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

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Abstract

In this paper, I exploit exogenous weather-induced shocks to household credit demand and variation in bank credit supply to demonstrate that informal moneylenders rely on bank credit to ease lending capital constraints in rural India. I document that informal moneylenders use loans from banks as lending capital, and they increase borrowing from banks following weather-induced increases in household credit demand. Moreover, following an equivalent demand shock, districts with higher predicted bank credit supply see larger increases in household borrowing from moneylenders than those with lower predicted 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, such as informal moneylenders in South Asia or payday lenders in the United States, meet a large share of consumer credit needs.[1,2] In 2017, almost three-fourths of individuals who borrowed worldwide did so from a non-institutional source (World Bank, 2019). In developing countries in particular, informal or non-institutional lenders continue to lend extensively despite decades of expansions in their formal financial sectors. Given this co-existence, the nature of the relationship between the formal and informal sectors is important for understanding the impact of credit policies.

Prior literature has either considered a horizontal interaction, where the formal and informal sectors directly compete (Bell, Srinivasan, & Udry, 1997; Giné, 2011; Jacoby, 2008; Jain, 1999; Kochar, 1997); or a vertical interaction, where informal lenders act as middlemen who on-lend formal credit (Floro & Ray, 1997; Hoff & Stiglitz, 1998; Jacoby, 2008). However, empirical evidence examining moneylenders themselves is limited. I re-visit this debate in the context of rural India, where the incidence of household borrowing from both formal *and* informal institutions more than doubled over the last three decades (NAFIS, 2017; NSSO, 2013b).

I first document descriptive evidence on the informal moneylending market in India. I find that while the median moneylender plausibly earns margins above their marginal cost *and* average cost,[3] some moneylenders also earn interest rates below their average costs. While this could be because of short-run shocks to the demand these lenders face, it might also indicate a supply constraint — with below profit-maximizing quantities arising due to a shortfall in lending capital or another input. I also find that moneylenders do rely on formal credit for lending capital, and that the median moneylender who does so has borrowed 45% of all the credit they advance. In this paper, I explore whether informal moneylenders use bank credit to ease lending capital constraints.

I exploit exogenous weather-induced credit demand shocks and variation in bank credit supply, in combination with household and moneylender survey data, to provide evidence on the implications of the vertical relationship between banks and moneylenders for the informal credit market. I

[1] Here, I use the term institution to refer to refer to formal financial institutions such as banks.

[2] Informal moneylending in South Asia is discussed more extensively in Aleem (1990); Bottomley (1963); Timberg and Aiyar (1984) among others; while examples of the literature on payday lending are Allcott, Kim, Taubinsky, and Zinman (2020); Baradaran (2015); Morse (2011).

[3] Data comes from a sub-sample of 372 private moneylenders in the NSS Unincorporated Non-Agricultural Enterprises surveys in 2015-16. Details on calculations are in section 3.

find that increases in household credit demand are associated with increases in moneylenders' own borrowing from banks, the amounts they lend to households and the interest rates they charge. In addition, I find that households borrow more from informal moneylenders when districts have a high supply of formal credit than when districts have a low supply of formal credit, following an equivalent demand shock. Since unanticipated demand shocks represent situations where informal moneylenders are more likely to be constrained, these results suggest that the availability of formal credit eases informal moneylenders' lending capital constraints.

The approach in this paper relies on the relationship between monsoon rainfall and incomes in rural India — increases in monsoon rainfall increase incomes (Emerick, 2018; Jacoby & Skoufias, 1998; Jayachandran, 2006; Kaur, 2019; Paxson, 1992; Santangelo, 2019; Wolpin, 1982), 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 the borrowing response to the positive shock here, and suggestive evidence indicates that it is driven by an increase in borrowing to finance lumpy expenditures (such as purchases of durable goods) when households lack savings.

Accompanying this increase in demand for informal credit is a contemporaneous increase 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, corresponding with the increase in borrowing and higher interest rates in the household sample. This effect is not driven by a change in the composition of households that borrow from moneylenders. A possible alternative explanation is that since a positive rainfall shock increases incomes all around, it increases the stock of lending capital that moneylenders have access to, therefore also increasing moneylender credit supply. However, the increase in the lenders' own borrowing from banks is inconsistent with an increase in lending capital, and instead consistent with borrowing to supplement lending capital. Another possibility is that banks are more likely to lend following a positive rainfall shock, and therefore lend more to moneylenders. However, I find that rainfall shocks do not impact total bank lending in a district.

To establish that a lack of bank credit constrains moneylenders' lending capital and results in fewer loans transacted, I then look at the differential impact of the credit demand shock across districts with high bank credit supply and those with low bank credit supply. Since observed bank credit is an equilibrium quantity, I predict bank credit supply in a district in a given year in the spirit of a 'shift-share' instrument (see for e.g., Greenstone, Mas, and Nguyen (2020)). While available district-level data does not disaggregate lending by banks, it does by bank-group,[4] loan-type,[5] and population group.[6] This enables purging bank-credit of district-level demand drivers, as well as sector-specific sorting or prioritizing by bank-groups. So, in this case, the 'shift' is the resultant growth in credit for a particular bank-group, while a 'share' is a particular bank-group's pre-period market share. The 'shift-share' for credit in a district is the inner-product of the shifts and shares in a given year. I use this measure to designate districts as having high formal credit supply when its value is above the median, and as having low formal credit supply when its value is below the median. I find that bank credit supply in districts predicted to have high supply is 10% higher than in those predicted to have low credit supply. Consequently, my findings indicate that a 10% expansion in bank credit enables 23% more rural household borrowing from moneylenders following a one standard deviation increase in monsoon rainfall in non-drought years.

Identification here relies on the assumption that a district having an above or below median credit supply does not also have above or below median unobserved shocks to outcomes. I address concerns that this might not hold by comparing observable district and household characteristics that might determine credit demand across high and low predicted credit supply district $\times$ years, and find no significant differences in these characteristics. I also find that these results hold when controlling for a variety of district characteristics, household characteristics, and household fixed effects. In addition, since my focus here is on the rainfall shock and its interaction with the supply environment, any possible differences driven by the supply measure are absorbed by the supply environment indicator, similar to a standard difference-in-differences design (Frison & Pocock, 1992).

A second concern that might arise when interpreting these results is that an increase in formal credit supply increases the demand for informal credit directly, rather than increasing informal

[4]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.

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

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

borrowing through its impact on moneylenders' supply. This might arise if formal and informal credit are complements for a borrower; or through a general equilibrium effect where the increase in formal credit increases economic activity, and thus increases the demand for informal credit. 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 low formal credit supply see lower borrowing from informal moneylenders following a positive rainfall shock than districts with high formal credit supply; at the same time, districts with low formal credit supply see *higher* interest-free borrowing from friends or relatives following a positive rainfall shock than districts with high formal credit supply. This suggests that it is moneylender credit supply rather than household demand that drives this result. Third, when a district has below median 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.

This paper contributes to several different strands of literature. First, this paper documents evidence that informal moneylenders in India rely on bank credit for part of their lending capital, and that this link helps them ease lending capital constraints, corroborating earlier theoretical analyses that consider a vertical relationship between informal moneylenders and banks (Floro & Ray, 1997; Hoff & Stiglitz, 1998; Madestam, 2014). In addition, by providing descriptive evidence on the current functioning of moneylender markets in India both from national sample survey data, and a unique primary survey in the state of Telangana, this paper updates our understanding of these markets in the Indian context, complementing Aleem (1990) and Irfan, Arif, Mubashir, and Nazli (1999).

The paper's findings, however, differ from those in Banerjee et al. (2020); Hoffmann, Rao, Surendra, and Datta (2021); Ruiz (2013) — where the authors find that formal or semi-formal credit crowds out informal credit and risk-sharing. While these papers consider changes on the extensive margin, with the entry of a new formal or semi-formal lender, here I consider an existing relationship between the formal and informal sector. In addition, a key difference from the present study is that in these cases, the banks, microfinance institutions or self-help groups focus on lending to households that might otherwise be excluded from the formal sector, while this paper considers business as usual formal lending in India, where banks are less willing to lend to poorer borrowers. In fact, as demonstrated in Kanz (2016) and Giné and Kanz (2018), when the formal sector's willingness to lend to rural households declines, households increase borrowing from the informal sector. Thus, this suggests that the interaction between formal and informal credit institutions depends on who is able to access credit through them.

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 suggests that bank expansions led to a decrease in poverty (Burgess & Pande, 2005) as well as an increase in inequality (Kochar, 2011; Ligon, 2005), with formal credit benefitting only certain households due to transaction costs (Ghate, 1992; Sharma, 2010), collateral requirements (Ghate, 1992; Ghosh, Mookherjee, & Ray, 1999) or poor enforcement mechanisms (Giné, 2011).

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, Duflo, Glennerster, & Kinnan, 2015; Kaboski & 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.

Relatedly, evidence in the Indian context indicates that households accumulate savings in the form of 'buffer-stocks' of different assets or durable goods (Imai & Malaeb, 2015; Lim & Townsend, 1998; Rosenzweig & Wolpin, 1993), usually due to credit constraints. The increase observed in this paper is consistent with these findings in situations where households require or prefer a commitment device (Ashraf, Karlan, & Yin, 2006), or are present-biased/lack self-control (Banerjee, 2013; Banerjee & Mullainathan, 2010; Karlan, Mullainathan, & Roth, 2019). Finally, the modest increase in borrowing by some rural households during drought years, on the other hand, is consistent with the findings relating to risk-coping and consumption smoothing that credit serves an insurance purpose (Demont, 2020; Eswaran & Kotwal, 1989; Kaboski & Townsend, 2005; Lane, 2020; Paxson, 1992; Udry, 1994), suggesting that households employ a variety of strategies to respond to income shocks.

The rest of this paper proceeds as follows: Section 2 describes the context of household borrowing in rural India, Section 3 describes the informal moneylending market, Section 4 presents a simple theoretical framework, Section 5 describes the data and empirical strategy used in the paper, Section 6 discusses the results, and Section 7 concludes.

2 Background

Around half of all households in rural India are indebted,[7] and the median indebted household owed approximately ₹40,000 to its creditors in 2012-13.[8] Households across all levels of wealth borrow (Banerjee, 2003; NAFIS, 2017). They do so from a variety of sources, best represented as belonging to a continuum of informality-formality, where banks represent the most formal sources. Bank loans are usually larger than less formal loans; but tend to have lower interest rates than interest-bearing informal loans (Figure 1). However, while 79% of individuals in rural India had a bank account by 2017, only 17% of those who borrowed in 2017 did so from an institutional source (World Bank, 2019).

For banks themselves, credit to small borrowers is largely made available through 'priority sector' lending, under which 40% of credit is to be lent to sectors such as agriculture, micro, small and medium enterprises, as well as disadvantaged population groups.[9] Most often, these loans require at least two acres of land or gold as collateral, and additional documentation requirements introduce more friction to these transactions (Mowl, 2017). While banks usually meet these 'priority sector' targets, the administrative cost of lending in the priority sector is higher than in other sectors, and banks are more likely lend to larger eligible borrowers (Banerjee & Duflo, 2014).[10]

[7] 53% of rural households were indebted in 2012-13 (NSSO, 2013b); 47.4% of them were indebted in 2016-17 (NAFIS, 2017); and this was up from 43% of households in 1993 (NSSO, 2013b)

[8] This is in 2012-13 prices, or ₹56,381 in current (2019-20) INR; and is equivalent to $730 in 2012-13 USD or $796 in current (2019-20) USD

[9] The Reserve Bank of India mandates that 40% of a bank's Adjusted Net Bank Credit in the preceding year

[10] Consistent with this, banks lent agricultural loans to just 615 accounts in 2016, according to data obtained by the news website, *The Wire*. "Agricultural Loans Worth Rs 59,000 Crore Went to 615 Accounts in One Year," by Dheeraj Mishra. Accessed on 11/12/2019 at: https://thewire.in/agriculture/modi-govt-gave-agricultural-loans-

Less formal than banks are loans from microfinance institutions or bank-linked self-help groups.[11] Self-help groups that are bank linked can themselves borrow from banks under 'priority sector' lending targets. Such loans formed just about 9% of loans taken and 3% of the amount borrowed by rural households in 2013 (NSSO, 2013b).[12]

Informal loans are either interest-free or interest-bearing, and the interest-bearing loans are usually from professional moneylenders, pawnbrokers, landlords, input-traders, local shop-keepers or friends and relatives, while interest-free loans tend to be from friends, relatives or patrons (Dréze, Lanjouw, & Sharma, 1998; ICRISAT, 2014). Despite there being no explicit interest charged, these interest-free loans often come with implicit interest in the form of obligatory reciprocity (Ambrus, Mobius, & Szeidl, 2014; Hayashi, Altonji, & Kotlikoff, 1996; Ligon, 2005; Ligon & Schechter, 2012; Udry, 1994). In 2013, 31% of all loans transacted were interest-bearing non-institutional loans, while 20% of all loans were interest-free (NSSO, 2013b).

Finally, while credit is fungible and it is sometimes hard to establish a precise purpose for a loan, households do usually report what they borrow for. Around 70% of all loans are reported as being taken for non-productive needs — consumption expenditures, purchases of assets and durable goods, education, medical expenses, and religious, cultural or life-cycle events (NAFIS, 2017; NSSO, 2013a).[13,14,15] Loans for different purposes tend to be from different sources — loans for production (both agricultural and non-agricultural) are more likely to be from institutional sources, while loans for consumption are more likely to be from non-institutional sources (NSSO, 2013a). More specifically, pawnbrokers might help smooth income, self-help groups and banks might provide loans allowing economic investments, local moneylenders might provide large loans for ceremonies and life-cycle events, and 'mobile lenders' might help with emergency loans (Guérin, Roesch, Venkatasubramanian, & D'espalliers, 2012).[16,17]

worth-rs-59000-crore-to-615-accounts-in-one-year

[11] Microfinance institutions often operate as RBI-regulated Non-Banking Financial Institutions (NBFCs) (RBI, 2018) and lend either to individual clients, or adopt the self-help group structure. Self-help groups (SHGs) themselves are groups of 10-15 individuals (usually women) who commit to weekly savings, and have access to loans through the group (Hoffmann et al., 2021).

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

[13] 74% of all loans were for non-productive needs in 2016-17 (NAFIS, 2017)

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

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

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

[17] The difference between 'mobile lenders' and other moneylenders appears to be that the latter are well-known,

3 A Description of the Moneylender Market

In this section, I consider informal moneylenders who lend locally at high interest rates, and describe how they operate using data from two sources — (1) a sample of 925 private moneylenders across India from two 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 (2019). Telangana has the highest incidence of indebtedness across all Indian states (NAFIS, 2017), and represents a context where rural households borrow extensively.

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 lends to their usual clientele of 12 to 14 borrowers; and half of lenders survey accept new clients only when someone they know vouches for the potential client, an additional third of lenders take on new clients when they can verify their backgrounds, and 5% of lenders do not intend to lend to new clients at all. This network-based screening makes one lender an imperfect substitute for another (Hoff & Stiglitz, 1998); and also indicates that these markets are segmented across the same caste and class lines that individuals' networks are (Khanna & Majumdar, 2020; Mookherjee & Motta, 2016). Forty-one percent of lenders had started their lending in the preceding five years, suggesting that relatively free entry is possible. So, similar to prior literature (Aleem, 1990; Hoff & Stiglitz, 1990, 1998), this market can be described as monopolistically competitive.

Informal moneylenders charge high interest rates (Hoffmann et al., 2021; ICRISAT, 2014; NSSO, 2013b; RBI, 2012; TNSMS, 2009) — annualized rates in Telangana were between 12 and 120 percent in 2019 (Figure 3).[18] Lenders report increasing 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, Nayar, & Associates, 1989); and borrower type (based on their relationship with the borrower, borrower's occupation, or wealth). Lenders also offer

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.

[18] 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 3), possibly due to instances of delayed payments or penalties.

some flexibility, adjusting repayment terms when necessary (also in Guérin et al., 2012). This often takes the form of higher interest rates when loans exceed their normal duration, and indicates that lenders effectively offer state-contingent contracts. Default is dissuaded through social or physical collateral.[19]

Moneylenders rely on profits from their business, their own wealth or savings, as well as 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.[20] Despite high margins on average, a large share of moneylenders are also estimated to earn interest or prices below their average costs (Figure 9). This might arise if lenders face short-term shocks that reduce demand; are close to exiting the market; or due to capacity constraints arising from shortfalls in lending capital or another input. Relating to the latter, I find that 35% of moneylenders surveyed in Telangana report that they borrowed from banks when faced with shortfalls in lending capital, while over 50% report that they would lend more if they were able to borrow from banks more easily (Figure 8). This motivates the analysis in the rest of the paper, where I evaluate whether loans from banks help moneylenders ease lending capital constraints.

4 Theoretical Framework

Motivated by evidence in section 3, I outline a model of a rural economy with borrowers and informal moneylenders. I assume that moneylenders and banks interact vertically, such that moneylenders may borrow part of their lending capital from banks; and that borrowers may themselves borrow from informal lenders or banks. I then consider comparative statics with respect to exogenous income shocks. The model draws on the theoretical literature on informal lending (for

[19]For instance, 58% of lenders surveyed either required land or property documents, gold or other assets, promissory notes or a co-signer (referred to as a witness, who might be called on to repay the loan upon default). In cases where lenders fear default, apart from additional interest or taking possession of collateral, lenders also report resorting to coercion or social pressure through the *Panchayat* or co-signer. A few lenders report seizing durables from borrowers' homes, and one lender reported potentially sending goons after the borrower.

[20]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, Mookherjee, Torero, and Visaria (2018) find 64% - 83% margins over farm-gate prices for agricultural middlemen in Eastern India.

e.g., Hoff & Stiglitz, 1998; Karaivanov & Kessler, 2018) and earlier work relating to household consumption and loan decisions (for e.g. Hanemann, 1984; Ligon & Worrall, 2020; Ngo, 2018).

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.

In addition, I assume that moneylenders are endowed with liquid capital, K, with an opportunity cost, ρ.[21] Motivated by evidence in section 3, I also assume that lenders borrow, $G \leq \bar{G}$, from banks at an exogenous interest rate, r_B, to supplement their stock of lending capital. $\bar{G}$ represents the local supply of bank credit in a given year. There are N_L monopolistically competitive lenders in this rural economy, 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 chooses an interest rate, r^*_{ML}, that satisfies $L^* = (r'_B - r^*_{ML})\frac{\partial L}{\partial r_{ML}}$.*[22]

Proof. See Appendix. ■

[21] 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.

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

4.2 Household Demand for Moneylender Credit

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, $u(\cdot)$ ($u'(\cdot) > 0$, and $u''(\cdot) < 0$) from the consumption of a numeraire good, c_t.[23] 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 the durable over both seasons.[24]

Household income depends on an exogenous season-specific productivity parameter, R_t.[25] In season 1, a household earns, $R_1\theta$, and expects to earn, $\mathbb{E}[R_2]\theta$ in season 2.

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).*

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

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

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

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 choose whether to purchase durables or not, and accordingly choose a loan size. This allows me to define $\hat{\theta}$ as the endowment at which a borrower in the moneylender market is indifferent

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

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

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

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 that 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:

$$\int_{\underline{\theta}}^{\hat{\theta}} b^*_{ML} f(\theta)d\theta + \int_{\hat{\theta}}^{\bar{\theta}} b^*_{ML,d} f(\theta)d\theta = (r'_B - r^*_{ML})\frac{\partial}{\partial r_{ML}}\left[\int_{\underline{\theta}}^{\hat{\theta}} b^*_{ML} f(\theta)d\theta + \int_{\hat{\theta}}^{\bar{\theta}} b^*_{ML,d} f(\theta)d\theta\right] \quad (2)$$

4.3 Implications of the Model

In the rural Indian context, rainfall during the monsoon increases local incomes (Table 4), and an increase in monsoon rainfall could be thought of as an increase in the season-1 exogenous income parameter, R_1. I relate the market equilibrium moneylender interest rate and equilibrium quantity borrowed to changes in R_1. Here, $L^* = \int_{\underline{\theta}}^{\hat{\theta}} b^*_{ML} f(\theta)d\theta + \int_{\hat{\theta}}^{\bar{\theta}} b^*_{ML,d} f(\theta)d\theta$.

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

The intuition behind this proposition is that an increase in R_1 increases the number of households that choose to borrow and purchase durables, and when this is sufficiently large, borrower demand increases. 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 Empirical Strategy

5.1 Data and Descriptive Statistics

Data on household borrowing, loan terms, and investment/asset expenditures are primarily constructed from the rural sample of the Debt and Investment surveys conducted by India's National Sample Survey Organization (NSSO). The resulting dataset comes from four survey rounds (2001-02, 2002-03, 2011-12, 2012-13), and is representative of India's over 600 districts.[26] The survey data records all outstanding loans a household has, as well as all loan transactions over a shorter recall period. Expenditure data for a six month period is also based on recall. I use this survey

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

structure to construct both a household-level dataset for outstanding loans and expenditures, and a household×month-level dataset for all loan transactions. Tables 1 and 2 show a number of household and loan characteristics from the NSS sample.

A second source of data on household borrowing is the ICRISAT Village Dynamics survey, with data from 866 households in 18 villages in 9 districts in the states of Andhra Pradesh,[27] Maharashtra, Karnataka, Gujarat, and Madhya Pradesh.[28] Each household is surveyed every month between 2010 and 2014,[29] and the survey records monthly loan transactions, monthly consumption expenditures and monthly purchases of durables and capital assets.

Data on moneylenders primarily comes from two rounds of the Unincorporated Non-Agricultural Enterprises surveys (or Informal Firms surveys) conducted by the NSSO (2010-11 and 2015-16). The surveys identify enterprises by their five-digit industrial codes, and include special codes specifically for private moneylenders. Across the rounds, a total of 925 moneylenders are surveyed, across 143 districts in 22 states. I pool the rural and urban samples in this dataset since rural households may borrow from nearby urban moneylenders, as indicated in Telangana Survey (2020). Data from this dataset allows identifying moneylenders' own borrowing from banks and other sources. In addition, surveys in the 2015-16 survey round also specifically collected data on total loans advanced to households and non-households, as well as interest payments received by the moneylenders.

Finally, the analyses that follow also make use of data on rainfall, and bank lending at the district level in India. Rainfall data is from the University of Delaware Global Precipitation Archive's Terrestrial Precipitation: 1900-2017 Gridded Monthly Time Series (version 5.01), and consists of monthly observations of rainfall from rain-gauge measurements interpolated to a 0.5° by 0.5° latitude-longitude grid (Willmott & Matsuura, 2018). Data on bank lending comes from the Reserve Bank of India's Basic Statistical Returns for the years 1998 – 2016.[30]

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

[28] ICRISAT is an acronym for International Crops Research Institute for the Semi-Arid Tropics. In addition, one issue to note is that some of the 866 households from 2010 split over the rounds, and there are 870 unique households in 2014.

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

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

5.2 The Effect of Rainfall on Rural Credit Market Outcomes

5.2.1 Rainfall Shocks and Rural 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. Using rainfall data from Willmott and Matsuura (2018), I define a rainfall shock as the deviation of a district's total monsoon precipitation in a year from its historical mean, normalized by its standard deviation (Emerick, 2018). The rainfall for a given district is the rainfall in the grid cell nearest to the district's centroid; and the historical mean and standard deviation for each grid-cell (and district) are computed from the 50-year distribution (1967-2017).

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., Emerick, 2018; Jayachandran, 2006; Kaur, 2019; Paxson, 1992; Rosenzweig & Wolpin, 1993; Santangelo, 2019; Townsend, 1995). I assume that rainfall shocks are transitory and serially uncorrelated, and demonstrate that they constitute shocks to income in Table 4.

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.[31] 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.

[31] 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.

5.2.2 Empirical Strategy

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:

$$Y_{hdsmt} = \beta_1 Rain_{dt} + \mathbb{1}\{Drought\}_{dt} + \beta_2 \mathbb{1}\{Drought\}_{dt} \times Rain_{dt} + \mu_m + \psi_d + \tau_{st} + X_{it}\delta + \varepsilon_{hdmst} \quad (3)$$

$$Y_{hdst} = \beta_1 Rain_{dt} + \mathbb{1}\{Drought\}_{dt} + \beta_2 \mathbb{1}\{Drought\}_{dt} \times Rain_{dt} + \psi_d + \tau_{st} + \lambda_h + \varepsilon_{hdst} \quad (4)$$

$$Y_{lhdmst} = \beta_1 Rain_{dt} + \mathbb{1}\{Drought\}_{dt} + \beta_2 \mathbb{1}\{Drought\}_{dt} \times Rain_{dt} + \mu_m + \psi_d + \tau_{st} + L_{lht}\phi + X_{ht}\delta + \varepsilon_{lhdmst} \quad (5)$$

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×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:

$$Y_{ML,dst} = \beta_1 Rain_{dt} + \mathbb{1}\{Drought\}_{dt} + \beta_2 \mathbb{1}\{Drought\}_{dt} \times Rain_{dt} + \psi_d + \tau_{st} + M_{ML,t}\omega + \varepsilon_{ML,dst} \quad (6)$$

where ψ_d denotes district fixed effects, τ_{st} denotes state×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.[32] All specifications also control for rainfall shocks in drought years, district fixed effects and state×year fixed effects. The state×year fixed effects account for state-level macroeconomic conditions or policies in a given year. Equation (3) represents a specification where the outcome is measured at the household×month level (e.g., any borrowing in that month), and so also controls for month-of-year fixed effects, and household characteristics. Equation (4) represents a specification where the outcome is measured at the household×year level, and where possible controls for household fixed effects. Equation (5)

[32] 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.

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 (6) represents a specification at the moneylender×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 transaction, the rainfall shock could potentially impact selection into borrowing. This might be of concern in the context of interest rates since 'riskier' borrowers might only get loans at higher interest rates. To address this, I also present loan-level results that correct for selection bias using a semi-parametric two-step procedure proposed by Newey (2009), discussed further in the appendix.

5.3 Heterogeneous Effects by District Bank Credit Supply

5.3.1 Predicting Bank Credit Supply

I employ the strategy in the previous section to establish that a positive rainfall shock increases rural household demand for moneylender loans. In addition, I use it to establish that the increase in household demand in turn affects moneylenders themselves by increasing a lender's own borrowing from banks. To further my argument, I now turn to establishing how variation in the availability or unavailability of credit from banks in a district affects rural household borrowing outcomes.

The second part of my empirical strategy relies on estimating the differential effect of a rainfall shock on household borrowing when bank credit supply in a district is low versus when it is high. Since lending by banks is an equilibrium quantity determined by both demand and supply in that district in a given year, I first predict banking sector credit supply by employing a strategy that is similar to the construction of a 'shift-share' instrument (used in the context of bank credit in Greenstone et al., 2020).[33] Bank presence varies across districts in India. In addition, banks in India largely rely on their deposits to extend loans, and can move loanable funds across their branches (Acharya & Kulkarni, 2019). As a result, there is a bank-specific component to its credit-supply overall, and purging bank-sector lending of location- and sector-specific demand drivers, will allow backing out a measure of the sector's credit supply.

To implement this, I use data from the Reserve Bank of India's (RBI) Basic Statistical Returns

[33] Autor and Hanson (2013); Bartik (1991); Blanchard and Katz (1992); Caldwell and Danieli (2018); Card (2001) use such a shift-share or 'Bartik' instruments in other contexts.

on the total credit banks have extended — the credit limit or sum of all credit lines (as opposed to the credit outstanding). This data is made available by the RBI aggregated to the loan type × population-group × bank group level for a district in a given year. There are twenty-one loan-type categories and the loan-type indicates the purpose of a loan (such as housing loan, personal loan or loan for purchase of a consumer durable) for individual borrowers, and the industry the borrower belongs to when it is a business loan (for e.g., mining or textiles); the population-group indicates whether the loan is extended in an urban, rural, semi-urban or metropolitan area; the bank-group is a group of banks and the groups are State Bank of India and its Associates, Nationalized Banks, Private Sector Banks, Regional Rural Banks and Foreign Banks.[34]

I use this data to predict the banking sector credit supply in a district×year. I first estimate an equation that decomposes the growth in credit extended between consecutive years as follows:

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

Here, the outcome is the change in credit between years, t and $t-1$ for an industry or sector, i, in a population sub-group, r, in a bank-group, j in district, d. The predicted bank-group specific change in credit supply, $\hat{g}^j_t$, is no longer driven by district-, industry-, or population-group- specific effects. For each pair of consecutive years, the predicted district-level credit supply is then the inner-product of $\hat{g}^j_t$ and each bank-group's market-share in that district in the initial year, s^{jd}_{t-1}.

$$\hat{B}^d_t = \sum_j s^{jd}_{t-1} \times \hat{g}^j_t$$

The paper's empirical strategy employs an indicator for whether a district experiences low bank credit supply in a given year, defined as follows:

$$\mathbb{L}_{dt} = \mathbb{1}\{B_{dt} < median\}$$

[34]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).

5.3.2 Empirical Strategy

In this section, I focus on the strategy that I employ to estimate the heterogeneous effects of a positive rainfall shock on household outcomes across district×years with above median predicted bank credit supply and below median predicted bank credit supply. I estimate the following specifications at the household-level, household×month-level and loan-level.

$$Y_{hdmst} = \delta_1 Rain_{dt} + \delta_2 \mathbb{L}_{dt} + \delta_3 Rain_{dt} \times \mathbb{L}_{dt} + \mu_m + \psi_d + \tau_{st} + X_{ht}\delta + \varepsilon_{hdmst} \tag{7}$$

$$Y_{hdst} = \delta_1 Rain_{dt} + \delta_2 \mathbb{L}_{dt} + \delta_3 Rain_{dt} \times \mathbb{L}_{dt} + \psi_d + \tau_{st} + \lambda_h + \varepsilon_{hdst} \tag{8}$$

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

where, similar to above, μ_m denotes month-of-year fixed effects, λ_h denotes household fixed effects, ψ_d denotes district fixed effects, τ_{st} denotes state×year fixed effects, X_{ht} denotes a vector of household characteristics, and L_{lht} is a vector of loan characteristics.

The coefficients of interest here are δ_1, which represents the impact of a positive rainfall shock on households when their district has above median or high bank credit supply; and δ_3 which represents the differential effect when the district has below median or low bank credit supply. All specifications also control for rainfall shocks in drought years (similar to the previous section, but not explicitly denoted in the equations here), district fixed effects and state×year fixed effects. In these, as in previous specifications, I control for state×year fixed effects to account for state-level macroeconomic conditions or policies in a given year. Equation (7) represents a specification where the outcome is measured at the household×month level, and additional controls include month-of-year fixed effects and household characteristics. Equation (8) represents a specification where the outcomes is measured at the household×year level and, where possible, controls for household fixed effects. Finally, equation (9) represents a specification where the outcome is measured at the loan level, and so also controls for month-of-year fixed effects, household characteristics and loan characteristics. As in the previous instance, robust standard errors in all specifications are clustered at the district level.

This empirical strategy exploring heterogeneous treatment effects relies on the assumption that districts with predicted bank credit supply above or below the median do not experience unobserved shocks to outcomes that are systematically above or below median. I probe the validity of this assumption in Table 5, where I compare district characteristics above and below the median of the predicted bank credit supply. Column 4 presents normalized differences in these means (Imbens & Rubin, 2015), which are estimated through linear regressions which control for district and state×year fixed effects and where standard errors are clustered at the district level (similar to the implementation in Hoffmann et al., 2021).[35] Reassuringly, none of the normalized differences are significant, nor do they exceed the 0.25 cut-off, above which linear regression methods are sensitive to specifications (Imbens & Wooldridge, 2009).

In the context of a standard 'shift-share' instrument, identification relies on the exogeneity of the pre-period market-shares (Goldsmith-Pinkham, Sorkin, & Swift, 2020), or at the very least, requires that the 'shift-share' is uncorrelated with unobserved shocks to the outcomes, conditional on the controls (Baum-Snow & Ferreira, 2015). However, the empirical strategy here is similar to a difference-in-differences design; and focuses on the interaction between an indicator for whether the predicted credit supply or 'shift-share' is above or below median, and an exogenous positive rainfall shock. And so, here, any possible correlates of the pre-period market-share are absorbed by the low-supply indicator (Frison & Pocock, 1992), allowing a straight-forward interpretation of the interaction term.

6 Empirical Results and Discussion

6.1 The Effect of Rainfall Shocks on Rural Household Borrowing

Results and Robustness

In this section, I show that a positive rainfall shock in a non-drought year increases household borrowing from moneylenders, and the interest rates at which loans are transacted. Motivated by the model in section 4 and evidence in section 5, I focus on the impact of *positive* rainfall shocks on rural household borrowing in non-drought years. Tables 6 and 7 indicate that a one standard deviation increase in rainfall in a non-drought year or a 1% increase in a district's per capita GDP (Table 4) results in 1.4 percentage points more households borrowing from moneylenders

[35] Normalized differences are a scale-free measure of differences in covariate values defined by Imbens and Rubin (2015) 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 the above median or below median groups.

(column 1, Table 7) — this is a 19% increase in the number of borrowers, and a 4% increase in the amounts borrowed by households over the seven months between two monsoons (columns 2 and 1 in Table 6).[36] However, there are no significant effects on either interest-free loans from friends or relatives (which tend to be smaller in size) or on loans from institutions (which may not readily lend to rural households for non-agricultural purposes). These results are robust to alternative definitions of the rainfall shock (Table B3), and iteratively dropping one state from the sample at a time does not significantly change these results (Figure A1).[37] Evidence from the ICRISAT sample (in Table A1) is similar, with a significant increase in borrowing from moneylenders following the year's monsoon. Reassuringly, a placebo test using the standardized deviation of the non-monsoon rainfall from its historical mean does not yield similar results (row 3, Table B3).[38]

Contemporaneous with this increase in borrowing from moneylenders, is a 3.5 percentage point increase in annualized moneylender interest rates (or an 8% increase over the mean of 41.83% per year) (Table 8). Figure 11 corroborates this, and demonstrates that in each month with higher household borrowing, interest rates tend to be higher. Finally, though there is no significant effect on moneylender interest rates in the ICRISAT sample, the point estimate is positive (column 7, Table A1). One concern while interpreting these results is that since moneylender interest rates are usually higher for more disadvantaged borrowers, this increase could well be driven by a change in the composition of borrowers alone. To address this, column 2 in Table 8 presents Newey (2009) selection corrected results, and reassuringly, the effect is similar. A second concern is that a positive income shock might not only impact household borrowing, but also increase lending capital that moneylenders have access to. In fact, Table A4 indicates that households are less likely to have old outstanding loans from moneylenders following a positive rainfall shock in a non-drought year, which is consistent with increased repayment. However, the increase in both household borrowing *and* in interest rates is consistent with a net increase in demand. Consistent with this, almost 93% of informal moneylenders in the Telangana Survey (2020) report increasing interest rates for all

[36]Column 1 in Table 6 represents a monthly rather than yearly increase

[37]The percentile shock follows the definition in Jayachandran (2006), where the shock takes values -1 when monsoon rainfall is below the 20th percentile of the district's historical rainfall distribution; 1 when rainfall is above the 80th percentile of the district's historical rainfall distribution; and 0 otherwise. The fractional deviation defines the rainfall shock as a the fractional difference between the monsoon rainfall in a given year from the district's Long Period Mean (or 50 year mean, as defined by the Indian Meteorological Department (IMD)).

[38]Non-Monsoon rainfall is the standardized deviation of the Oct - May rainfall in a given year from the district's historical mean, and is meant as a placebo test.

clients when demand goes up (Figure 5).

Interpretation and Alternative Explanations

A look at what households borrow for, in Table 9, suggests that this increase is driven by loans reported as being for consumption (though significant only at the 10% level); while Table 10 indicates that households spend significantly more on land and buildings following a positive rainfall shock. Similarly, results from the ICRISAT sample (Table A2) indicate that households increase consumption expenditures as well as purchases of durable goods following a positive rainfall shock. Further, correlational evidence in Table A3 suggests that the increase in borrowing from moneylenders following a positive rainfall shock is driven by households that also purchase durables in the same period. These results are consistent with predictions from the model in section 4, which demonstrates that an increase in household borrowing following an exogenous increase in incomes might arise due to an increase in borrowing to finance lumpy expenditures, such as purchases of durables and assets, or improvements to land and housing. These findings are also consistent with those in the literature that considers an increase in access to credit rather than an increase in incomes — where households borrow more for spending that has a durable component (Banerjee et al., 2015; Kaboski & Townsend, 2012; Ruiz, 2013).

A competing explanation might be that the increase in incomes increases the demand for non-tradable goods or services, leading to an increase in demand for credit for operating expenses in non-agricultural businesses.[39] However, Table 10 indicates lower expenditures on non-farm businesses. Yet another explanation might be that the positive rainfall shock increases demand for loans for agricultural expenses in the non-rain-fed *Rabi* season (which extends from October to January). However, the main household results persist when restricting the sample entirely to the lean season (February to May). Overall, given the fungibility of money and credit, this gives us an understanding of the proximate purpose for credit rather than the ultimate driver. In addition, 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.

Households are also less likely to have outstanding moneylender loans from preceding years (Table A4) following positive rainfall shocks in non-drought years. On the one hand, this suggests

[39] This is similar to the aggregate demand channel that the authors propose in Breza and Kinnan (2020).

that some of the increased income might go towards repaying old loans, which could contribute to a need to borrow for lumpy expenditures. On the other hand, it is also consistent with a reduction in debt overhang, which might allow households to borrow more.[40] In addition, I find that the increase in borrowing following an increase in incomes is driven by households which lack savings (Table B1). This explains the need for credit, especially if households also want to improve their standards of living (González, 2017) or have growing social aspirations (Guérin, Roesch, Venkatasubramanian, & Kumar, 2011). However, it is not clear why households are unable to save for such expenditures. Possible explanations are that this arises from a lack of access to a convenient savings avenue, a lack of a commitment device (such as in Ashraf et al., 2006) or from present-bias (such as in Banerjee & Mullainathan, 2010), but the analyses presented here cannot distinguish between these mechanisms.

6.2 The Effect of Rainfall Shocks on the Informal Moneylending Business

Results and Robustness

In this section, I establish that an increase in rural household demand for moneylender loans leads to an increase in moneylenders' own borrowing from banks. Table 11 indicates that a one standard deviation increase in rainfall in a non-drought year or a 1% increase in a district's per capita GDP (Table 4) results in a 4.4 percentage point or 31% increase in the incidence of moneylenders themselves borrowing from banks (column 1, Table 11). This accompanies the 19% increase in the number of borrowers observed in the household sample. Cross-sectional data on moneylenders' loan advances and interest receipts also indicates that moneylenders report lending 12% more to households who are their clients, and that they charge interest rates that are effectively 19% higher (columns 2 and 3, Table 11). This corroborates findings from the household sample.

Since there is an unanticipated increase in rural household demand for moneylender loans following the positive rainfall shock, this represents a situation where moneylenders are more likely to face lending capital constraints and therefore turning to bank credit to meet demand. Consistent with this, over 35% of moneylenders surveyed in Telangana (Telangana Survey, 2020) report

[40]Notably, however, Kanz (2016) finds that a a reduction in debt overhang in the formal sector following a government debt relief program in India in 2008 did not lead to more borrowing from banks subsequently. However, in the context of debt relief, borrowers' repayment incentives changes and so the context differs.

borrowing from banks to meet lending capital shortfalls (Figure 8).[41]

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 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 possibly increases in supply. A separate concern might be that banks are more willing to lend following a positive rainfall shock. Moneylenders surveyed in Telangana (Telangana Survey, 2020) report borrowing from banks largely through agricultural loans, gold loans, business loans and sometimes personal loans. Table 12 addresses concerns about loans in general, and indicates that rainfall does not impact the total bank credit lent in a district. While this does not address banks targeting lending more specifically to moneylenders in good rainfall years, it is unlikely that this occurs since moneylenders borrow under a variety of schemes.

6.3 Heterogeneity in Rural Household Borrowing Responses to Rainfall Shocks

Results and Robustness

Having established the nature of the interaction between moneylenders and banks, I now evaluate whether the availability, or lack of availability, of bank credit impacts households indirectly through the informal moneylending market. I use the predicted bank credit supply described in section 5 to designate districts as having low bank credit supply when this measure is below the median. I focus on the interaction between the rainfall shock and this low bank credit supply indicator to analyze differential effects of an exogenous increase in rural household credit demand across districts with high and low bank credit supplies.

Tables 13 and 14 demonstrate that, following an equivalent shock to household credit demand, the increase in household borrowing from moneylenders in a district with low bank credit supply is significantly smaller than the increase in a district with high bank credit supply (columns 1 and 2). So, a one standard deviation increase in rainfall in a non-drought year (or a 1% increase in district per capita incomes) leads to 1 percentage point more households borrowing from moneylenders when

[41] In fact, one lender reported that he does so because his clients would not believe that he didn't have the money. In addition, moneylenders

districts have low bank credit supply, but almost 3 percentage points more households borrowing from moneylenders when districts have high bank credit supply. So, effectively, 10% higher bank credit supply facilitates 1.8 percentage points or 12% more borrowing in the informal moneylender market during periods of high credit demand. These results persist when iteratively dropping one state from the sample at a time (Figure A2), and when I predict bank credit supply using outstanding credit or the number of loan accounts rather than the credit limit/credit line (Table B4).

Interpretation and Alternative Explanations

While this does not impact the interpretation of results in the preceding sections, a concern here is that the observed heterogeneity might arise through a demand channel rather than the moneylender supply channel. One possibility is that this occurs because bank and moneylender credit are complements for borrowers, and so lower bank credit leads to lower demand for moneylender credit overall. For this to confound results, the same borrower should be borrowing from both a moneylender and a bank, and be more likely to do so when bank credit supply is high, and less likely to do so bank credit supply is low. While column 5 in tables 13 and 14 might suggest that this is plausible, a further look at household data indicates that only 4% of households that borrow (and only 0.05% of households overall) borrow both from banks and moneylenders in a given year (including during the agricultural season). Thus, even if present, this effect is unlikely to solely drive these results.[42,43]

A second possibility is that low bank credit supply decreases the demand for informal moneylender loans through a general equilibrium effect since it decreases overall economic activity (see for e.g., Breza & Kinnan, 2020; Burgess & Pande, 2005; Young, 2019). However, columns 3 and 4 in Tables 13 and 14 indicate that — following a positive rainfall shock in non-drought years, households in districts predicted to have low bank credit supply increase their interest-free borrowing from friends or relatives. Table 15 indicates that low bank credit supply districts have significantly higher moneylender interest rates, and while interest rates increase following a positive rainfall shock in high bank supply districts, they do not increase by as much in low bank supply districts.

[42] 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

[43] Conversely, low bank credit supply might lead to greater borrowing from both sources if households borrowing from banks are now rationed and so supplement the bank loan with a moneylender loan. However, this again is unlikely given the small fraction of households who borrow from both sources.

This, together with the substitution to interest-free borrowing, suggests that low bank credit supply makes the marginal cost of borrowing from banks,[44] and hence of moneylender loans higher — with the higher cost likely dissuading borrowing from moneylenders, and making interest-free borrowing preferable.

6.4 Welfare Implications

These results thus indicate that as a result of the vertical interaction between moneylenders and banks, bank credit supply also impacts lending in the moneylender market. A 10% higher bank credit supply effectively facilitates 23% more loans in the moneylender market following a one standard deviation increase in rainfall in non-drought years. Households, however, are not entirely without options when bank credit supply is low – they are able to substitute interest-bearing moneylender loans with interest-free loans from friends or relatives. This substitution is not complete, however. Only 40% of the decline in moneylender borrowing is compensated by an increase in interest-free borrowing. So, from a household's perspective, a 10% higher bank credit supply enables a 14% increase in borrowing in the informal market (both interest-bearing and interest-free) following a positive rainfall shock in non-drought years.

Since the substitution towards interest-free borrowing occurs when moneylender loans are more expensive, this also underscores the fact that interest-free loans also bear an implicit cost (Ambrus et al., 2014; Hayashi et al., 1996; Ligon, 2005; Ligon & Schechter, 2012; Udry, 1994). The increase in interest-free borrowing observed here is unlikely to be driven by a change in interest-free credit supply since borrowers do not increase interest-free borrowing when bank credit supply is high. Using values from Tables 14 and 15, back-of-the-envelope calculations suggest that the marginal borrower who is able to substitute from moneylender loans to interest-free loans when bank credit supply is low implicitly values the cost of 'interest-free' credit (in terms of the obligations it comes with) at 49.42% per year. This, however, does not take into consideration the complex social dynamics that render one source of credit preferable to another in different contexts.[45]

[44] The supply constraint can be thought of as an increase in the shadow price here.

[45] For instance, borrowers value privacy and dignity when conducting financial transactions in any sphere (Mowl, 2017), and this likely factors into their decisions.

7 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.

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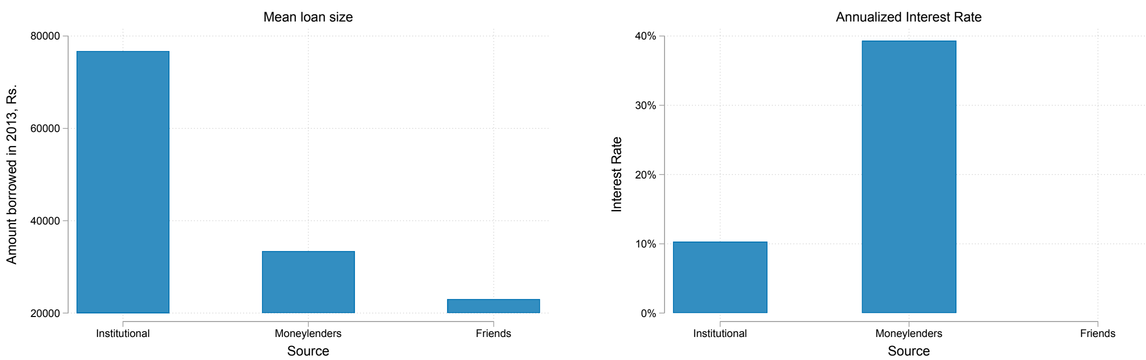
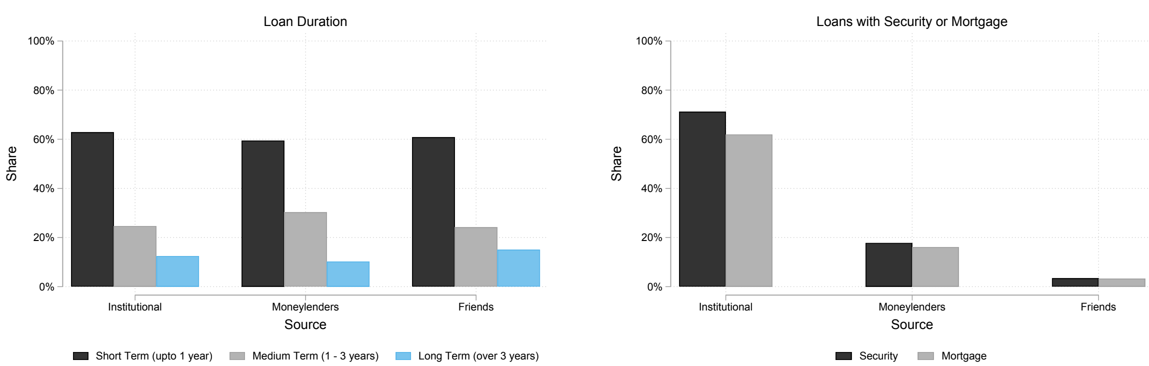
Figures

Figure 1: Loan Size and Interest Rates by Lender Type



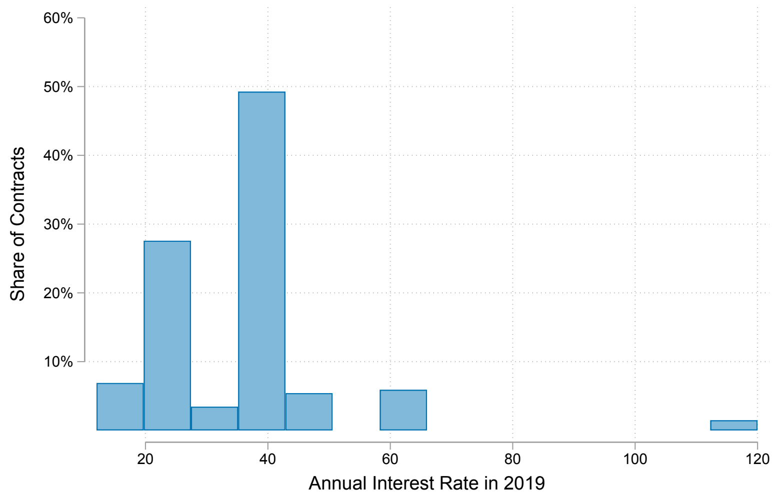
Data: NSS Debt and Investment Survey, 2013

Figure 2: Loan Terms by Lender Type



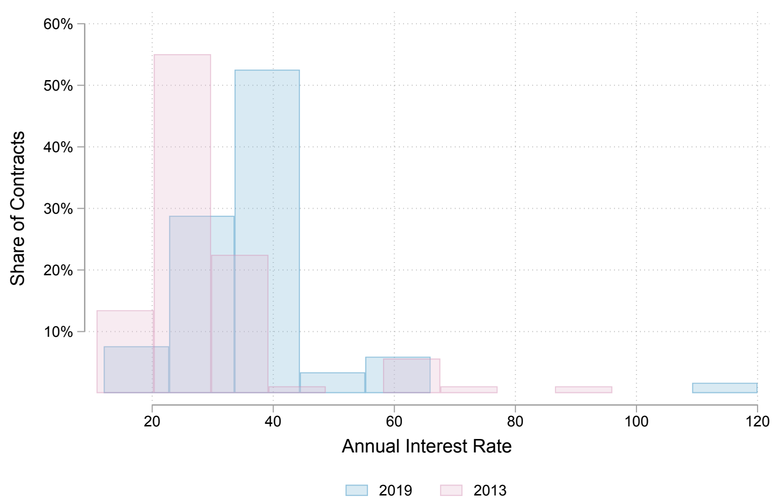
Data: NSS Debt and Investment Survey, 2013

Figure 3: Moneylender Interest Rates, 2019



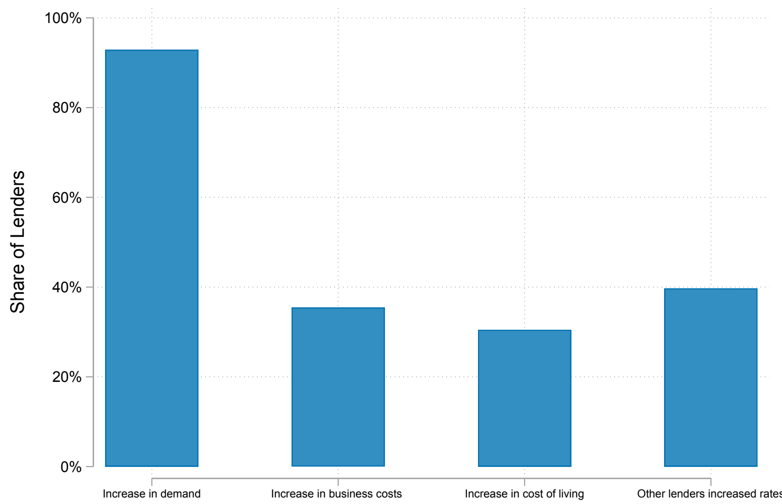
Data: Moneylender Survey (Telangana), 2020

Figure 4: Moneylender Interest Rates, 2013 and 2019



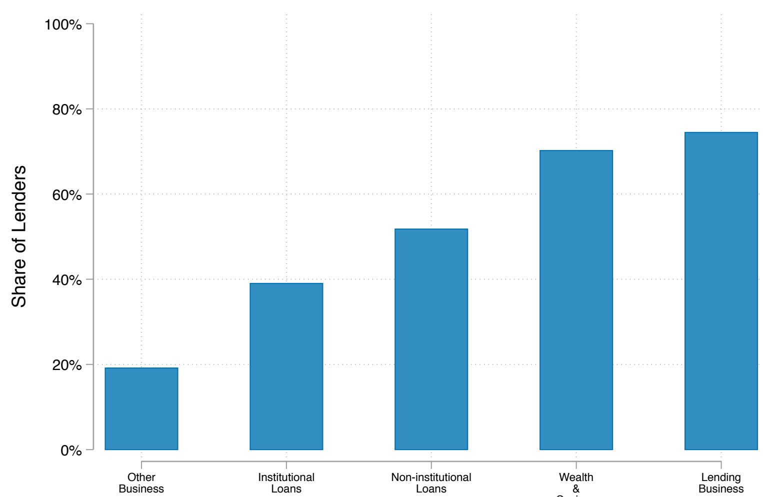
Data: Moneylender Survey (Telangana), 2020

Figure 5: Reasons for which Moneylenders increase Interest Rates



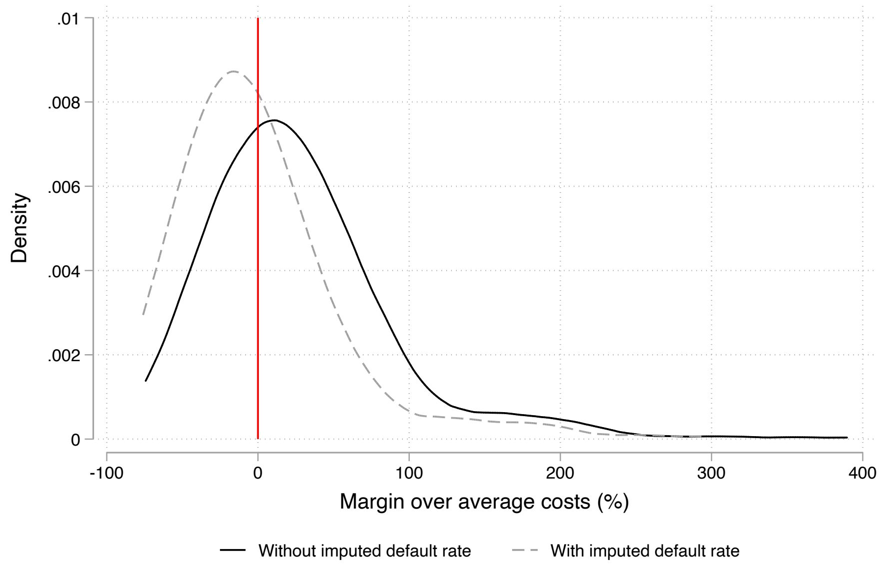
Data: Moneylender Survey (Telangana), 2020

Figure 6: Moneylenders' Source of Lending Capital



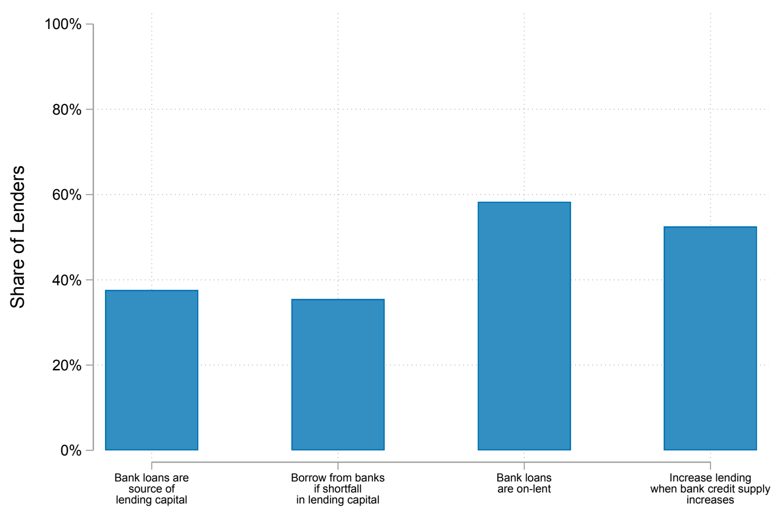
Data: Moneylender Survey (Telangana), 2020

Figure 7: Moneylender Margins over Average Costs



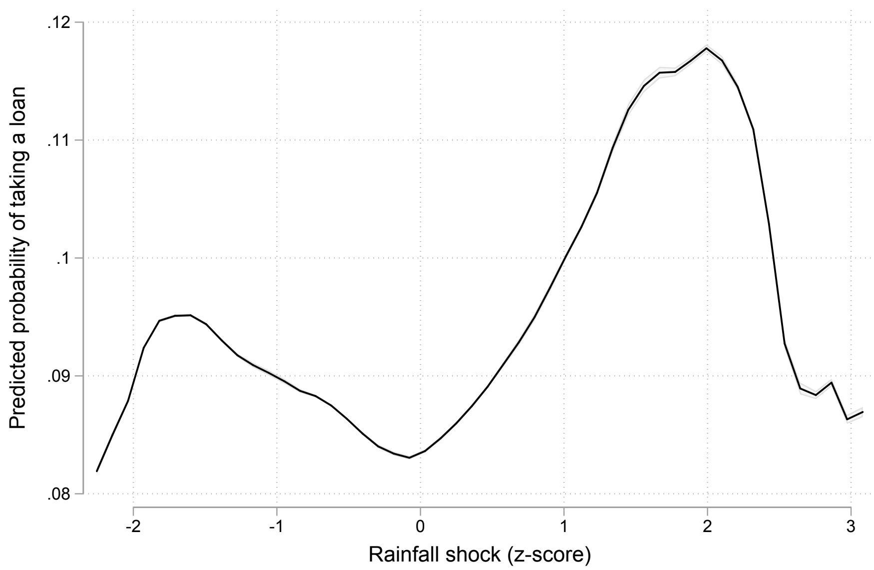
Data: NSS Informal Firms Survey, 2015-16

Figure 8: Moneylenders' Bank Borrowing



Data: Moneylender Survey (Telangana), 2020

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

Figure 10: Monsoon Timing

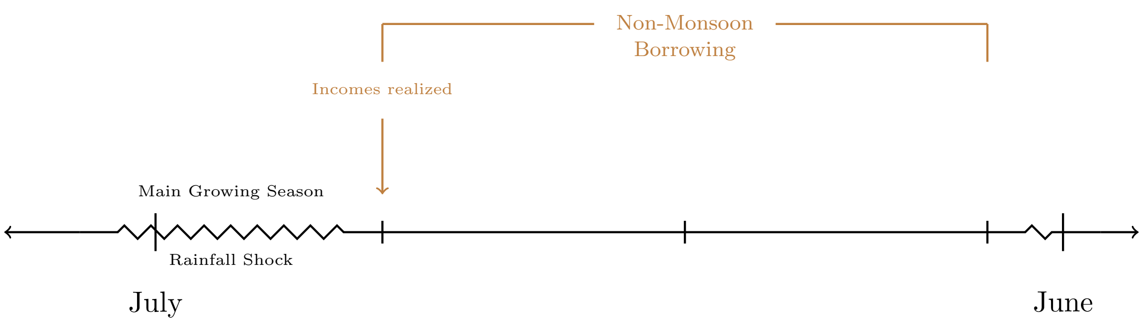
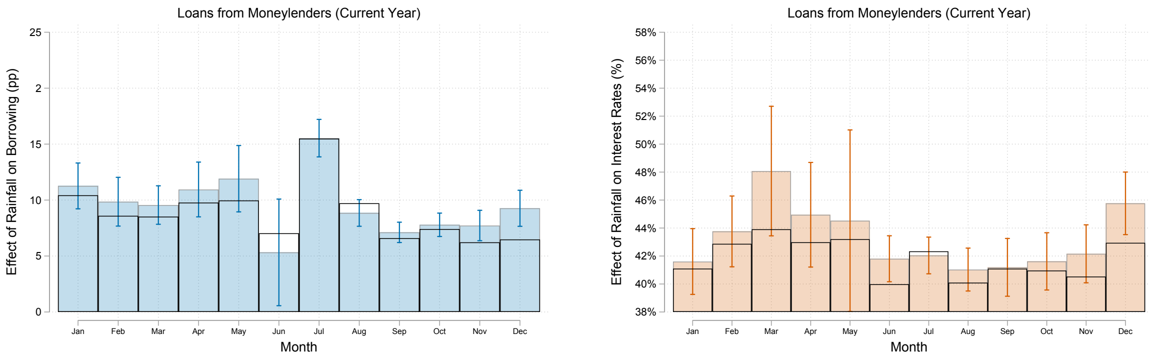


Figure 11: Impact of Rainfall Shocks on Household Borrowing and Interest Rates (Month-wise)



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

Tables

Table 1: Household Summary Statistics

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

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

Table 2: Summary Statistics - Household Credit

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

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

Table 3: 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 4: Rainfall and District GDP

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

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

Table 5: District characteristics above and below median in predicted bank lending

	Means			Normalized Differences (Low - High)	p-value
	Obs	Above median (High)	Below median (Low)		
Rainfall (z-score)	2280	-0.344	0.131	-0.018	0.663
Irrigated Land (Area irrigated/ Area cultivated)	1091	33.6%	33.6%	0.005	0.798
Landless Households	2280	39.8%	39.2%	0.003	0.961
SC/ST Households	2280	36.5%	39.5%	0.018	0.619
Non-Agricultural Households	2280	39.5%	37.5%	0.035	0.510
Population per bank branch	6435	12848.6	14484.1	0.002	0.894
Private bank branch share	6237	11.9%	7.5%	-0.008	0.336
GDP per capita last year	3925	₹16,659.5	₹17,935.3	-0.011	0.283

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 the above median or below median 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. GDP per capita in the preceding year is from the *Niti Aayog*/former Planning Commission, for the years 2000 - 2008. Values are in 1999-2000 prices. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: 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 7: 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 8: 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 × 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 9: 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 10: 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 11: 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 12: Rainfall and District Total Formal Credit

	Credit Limit (ln real ₹)	Credit Amount (ln real ₹)	No. Accounts (ln)	Predicted Credit Supply (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 13: 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)
Low 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 × Low 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. Low supply is an indicator that takes a value of 1 when the predicted bank credit supply is below the median. Sample 1 consists of all laons taken by a household in the survey year between October and May; the unit of observation is a household ×month. Sample 2 consists of all loans taken by a household in the reference year and that are still outstanding at the end of the reference year; the unit of observation is a household. The outcome is the inverse hyperbolic sine transformation of the real amount borrowed. Standard errors are clustered at the district level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 14: 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)
Low 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 × Low 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. Low supply is an indicator that takes a value of 1 when the predicted bank credit supply is below the median. 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. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

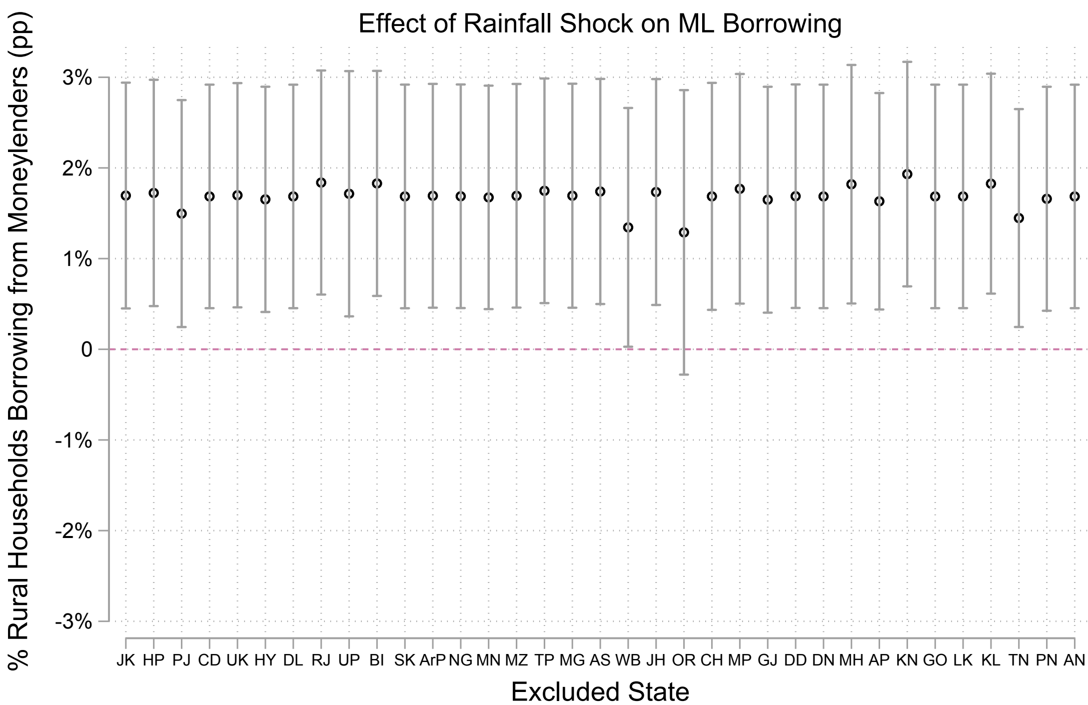
Table 15: Rainfall, Formal Credit Supply and Interest Rates on Loans from Moneylenders

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

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

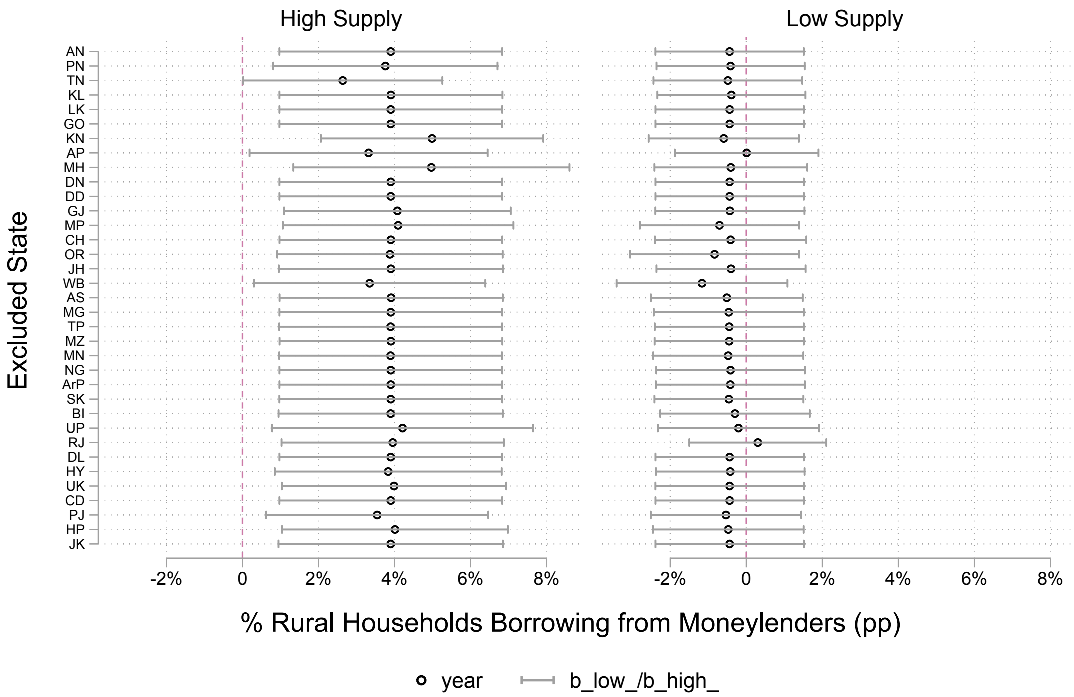
Additional Figures

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



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

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



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

Additional Tables

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

Additional Tables: Heterogeneity and Robustness Checks

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

	Moneylender		Friends & Relatives		Institutional	
	Sample 1	Sample 2	Sample 1	Sample 2	Sample 1	Sample 2
	(1)	(2)	(3)	(4)	(5)	(6)
Rainfall Shock	0.021***	0.060***	0.003	0.026	0.006	0.033
	(0.007)	(0.021)	(0.005)	(0.016)	(0.009)	(0.023)
Savings	-0.003		-0.004		0.086***	
	(0.003)		(0.003)		(0.005)	
Rainfall Shock × 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 B2: Asymmetric Effects of Rainfall Shocks on Rural Household Borrowing

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

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

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

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

Data: NSS Debt and Investment Survey (2001-02, 2002-03, 2011-12 and 2012-13)
Notes: Following Jayachandran (2006), percentile shock takes values -1 when monsoon rainfall is below the 20th percentile of the district's historical rainfall distribution; 1 when rainfall is above the 80th percentile of the district's historical rainfall distribution; and 0 otherwise. Fractional deviation defines the rainfall shock as a the fractional difference between the monsoon rainfall in a given year from the district's Long Period Mean (or 50 year mean, as defined by the Indian Meteorological Department (IMD)). Non-Monsoon rainfall is the standardized deviation of the 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 B4: Alternate Definitions of Formal Credit Supply Shocks:
Effect of Formal Credit Supply on Household Borrowing Response to Rainfall Shocks

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

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

Mathematical Appendix

Proof of Proposition 1:

In period 1, a moneylender solves:

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

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:

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

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 $b^*_{ML}(\theta) = \underset{b}{\text{argmax}}\ u\big(R_1\theta + b\big) + \beta\mathbb{E}_1\Big[u\big(R_2\theta - r_{ML}b\big)\Big]$, the optimal loan size when a household with endowment, θ, does not purchase D; and define $b^*_{ML,d}(\theta) = \underset{b}{\text{argmax}}\ u\big(R_1\theta + b - p\big) + \beta\mathbb{E}_1\Big[u\big(R_2\theta - r_{ML}b\big)\Big] + (1+\beta)d$, 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:

$$\frac{\partial L^*}{\partial R_1} = \overbrace{[b^*_{ML}(\hat{\theta}) - b^*_{ML,d}(\hat{\theta})]f(\hat{\theta})\frac{\partial \hat{\theta}}{\partial R_1} - b^*_{ML}(\underline{\theta})f(\underline{\theta})\frac{\partial \underline{\theta}}{\partial R_1}}^{\text{positive extensive margin change}} + \underbrace{\int_{\underline{\theta}}^{\hat{\theta}} \frac{\partial b^*_{ML}}{\partial R_1} f(\theta)d\theta + \int_{\hat{\theta}}^{\bar{\theta}} \frac{\partial b^*_{ML,d}}{\partial R_1} f(\theta)d\theta}_{\text{negative intensive margin change}} \tag{6}$$

Define $\Phi_1 = \left|[b^*_{ML}(\hat{\theta}) - b^*_{ML,d}(\hat{\theta})]f(\hat{\theta})\frac{\partial \hat{\theta}}{\partial R_1} - b^*_{ML}(\underline{\theta})f(\underline{\theta})\frac{\partial \underline{\theta}}{\partial R_1}\right|$ and $\Phi_2 = \left|\int_{\underline{\theta}}^{\hat{\theta}} \frac{\partial b^*_{ML}}{\partial R_1} f(\theta)d\theta + \int_{\hat{\theta}}^{\bar{\theta}} \frac{\partial b^*_{ML,d}}{\partial R_1} f(\theta)d\theta\right|$. 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 $\left|\frac{\partial L^*}{\partial R_1}\right| > \left|\frac{\partial L^*}{\partial r^*_{ML}}\frac{dr^*_{ML}}{dR_1}\right|$.

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 $\left|\frac{\partial L^*}{\partial r^*_{ML}}\right|_{\bar{G}\ binding} > \left|\frac{\partial L^*}{\partial r^*_{ML}}\right|_{\bar{G}\ not\ binding}$. And, $\left|\frac{\partial r^*_{ML}}{\partial R_1}\right|_{\bar{G}\ binding} > \left|\frac{\partial r^*_{ML}}{\partial R_1}\right|_{\bar{G}\ not\ binding}$. 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.