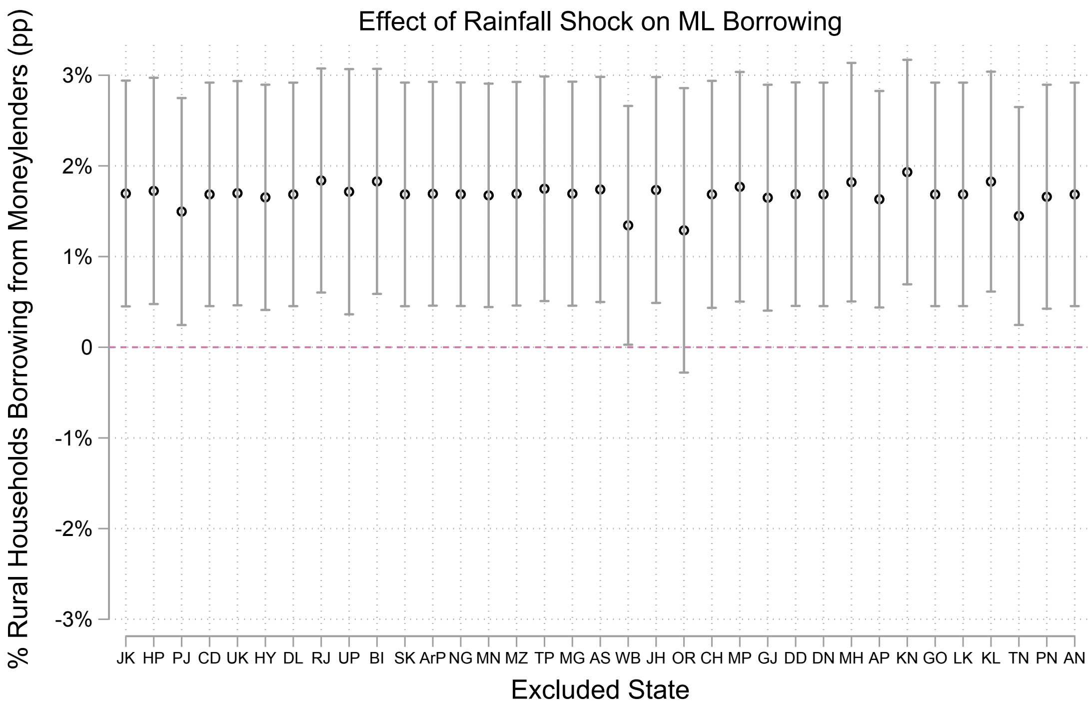
Table 14: Rainfall, Formal Credit Supply and Interest Rates on Loans from Moneylenders

	Sample 1	Sample 2
	(1)	(2)
Rainfall Shock	5.672***	1.562**
	(1.432)	(0.652)
Contracting Supply	3.270*	2.431***
	(1.823)	(0.912)
Rainfall Shock $\times$ Contracting 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. Contracting supply is an indicator that takes a value of 1 when the predicted bank credit supply is negative. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

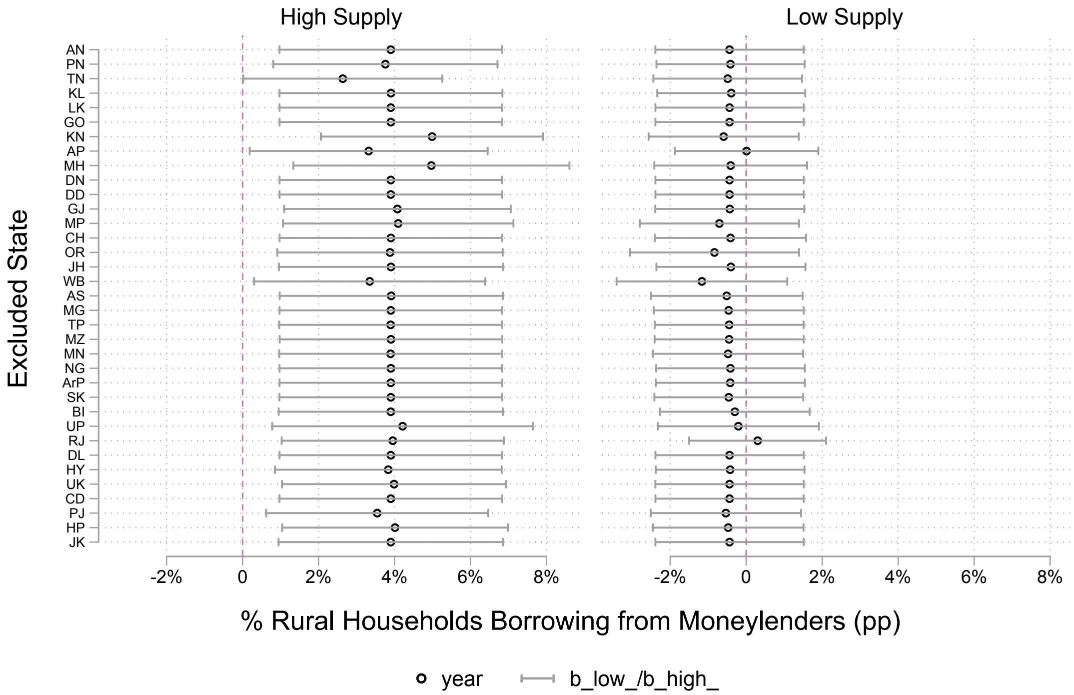
Additional Figures

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



Data: NSS Debt and Investment Survey, 2001-02, 2002-03, 2011-12, 2012-13
Alt text: A graph depicting the effect of the rainfall shock on household borrowing from moneylenders, dropping one state at a time as a robustness check.

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
Alt text: Two graph depicting the effect of the rainfall shock on household borrowing from moneylenders, dropping one state at a time as a robustness check. The first is for Expanding credit supply districts, and the second is for the contracting credit supply districts.

Additional Tables

Table A1: Positive Rainfall Shocks and Household Borrowing (ICRISAT Sample)

	Moneylenders		Friends & Relatives		Institutions		Moneylender Interest
		Asinh real ₹		Asinh real ₹		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	0.24	₹5729.59	0.18	₹2103.75	0.09	₹6736.23	0.29

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 Nov - May in the year. The outcome in columns (2), (4) and (6) is the inverse hyperbolic sine of the amount a household borrowed between Nov - 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 (ICRISAT Sample)

	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	0.37	₹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 Nov - May. The outcome in column (4) is a dummy which takes a value of 1 if the household has purchased any durables between Nov - May. The outcome in column (5) is the inverse hyperbolic sine of the real expenditure on durable goods between Nov - 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 (ICRISAT Sample)

	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)	0.20	0.15	0.06

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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A4: Rainfall and Incidence of Outstanding Loans from Prior Years

	Moneylenders	Friends & Relatives	Institutional
	(1)	(2)	(3)
Rainfall Shock	-0.003***	-0.000	-0.003***
	(0.001)	(0.001)	(0.001)
Obs	302512	302512	302512
Clusters	583	583	583
Fixed Effects	District, State × Year		
Mean	0.05	0.03	0.11

Data: NSS Debt and Investment Survey (2011-12, 2012-13)
Notes: Unit of observation is a household. Outcome is an indicator that takes a value of 1 when the household has outstanding loan borrowed prior to the reference year. 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). Standard errors are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A5: 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 × 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 × 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 ×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 A6: 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. * $p < 0.10$, ** $p < 0.05$, ***

Table A7: 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 Nov - 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 A8: 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)
Panel A: Predicting Bank Credit Supply Growth 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)
Contracting Supply	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 × Contracting Supply	-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
Panel B: Predicting Bank Credit Supply Growth 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)
Contracting Supply	-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 × Contracting Supply	-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. As in our main specifications, contracting supply is an indicator that takes a value of 1 when the predicted bank credit supply is negative. In panel A, credit supply is predicted using a measure of outstanding credit in the district-year, while in panel B, credit supply is predicted using a measure of the number of accounts in the district-year. Our main specification relies on credit supply predicted using a measure of the total amount of credit lines extended. 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

Modeling Assumptions

For analytical tractability, the model adopts several standard simplifications. Borrowers' optimal loan choices are assumed to yield interior solutions, with differentiable demand functions and well-defined thresholds. The borrower density is assumed to be positive and continuous near these thresholds. On the supply side, moneylenders operate in a monopolistically competitive market under free entry, with zero long-run profits. Fixed costs of entry and dynamic considerations are abstracted from. I also assume that access to formal and informal credit is segmented by wealth and that there is no default in equilibrium. Finally, the shadow price λ associated with binding bank credit constraints enters the effective cost of funds for moneylenders. These assumptions are common in the literature and help isolate the mechanisms of interest.

Proofs

Proof of Proposition 1:

In period 1, a moneylender solves:

$$\begin{aligned} \max_{r_{ML},G} \quad & \Pi = r_{ML}\tfrac{L}{N_L} - \rho K - r_B G \\ \text{s.t.} \quad & G = \begin{cases} 0, \text{ if } \frac{L}{N_L} < K \\ \bar{G}, \text{ if } \frac{L}{N_L} \geq K + \bar{G} \\ \frac{L}{N_L} - K, \text{ otherwise} \end{cases} \end{aligned} \tag{1}$$

I consider the symmetric equilibrium, and so the long-run zero-profit condition is $r_{ML}\frac{L}{N_L} = B(\frac{L}{N_L})$, and this determines the number of lenders, N_L. Fixed costs of lending are assumed to be zero. The first order conditions with respect to r_{ML} and G together yield, $L^* =$

$(r_B + \lambda_1 - r)\frac{\partial L}{\partial r}$ when $G > 0$ and $L^* = (\rho - r)\frac{\partial L}{\partial r}$ when $G = 0$, where λ_1 is the shadow price of bank credit when the bank credit constraint binds, and 0 otherwise. Define $r'_B = r_B + \lambda_1$. So, $L^* = (r'_B - r)\frac{\partial L}{\partial r}$ when moneylenders are capital constrained.

Proof of Proposition 2:

Households make decisions pertaining to a two-season horizon. They are indexed by an exogenous endowment, θ, and earn an income $R_t\theta$ in each season. R_t is an *i.i.d* exogenous season-specific income shock or a productivity parameter. They derive utility from a numeraire good, c_t, and can choose whether to purchase a durable good or asset, D at price, p. Purchasing D results in a per-season utility, d, from the services that D provides if D is to be interpreted as a durable good. Alternatively, d represents the additional per-season income from the purchase of a production asset, D. Households are not endowed with a savings technology, but have access to credit. So, households choose borrowing, b and whether to purchase the durable good/asset, D. In the case where households have access to loans from a moneylender, they solve:

$$\max_{D,b} \quad U_{ML} = u(R_1\theta + b - p\mathbb{1}\{D = 1\}) + d\mathbb{1}\{D = 1\} + \beta\mathbb{E}_1\Big[u(R_2\theta - r_{ML}b) + d\mathbb{1}\{D = 1\}\Big] \tag{2}$$

Households observe their season-1 income, $R_1\theta$ while making their decisions, and expect income in season-2 to be $\mathbb{E}[R_2]\theta$. Recall the assumption that the cost of defaulting is high enough for incentive compatibility constraint to be satisfied, and so households always repay their loans. The model does not consider state-contingent contracts, for simplicity.

Define $b^*_{ML}(\theta) = \underset{b}{argmax}\ u(R_1\theta + b) + \beta\mathbb{E}_1\Big[u(R_2\theta - r_{ML}b)\Big]$, the optimal loan size when a household with endowment, θ, does not purchase D; and define $b^*_{ML,d}(\theta) = \underset{b}{argmax}\ u(R_1\theta +$

$b - p) + \beta \mathbb{E}_1 \Big[u(R_2\theta - r_{ML} b) \Big] + (1+\beta)d$, the optimal loan size when a household with endowment, θ purchases, D.

Households do not purchase D when $U(\theta, b^*_{ML}; D=0) > U(\theta, b^*_{ML,d}; D=1)$; and households purchase D when $U(\theta, b^*_{ML}; D=0) \leq U(\theta, b^*_{ML,d}; D=1)$. Define $\hat{\theta}$, the endowment where $U(\theta, b^*_{ML}; D=0) = U(\theta, b^*_{ML,d}; D=1)$. So, households with $\theta < \hat{\theta}$ do not purchase D, and those with $\theta \geq \hat{\theta}$ purchase D. So, total household demand is:

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

Proof of Proposition 3:

The moneylending market equilibrium equates household demand with moneylender supply, $\int_{\underline{\theta}}^{\hat{\theta}} b^*_{ML} f(\theta) d\theta + \int_{\hat{\theta}}^{\bar{\theta}} b^*_{ML,d} f(\theta) d\theta = (r'_B - r^*_{ML}) \frac{\partial}{\partial r_{ML}} \Big[\int_{\underline{\theta}}^{\hat{\theta}} b^*_{ML} f(\theta) d\theta + \int_{\hat{\theta}}^{\bar{\theta}} b^*_{ML,d} f(\theta) d\theta \Big]$, where $L^* = \int_{\underline{\theta}}^{\hat{\theta}} b^*_{ML} f(\theta) d\theta + \int_{\hat{\theta}}^{\bar{\theta}} b^*_{ML,d} f(\theta) d\theta$. Totally differentiating this gives us:

$$\frac{dr^*_{ML}}{dR_1} = \frac{-\frac{\partial L}{\partial R_1} - \frac{\partial r'_B}{\partial R_1}\frac{\partial L}{\partial R_1} - (r^*_{ML} - r'_B)\frac{\partial^2 L}{\partial r \partial R_1}}{2\frac{\partial L}{\partial r} + (r^*_{ML} - r'_B)\frac{\partial^2 L}{\partial r^2}} \tag{4}$$

and,

$$\frac{dL^*}{dR_1} = \frac{\partial L^*}{\partial R_1} + \frac{\partial L^*}{\partial r^*_{ML}} \frac{dr^*_{ML}}{dR_1} \tag{5}$$

We know that:

$$\frac{\partial L^*}{\partial R_1} = \overbrace{[b^*_{ML}(\hat{\theta}) - b^*_{ML,d}(\hat{\theta})] f(\hat{\theta}) \frac{\partial \hat{\theta}}{\partial R_1} - b^*_{ML}(\underline{\theta}) f(\underline{\theta}) \frac{\partial \underline{\theta}}{\partial R_1}}$$

positive extensive margin change $+ \underbrace{\int_{\underline{\theta}}^{\hat{\theta}} \frac{\partial b^*_{ML}}{\partial R_1} f(\theta) d\theta + \int_{\hat{\theta}}^{\bar{\theta}} \frac{\partial b^*_{ML,d}}{\partial R_1} f(\theta) d\theta}$

negative intensive margin change (6)

Define $\Phi_1 = |[b^*_{ML}(\hat{\theta}) - b^*_{ML,d}(\hat{\theta})] f(\hat{\theta}) \frac{\partial \hat{\theta}}{\partial R_1} - b^*_{ML}(\underline{\theta}) f(\underline{\theta}) \frac{\partial \underline{\theta}}{\partial R_1}|$ and $\Phi_2 = |\int_{\underline{\theta}}^{\hat{\theta}} \frac{\partial b^*_{ML}}{\partial R_1} f(\theta) d\theta + \int_{\hat{\theta}}^{\bar{\theta}} \frac{\partial b^*_{ML,d}}{\partial R_1} f(\theta) d\theta|$. When $\Phi_1 > \Phi_2$, the exogenous in income is large enough such that the extensive margin changes dominate, and we observe an increase in household demand. This implies that the numerator in (4) is negative when the moneylender borrows from banks and the bank credit constraint does not bind (i.e., $\frac{\partial r'_B}{\partial R_1} = 0$). When the bank credit constraint binds, an increase in R_1 reduces the shadow price of capital since K increases. In this case, the numerator in (4) is negative only when $\frac{\partial L}{\partial R_1} > 0$ is large enough. Finally, by the second order condition, the denominator is negative. Thus, $\frac{dr^*_{ML}}{dR_1} > 0$. In addition, this implies that $\frac{dL^*}{dR_1} > 0$ since $|\frac{\partial L^*}{\partial R_1}| > |\frac{\partial L^*}{\partial r^*_{ML}} \frac{dr^*_{ML}}{dR_1}|$.

Proof of Proposition 4:

Recall that, for moneylenders, borrowing from banks, G meets shortfalls in lending capital. So, $G = \frac{L^*}{N_L} - K$ when the bank credit constraint does not bind. So, $\frac{dG}{dR_1} = \frac{1}{N_L} \frac{dL^*}{dR_1} - \frac{dK}{dR_1}$. So, $\frac{dG}{dR_1} \lesseqgtr 0$ as $\frac{dL^*}{dR_1} \lesseqgtr N_L \frac{dK}{dR_1}$. When the bank credit constraint binds, and increase in R_1 does not change the amount borrowed, but reduces the shadow price on bank credit. Finally, when moneylenders do not borrow from banks, an increase in R_1 may not impact borrowing, or cause banks to switch into borrowing when $\frac{dL^*}{dR_1} > N_L \frac{dK}{dR_1}$.

Proof of Proposition 5:

When the bank credit supply binds, an increase in R_1 drives up the shadow price of capital, and hence r^*_{ML}. In addition, at L^*, $\frac{\partial^2 L}{\partial r^2} > 0$, so $|\frac{\partial L^*}{\partial r^*_{ML}}|_{\bar{G}\ binding} > |\frac{\partial L^*}{\partial r^*_{ML}}|_{\bar{G}\ not\ binding}$. And, $|\frac{\partial r^*_{ML}}{\partial R_1}|_{\bar{G}\ binding} > |\frac{\partial r^*_{ML}}{\partial R_1}|_{\bar{G}\ not\ binding}$. So, $\frac{dL^*}{dR_1}_{\bar{G}\ binding} < \frac{dL^*}{dR_1}_{\bar{G}\ not\ binding}$.

Selection Correction Procedure

Newey (2009) proposes a semi-parametric selection-correction method. The method relies on a control function that is the a power series of the probability of selection into the sample under consideration. In this paper, I use a third-order power series control function of the probability of selection, following the implementation in Botsch and Malmendier (2020) and Hoffmann et al. (2021). The probability of selection is computed using a probit model that includes an instrument for selection and the same set of controls as in the household specification. Standard errors are bootstrapped with 5000 repetitions. I use the incidence of births in the household in the preceding year as an instrument for selection into the sample. The incidence of a birth in the preceding year is a plausibly exogenous event that is likely to increase household expenses due to expenditures relating to child-birth. An increase in expenditures is likely to require borrowing for any purpose later in the year. This is similar in spirit to the instrument used in (Hoffmann et al., 2021), where the authors use the incidence of health shocks as an instrument for selection into the credit market.