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An empirical investigation of rationing constraints in rural credit markets in India

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Abstract

The literature on rural credit markets has generally assumed that households are rationed in their access to subsidized 'formal' credit. The validity of this assumption depends on the level of effective demand for formal credit, in turn a function of the demand for credit and its availability from 'informal' sources. This paper estimates the demand and the sector-specific costs of credit, and hence the extent of formal sector rationing, through an analysis of household participation in both the formal and the informal credit sectors. The results show that the extent of rationing is considerably less than what is conventionally assumed.

JEL classification: O12; O16; O17; E51

Keywords: Credit rationing; Formal; Informal

1. Introduction

This paper estimates the extent to which rural cultivator households in India are effectively constrained by government regulations which control access to production credit from government or formal sources. Since these regulations require banks to offer loans for purposes of agricultural investment at a relatively low and fixed interest rate, it is widely believed that all cultivator households are effectively constrained in the amount, frequently assumed to be zero, that they can borrow in this market. This assumption is commonly imposed on theoretical

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models of the rural credit sector in developing economies (Eswaran and Kotwal, 1989, Braverman and Stiglitz, 1989). The assumption that there is an excess demand for bank credit at prevailing interest rates also underlies the oft-repeated objective of the government of increasing credit disbursements in order to stimulate agricultural investment (Government of India, 1985).

This assumption is at odds with the experience of rural bankers who frequently report difficulties in finding qualified borrowers for agricultural loans (National Bank for Agriculture and Rural Development, 1983). Such difficulties suggest that the demand for formal credit is low. This could be due to constraints other than capital which reduce agricultural productivity, or because of the availability of low-cost substitutes for formal credit. One obvious substitute is credit from nonbank or informal sources such as other cultivators in the village, relatives and friends.

If some households do not demand credit or if informal credit is less costly than formal credit for a significant percentage of households, credit market outcomes will typically reflect the demand for credit as well as the costs of both formal and informal credit. A growing number of in-depth studies of village credit markets suggest that this is so (Binswanger et al., 1985, Binswanger and Rosenzweig, 1986, Siamwalla et al., 1990). There is little empirical work, however, which separates the demand for credit from the lender's decision on access, or which takes into account the dual nature of the credit market. Consequently, the extent of effective credit rationing practiced by the formal sector is not known. Further, while several empirical studies estimate the determinants of observed loan amounts and interest rates (Iqbal, 1981, 1986), the failure to separate the demand schedule for credit from the sector-specific supply schedules limits the usefulness of such studies for designing effective credit policy.

This paper attempts to distinguish the demand for credit from the lender's decision on access in order to correctly infer the extent of effective credit rationing, or the probability of access to formal credit that is conditional on household demand. The empirical results of this paper are based on an analysis of household participation in both the sectors which comprise the rural credit market: the informal or private sector, and the formal or government regulated sector. The methodology employed herein not only assesses the extent of formal sector rationing, but also sheds light on the determinants of the demand and supply schedules which underlie credit market outcomes.

This study finds the incidence of formal sector rationing to be considerably less than what has been conventionally assumed. While the results are conditional on the validity of the econometric model, they question the assumptions behind the numerous models of the agricultural sector which take constrained access to credit as a maintained hypothesis and trace agricultural inefficiencies, income inequality and poverty to its existence (Eswaran and Kotwal, 1989, Braverman and Stiglitz, 1989). While such studies lead to the conclusion that agricultural reform must originate with the credit sector, this study, on the other hand, suggests the need to

focus on other factors, primarily in the land market, which may be responsible for both low demand and high credit costs. This study thus questions the focus of governments in many developing countries on credit as a primary instrument of agricultural development.

This paper is organized as follows. Section 2 describes the data used in this study. Section 3 discusses the various factors which could explain the observed distribution of formal credit in rural India, drawing on data on credit transactions for the country as a whole, but also on the more detailed survey data. Building on this discussion, Section 4 sketches a theoretical framework which incorporates household demand decisions, as well as sectoral supply decisions. An econometric model of sectoral choice which allows us to take this framework to the data is then specified in Section 5. Section 6 discusses the results of this study, and finally, Section 7 contains the conclusion.

2. Data

The data used in this study are drawn from a 1981–1982 Government of India household survey on credit transactions, indebtedness and household and farm investments called the All-India Debt and Investment Survey (AIDIS), 1981–1982. The sample used in this study pertains to the northern part of Uttar Pradesh, the most populous and one of the most agriculturally diverse states in India. Two subsamples of data are available, the 'state' subsample collected by state-level agencies and the 'central' subsample collected by the Government of India's National Sample Survey Organization. Collectively, the two subsamples provide data on 7053 rural households. However, while both subsamples provide information on credit transactions, data on landholding and family structure are only available for the 3672 households in the central subsample. The empirical analysis of this paper thus primarily uses the data on this subsample of households [1]. Since both the demand for credit and the costs of supplying credit can be expected to differ between cultivators and noncultivating households, this study focuses on explaining credit outcomes for cultivator households only. Deleting noncultivator households (approximately 18% of the sample) and observations with missing variables reduces the sample size to 2415 households.

Sample households were surveyed twice between July 1981 and June 1982, with data on transactions collected at six-month intervals. The broad sample design is a two-stage stratified sample. The 56 districts in the state were divided into 82 homogenous agroeconomic 'strata', and villages were randomly selected from each stratum. The village population was divided into four substrata based on

[1] The data in the central subsample have generally been credited with a higher degree of accuracy than the data in the state subsample (Bell, 1990).

farm size. Two households were randomly chosen from each substrata. For the purposes of this study, the household survey data have been supplemented by village and district level data from several secondary sources.

3. Explaining the distribution of formal credit in rural India

The government of India is among a number of governments in developing countries which have intervened actively in credit markets, particularly in the agricultural credit market, providing low-cost loans in an attempt to increase levels of investment. The provision of such 'formal' credit at a relatively low interest rate has led to concerns that the credit sector is characterized by an excess demand for formal credit, and that rationed access to formal credit in favor of large farms and those in the more productive regions may exacerbate existing levels of income inequality [2].

Data from the AIDIS indeed reveal limited participation in the formal sector and considerable inequality in its distribution (National Sample Survey Organization, 1985). Only 13% of rural cultivator households in India reported outstanding loans from the formal sector in 1981–1982. Wealthy households received a disproportionately large share of such credit, with cultivators who owned more than Rs100,000 in assets accounting for 10% of all cultivator households, but as much as 17% of cultivators reporting formal loans. Similar patterns in the distribution of formal credit are revealed in the survey data for Uttar Pradesh. A total of 20% of the 2415 cultivator households who form the effective sample for the empirical work of this paper reported formal loans. As at the national level, the distribution of formal loans in this sample favors large farms and farms in the more productive regions of the state, with 31% of large farms owning more than 20 acres and 30% of farms in the highly productive Western region reporting formal debt (Tables 1 and 2).

This observed distribution of formal credit may, however, stem from factors other than the lending rules followed by the formal sector. For example, a low rate of return on capital in small and fragmented farms and in regions characterized by poor infrastructure may restrict the demand for production loans even if they were available. The return on capital may also be low in farms with existing high capital stocks. This may explain the distribution of nonborrowers in the sample households. Nonborrowers dominate not just among potentially 'high risk' farms such as small farms and those in low productivity regions of the survey area like the Eastern region and Bundelkhand, but also among large farms and farms in the

[2] See, for example, Gonzalez-Vega (1984), as well as other papers by Adams et al. (1984). The argument that credit rationing affects income inequality is also made by Eswaran and Kotwal (1989) and Braverman and Stiglitz (1989).

Table 1
Distribution of borrowers by farm size

	Farm size (acre)					
	0–1	1–5	5–10	10–20	> 20	Total
Total households	311 (12.9)	1101 (45.6)	596 (24.7)	307 (12.7)	100 (4.1)	2415 (100.0)
All borrowers						
Total	91 (10.9)	397 (47.4)	204 (24.4)	113 (13.5)	32 (3.8)	837 (100.0)
% to total households	29.3%	36.1%	34.2%	36.8%	32.0%	34.7%
Formal borrowers						
Total	25 (5.2)	199 (41.1)	138 (28.5)	91 (18.8)	31 (6.4)	484 (100.0)
% to total households	8.0%	18.1%	23.2%	29.6%	31.0%	20.0%
Informal Borrowers						
Total	68 (16.4)	229 (55.1)	82 (19.7)	33 (7.9)	4 (1.0)	416 (100.0)
% to total households	21.9%	20.8%	13.8%	10.8%	4.0%	17.2%

The data in this table relate to the sample of 2415 rural cultivator households used in the regression analysis.

highly productive Western region which may have access to formal credit. Of cultivators in the Western region and of landowners owning more than 20 acres of land, as many as 69% report no formal loans (Tables 1 and 2).

Nonparticipation in the formal sector will also occur if cheaper credit is available from alternative 'informal' sources including other farmers, relatives and

Table 2
Distribution of borrowers by region

	Hill	West	Central	East	Bundelkhand	Total
Total households	184 (7.6)	818 (33.9)	429 (17.8)	850 (35.2)	134 (5.6)	2415 (100.0)
All borrowers						
Total	59 (7.1)	417 (49.8)	112 (13.4)	194 (23.2)	55 (6.6)	837 (100.0)
% to total households	32.1%	51.0%	26.1%	22.8%	41.0%	34.7%
Formal borrowers						
Total	30 (6.2)	249 (51.5)	56 (11.6)	120 (24.8)	29 (6.0)	484 (100.0)
% to total households	16.3%	30.4%	13.1%	14.1%	21.6%	20.0%
Informal borrowers						
Total	31 (7.5)	215 (51.7)	60 (14.4)	79 (19.0)	31 (7.5)	416 (100.0)
% to total households	16.9%	26.3%	14.0%	9.3%	23.1%	17.2%

The data in this table relate to the sample of 2415 rural cultivator households used in the regression analysis.

friends, landlords, traders and professional moneylenders. In fact, the informal sector is the predominant source of credit in rural India, accounting for 58% of the outstanding loans of all cultivator households in 1981–1982 (National Sample Survey Organization, 1985). Informal credit also accounts for 58% of the 4029 outstanding loans reported by sample cultivator households in Uttar Pradesh.

While credit from some informal sources may be relatively costly, reflecting high risk and administrative costs and possibly high opportunity costs, such costs may be relatively low in transactions between relatives and friends. Minimal screening, monitoring and enforcement costs in such instances will lower the costs of informal credit, possibly yielding a set of households for whom informal sector costs are lower than the formal rate which is uniformly fixed for all households by the government [3]. Loans among relatives and friends have grown significantly. While they accounted for only 12% of the total informal loans in the country in 1951, they soared to 24% in 1981, making relatives and friends the single most important source of informal credit (Bell, 1990). Conversely, loans from high-cost sources such as professional moneylenders declined from 51% of the total informal loans to 21% in the same period.

If demand considerations are important in explaining credit market outcomes, the extent of effective formal sector rationing cannot be inferred from the proportion of nonborrower households but requires knowledge of the number of households who demand formal credit but do not have access to it. Such information is rarely available in household surveys. As a result, there has been little attempt to date to estimate the extent of formal sector credit rationing, taking into accout both the demand for credit and the availability of credit from alternative sources, although such an analysis is clearly necessary for the design of effective credit policy. Such estimates are possible if we are willing to put some structure on the data, as is done in the econometric model of this paper. While the results are conditional on the validity of the econometric model, they do provide initial estimates of the extent of effective credit rationing by the formal sector.

4. Theoretical framework

The empirical model of the following section applies under three conditions regarding the demand and supply of credit: (i) a downward sloping demand curve for credit; (ii) an upward sloping supply schedule for informal credit; and (iii) formal sector rationing which generates a horizontal supply schedule for formal

[3] While sector specific data on interest rates could potentially provide information on the relative costs of formal vs. informal credit, it is widely believed that interest rates do not accurately reflect the costs of informal credit, particularly the case of loans between relatives and friends where the interest rate is frequently reported to be 0%.

credit. Standard models of agricultural households generate a downward sloping demand curve for credit, and, in the interests of brevity, a theoretical derivation of such a schedule is omitted [4]. Similarly, in what follows, I only briefly describe the features which generate the informal sector supply schedule. The empirical model builds on several assumptions regarding the informal sector, as will be discussed later. The formal sector supply schedule stems from the lending rules which characterize the formal sector in the rural Indian economy. These rules are discussed in Section 4.3. This section concludes with a description of the household's equilibrium position in the credit market.

4.1. Assumptions regarding the informal sector

An upward sloping supply schedule for informal credit is obtained from any model with a probability of default such that an increase in the loan amount increases returns in the event of default less than proportionately. The lender's opportunity cost then increases compared with the expected income as the loan amount increases, causing the lender to increase the interest rate. Details of such a model are shown by Kochar (1991). Here, I start by assuming the existence of such a supply schedule, $B(r, X)$, which specifies all the (r, B) pairs offered to a household with characteristics X which affect the return on the loan.

This supply schedule defines the reservation cost ($MC^{I}(B = 0)$) at which the lender is willing to lend to the household. Since the schedule shifts with borrower characteristics, this rate may be very high for 'risky' households, reflecting the significant screening and monitoring costs lenders have to bear in such cases. Such households are 'rationed' out of the market in that informal credit is only available to them at rates at which they find it optimal not to borrow [5]. The upward sloping supply schedule also implies an additional form of credit rationing in that a household is not free to borrow as much as it wants at any given interest rate, reflecting again the risk of default.

The econometric model builds on several assumptions regarding the nature of the informal sector supply schedule which are discussed later. Relaxing these assumptions does not alter the empirical model or the predictions generated by the

[4] Details of a theoretical model which delivers a downward sloping demand schedule and an upward sloping supply schedule for informal credit are shown by Kochar (1991), as is a formal treatment of the formal sector.

[5] Such a model which allows for arbitrarily high informal interest rates departs from the theoretical literature which models the interest rate as a screening device, thereby suggesting a ceiling on interest rates given by the profit maximizing rate (Stiglitz and Weiss, 1981). The framework of this paper builds on alternative models, wherein informal lenders are viewed as solving their informational problems by providing loans only to households they know well or can closely monitor (Basu, 1983). Monitoring costs, however, may be very well substantial. A number of in-depth analyses of informal credit markets also subscribe to the view that the Stiglitz–Weiss model may best apply to non-resident and formal lenders (Siamwalla et al., 1990).

model regarding the extent of formal sector rationing, but it affects the interpretation of the equations underlying credit market outcomes in a way I specify at the appropriate points. This qualification should be kept in mind while interpreting the results of the paper, and I reiterate this point in my discussion of the results in Section 6 of this paper.

I assume that the informal sector is homogenous in that all informal lenders maximize the same objective function. In Section 5 of this paper, I consider the implications of this assumption for the interpretation of the results. I also assume that borrowers transact with only one informal lender. The theoretical justification for this assumption is given by Keeton (1979) who shows that borrowers will only borrow from the lender who has first claim on the loan. There is some support for this in the data which show that only 18% of informal borrowers hold more than one concurrent loan, and only 5% have concurrent loans from different informal sources. This evidence is only suggestive, however, since households could have borrowed from different lenders who were classified in the same source category. Stronger evidence comes from in-depth village studies which report that borrowers generally have a long term association with just one lender (Binswanger et al., 1985, Siamwalla et al., 1990).

In the interest of maintaining a tractable econometric model, I also assume that any formal loan obtained by the household does not affect the cost of informal credit. If informal lenders have priority over formal lenders, any formal loans obtained by the household will not adversely affect informal lenders. The informal lender's secured claim may, however, imply that a concurrent formal loan will increase his expected return and lower the costs of credit (Bell, 1990). This is less likely to be true if lenders and borrowers are engaged in long term contracts; lenders will find it in their interest to maintain the productivity of the borrower and not jeopardize future income flows by causing him to default on formal loans. The relationship between formal and informal credit is an important topic which merits further research. In a step in this direction, I analyze the empirical implications of a link between formal loan amounts and the cost of informal credit, and the effect of such a link, if it exists, on the interpretation of the results of this paper in Section 6.

4.2. The formal sector supply schedule

The distinguishing characteristic of the formal credit sector during the period of this study is the extent to which the government regulated lending operations for the agricultural sector. The overall scale of agricultural lending was controlled by the requirement that 'priority' sectors receive 40% of total bank loans, with agricultural loans constituting 40% of this amount or 16% of the total. Interest rates on agricultural loans were set by the government, and while they varied by farm size and type of investment, they did not vary with loan amounts. Government regulations also specified borrower criteria. Banks were required to base

their calculations of borrower eligibility on the incremental income expected on the investment financed, and on the productivity of that investment alone.

Maximization of expected profits subject to the constraint requiring a certain volume of overall agricultural lending generates a household specific formal sector supply schedule, $B(r, X, T)$, which is a function of the interest rate, borrower characteristics, X, and the bank's overall credit target, T. The data on bank operations suggest that the constraint on the volume of agricultural lending was binding. Thus, priority sector advances constituted 37% of the total formal sector credit to all sectors as of December 1982, with agricultural advances being exactly 16% of the total as required (Reserve Bank of India, 1985). As in the informal sector, the formal sector supply schedule varies across households with the bank's perception of the probability of loan repayment, and is upward sloping in the interest rate due to the probability of default. Differences between informal and formal lenders in their assessment of this probability, however, imply corresponding differences between the sectoral supply schedules.

The formal sector supply schedule is 'notional', in that it is not offered to the borrower. Since the formal sector is constrained to lend at a fixed interest rate, r_f, it offers the borrower only the fixed loan amount, $B^f(r_f)$, which corresponds to this interest rate. The effective formal sector supply schedule is thus horizontal at r_f. The household is denied access to the formal sector if $B^f = 0$. Following standard analyses of corner solutions, this occurs if the formal sector's reservation cost of lending to the household, evaluated at $B = 0$, exceeds the marginal return. In this application, the lender's marginal cost is given by the expected marginal loss in income if the borrower defaults, while the marginal return includes the interest rate r_f as well as the extent to which the loan allows the bank to meet its targeted agricultural loans. The determination of access is thus based on the formal sector's notional supply schedule for a household.

4.3. The household's equilibrium position

Since the credit market comprises both the formal and informal sectors, a household chooses the least cost source at each loan amount, taking formal sector constraints into account. The 'aggregate' supply schedule for household j, $MC_j(B)$, is:

$$
\begin{aligned}
\text{for } B_j^f = 0, MC_j(B) &= MC^i(B) \\
\text{for } B_j^f > 0, MC_j(B) &= \min\left(MC^i(B), r_f\right) \\
&\quad \text{for } 0 \le B \le \bar{B} = B^i(r_f) + B_j^f, B^i(r_f) \ge 0 \\
&\quad MC^i(B - \bar{B}) \text{ for } B > \bar{B},
\end{aligned}
\tag{1}
$$

where B^f is the loan available from the formal sector, $MC^i(B)$ is the informal sector supply schedule, and $B^i(r_f)$ is the loan amount available from the informal sector at r_f. Since B^f and MC^i vary with household characteristics, so will the marginal cost schedule facing households. Possible supply schedules are depicted in Fig. 1. If households are constrained in the amount, they can borrow from the formal sector (Fig. 1b,c), or if the informal sector is a cheaper source of credit over a certain range (Fig. 1d), the overall supply schedule facing a household is the union of the sectoral supply schedules which is characterized by kinks.

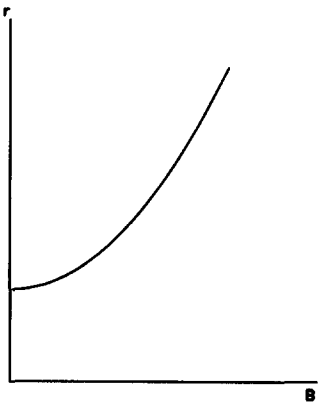


figure 1a

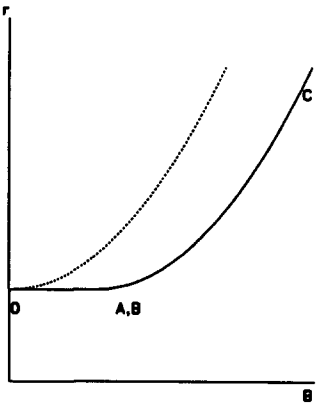


figure 1b

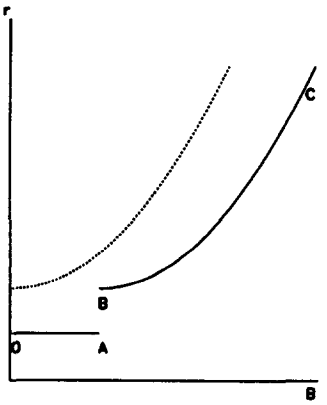


figure 1c

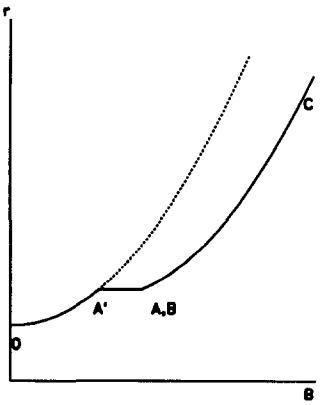


figure 1d

Fig. 1. Possible supply schedules.

Specify the supply schedule in Eq. (1) as $r(B)$, where r is continuous but not everywhere differentiable in B. Let $\pi(r, B)$ refer to the household's profit (or utility) function [6]. The optimal loan for the household then maximizes $\pi(r, B)$ subject to the supply schedule $r = r(B)$ and a nonnegativity constraint on the loan amount, $B \geq 0$.

Since the focus of the empirical analysis is on the household's choice of sectors, I concentrate on analyzing the determinants of this choice. A household's location along with its relevant supply schedule (Fig. 1) is determined by the slope of $\pi(r, B)$ and the supply schedule at the various corners, as follows:

$$
\begin{array}{lll}
\text{(i)} & \text{Corner at O} & \dfrac{d\pi}{dB}(\mathrm{MC}(B=0),0) \leq \dfrac{dr}{dB}(0) = 0 \\
\text{(ii)} & \text{Equilibrium at} & \dfrac{d\pi}{dB}(\mathrm{MC}(B=0),0) >) \text{ and } \dfrac{d\pi}{dB}(r_f B^f) < 0 \\
 & \text{OA (Fig. 1b, 1c)} & \\
 & \text{OA′ (Fig. 1d)} & \dfrac{d\pi}{dB}(r_f B^i(r_f)) \leq 0 \\
\text{(iii)} & \text{Equilibrium at AB (Fig. 1d)} & \dfrac{d\pi}{dB}(r_f, B^i(r_f)) > 0 \text{ and } \dfrac{d\pi}{dB}(r_f, \bar{B}) < 0 \\
\text{(iv)} & \text{Corner at A (Fig. 1b, 1d)} & \dfrac{d\pi}{dB}(r_f, \bar{B}) = \dfrac{dr}{dB}(\bar{B}) \\
 & \text{(Fig. 1c)} & \dfrac{d\pi}{dB}(r_f, \bar{B}) > 0 \text{ and } \dfrac{d\pi}{dB}(\mathrm{MC}^i(B=0), \bar{B}) \leq 0 \\
(v) & \text{Equilibrium at BC} & \dfrac{d\pi}{dB}(r_f, \bar{B}) > \dfrac{dr}{dB}(\bar{B}) \\
 & \text{(Fig. 1b, 1d)} & \\
 & \text{(Fig. 1c)} & \dfrac{d\pi}{dB}(\mathrm{MC}^i(B=0), \bar{B}) > 0,
\end{array}
\qquad (2)
$$

where, as before, B^f is the available formal loan, $B^i(r_f)$ is the amount that can be borrowed from the informal sector at r_f, and $\bar{B} = B^f + B^i(r_f)$.

An evaluation of the conditions in Eq. (2) reveals that the household's choice of sector(s) is determined by the intersection of demand and supply schedules. For example, a household chooses not to borrow if (Eq. (2)i) holds. This yields the standard result (Kochar, 1991) that the participation decision is based on a comparison of the expected reservation demand rate ($\mathrm{MR}(B=0)$) and the relevant reservation cost ($\mathrm{MC}(B=0)$). Since the household's supply schedule and its reservation cost varies with access to the formal sector, nonparticipation in the

[6] As mentioned earlier, any utility function which generates a downward sloping demand curve for credit will suffice for the econometric model of the next section.

credit market could stem from either an effective constraint on access to the formal sector ($B_j^f = 0$, $MC^i(B = 0) > MR(B = 0) > r_f$), or low demand ($MR(B = 0) < \min(MC^i(B = 0), r_f)$). The latter is likely to be the case for wealthier households and for households in low productivity regions.

The decision to borrow from both the formal and the informal sector reflects not only the reservation costs of credit but also the amount of the formal loan. A household may be 'quantity' rationed if the demand for credit at r_f, $B^d(r_f)$, exceeds the available supply, B^f. This occurs if demand and supply schedules intersect to the right of A in Fig. 1. Depending on the demand for credit, such rationing could result in a household borrowing only from the formal sector, or from both sectors at an informal interest rate which exceeds the formal.

5. An econometric model of sectoral choice in rural credit markets

5.1. The two sector model

The theoretical model developed in the previous section provides the basis for the econometric model of rural credit market outcomes developed in this section. The empirical model concentrates on participation decisions, ignoring the information contained in loan amounts and interest rates. While this reduces the efficiency of estimates, it has the distinct advantage of not using information on either observed or predicted informal interest rates. Thus, the results of this paper are not conditional on the accuracy of reported loan details, which are frequently held to be inaccurate, particularly for the informal sector.

The household's loan demand and sectoral supply schedules yield the 'reservation' interest rate equations, which are the equations estimated, defined as the interest rate at which the optimal loan is zero:

$$\begin{aligned} MR(0, X_1, u_1) &= X_1\beta_1 + u_1 && \text{reservation demand rate} \\ MC^f(0, X_2, u_2) &= -(X_2\beta_2 + u_2) && \text{reservation cost, formal sector} \\ MC^i(0, X_3, u_3) &= -(X_3\beta_3 + u_3) && \text{reservation cost, informal sector.} \end{aligned} \tag{3}$$

Since these schedules are derived from the household's loan demand and sectoral supply schedules, the coefficients and the error terms represent scaled transformations of the loan demand and supply parameters, with the scaling coefficients being the interest rate parameter in the underlying function. The random variable u_i, $i = 1$ to 3, represents the inherent randomness in the schedules and the effect of omitted variables, such as past loan histories and other indicators of lender–borrower relationships. Though I assume each u_i to be independently and identically distributed across households, such omitted variables can be

expected to enter into all three equations, yielding a nondiagonal variance matrix of the error terms.

The reservation interest rate schedules in Eq. (3), in turn, form the basis for the index functions underlying household participation decisions and the formal sector's access decision, which generate observed credit market outcomes. These index functions are:

$$\begin{aligned}
&\Pr(\text{demands formal sector loan}) = \Pr\left[\mathrm{MR}(0, X_1, u_1) > r_f\right] \\
&\Pr(\text{demands informal sector loan}) = \Pr\left[\mathrm{MR}(0, X_1, u_1) > \mathrm{MC}^i(0, X_3, u_3)\right] \\
&\Pr(\text{access to formal}) = \Pr\left[\mathrm{MC}^f(0, X_2, u_2) < r_f\right] \\
&\Pr(\text{formal sector is lower cost}) = \Pr\left[\mathrm{MC}^i(0, X_3, u_3) > r_f\right].
\end{aligned} \tag{4}$$

To facilitate the discussion, credit market outcomes are diagrammatically presented as a decision tree in Fig. 2. While sectoral choice outcomes are determined by household demand decisions and by the supply decisions of formal and informal sector lenders, the data set only provides information on the final outcome or the observed sector of choice. Information on the individual schedules from which this decision is made is not available. Thus, I divide households into those that borrow formal credit ($I = 1$), those that borrow informal credit ($I = 2$) and those that do not borrow at all ($I = 3$).

This division reflects the index functions in Eq. (4), except for the sample of households borrowing from both sectors. As shown in the previous section, the decision to borrow from both sectors is based on the amount of formal credit the household has access to and on a random variable which differs from those in the reservation cost schedules. Rather than further complicate the problem in this way, I divide households into formal borrowers, informal borrowers and nonborrowers. The separation of households which borrow from both sectors into those for whom the formal sector is the lower cost sector ($I = 1C$) and those for whom the informal sector is the cheaper source of credit over a certain range ($I = 2C$) is made using reported interest rates. Specifically, of the households borrowing from both sectors, those borrowing at a lower formal rate are classified as formal borrowers [7].

[7] While incorrect sample selection will bias results, the alternative of not providing sample separation requires the estimation of an additional equation with very little information, yielding possibly even greater bias. Given the small percentage of borrowers who report loans from both sectors (8%), I choose the option of separating the sample of households borrowing from both sectors on the basis of reported interest rates.

Sectoral outcomes are then generated by the four selection rules in Eq. (4) as follows:

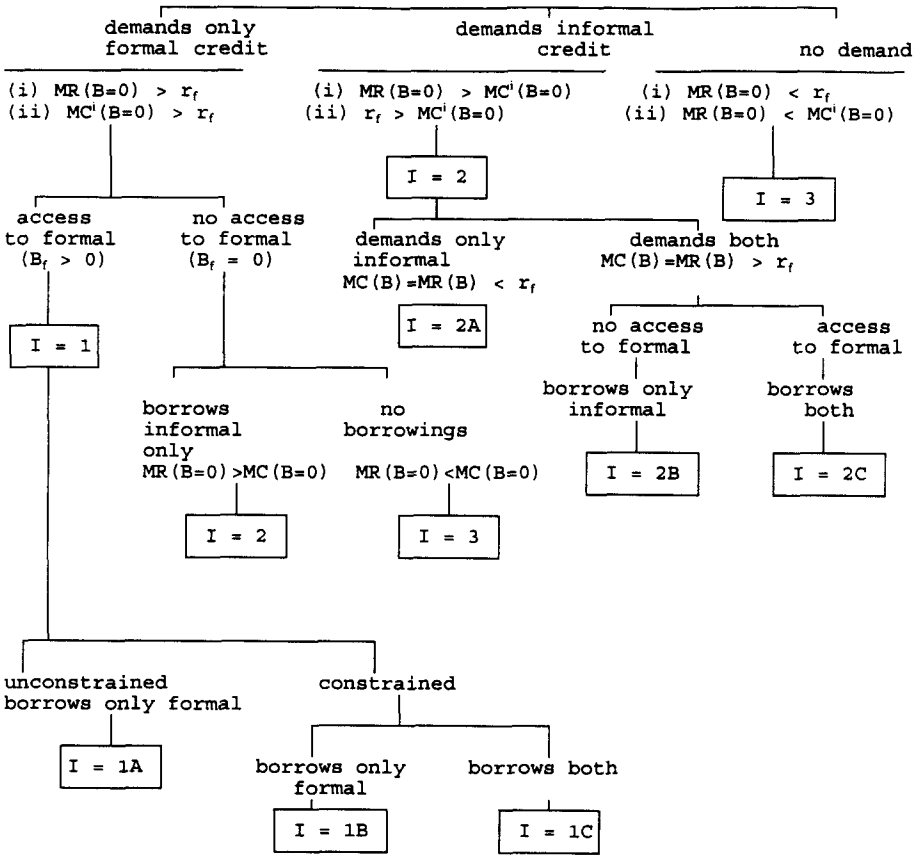
$$
\begin{aligned}
&\text{Pr(borrows formal)} = \quad \Pr\big(\mathrm{MR}(0,X_1,u_1) > r_f, \mathrm{MC}_f(0,X_2,u_2) < r_f, \mathrm{MC}^i(0,X_3,u_3) > r_f\big)\\
&\text{Pr(borrows informal)} = \quad \Pr\big(\mathrm{MR}(0,X_1,u_1) > \mathrm{MC}^i(0,X_3,u_3), \mathrm{MC}^i(0,X_3,u_3) < r_f\big)\\
&\qquad + \Pr(\mathrm{MR}(0,X_1,u_1) >\\
&\qquad \mathrm{MC}^i(0,X_3,u_3), \mathrm{MC}^i(0,X_3,u_3)\\
&\qquad > r_f, \mathrm{MC}_f(0,X_2,u_2) > r_f)\\
&\mathrm{PR(not\,borrowing)} = \quad \Pr\big(\mathrm{MR}(0,X_1,u_1) < r_f, \mathrm{MR}(0,X_1,u_1) < \mathrm{MC}^i(0,X_3,u_3)\big)\\
&\qquad + \Pr(\mathrm{MR}(0,X_1,u_1) <\\
&\qquad \mathrm{MC}^i(0,X_3,u_3), \mathrm{MR}(0,X_1,u_1)\\
&\qquad > r_f, \mathrm{MC}_f(0,X_2,u_2) > r_f).
\end{aligned}
\tag{5}
$$

This general formulation of credit market outcomes reflects both formal sector rationing and optimal choices by households. Thus, as discussed in the previous section, nonborrowers comprise households who do not demand credit from either sector ($\mathrm{MR}(0,\ X_1,\ u_1) < r_f$, $\mathrm{MR}(0,\ X_1,\ u_1) < \mathrm{MC}^i(0,\ X_3,\ u_3)$) as well as those who demand formal credit but lack access to it ($\mathrm{MR}(0,\ X_1,\ u_1) > r_f$, $\mathrm{MC}^f(0,\ X_2,\ u_2) > r_f$) and choose not to borrow from the informal sector ($\mathrm{MR}(0,\ X_1,\ u_1) < \mathrm{MC}^i(0,\ X_3,\ u_3)$).

As indicated in Eq. (5), the estimation of the probability of borrowing from each sector recovers the reservation interest rate schedules of Eq. (3). However, since we only observe final outcomes, the parameters of these equations must be inferred from the joint occurrence of the individual decision rules or index functions in Eq. (4). This is the problem of partial observability. Poirier (1980) describes the basic econometric framework and Farber (1983) and Feinstein (1986), among others, present applications of these types of models. The identification criteria for such models are relatively weak, only requiring us to distinguish one equation from the other. This is possible if the set of explanatory variables differs across equations. In this particular context, sector-specific lending costs enter the set of X_2 and X_3 variables, but not X_1. The likelihood of the model is specified in Appendix A.

5.2. Interpreting the model with multiple informal sectors

The analysis so far has assumed the informal sector to be homogenous in that all lenders are assumed to offer the same supply schedule to any given household. In fact, the analysis of participation in the formal sector is little changed if the supply schedule is allowed to vary across informal lenders, provided that the informal sector with the minimum reservation cost is the same for all households. This assumption would hold if, for example, relatives and friends provide the cheapest source of credit at small loan amounts for all households. The probability



I = 1 borrows from formal
I = 2 borrows from informal
I = 3 no borrowings

Fig. 2. Decision tree for observed sectoral outcomes in rural credit markets.

of borrowing from the formal sector in Eq. (5) is then respecified in terms of the reservation cost of credit in this least-cost sector:

$$\Pr(\text{borrows formal}) = \Pr(\text{MR}(0, X_1, u_1) > r_f, \text{MC}_f(0, X_2, u_2) < r_f,$$

$$\min \text{MC}^i(0, X_3, u_3) > r_f)$$

The analysis of the set of informal borrowers is not so straightforward. In order to explain exclusive transactions with higher cost lenders, it is necessary to resort to transaction costs or to the assumption that such lenders are able to enforce

exclusive contracts (Aleem, 1990). The probability of borrowing from either one of the two informal sectors will then be a function of loan amounts in addition to the reservation interest rates in Eq. (3). This necessitates identifying loan schedules as distinct from the reservation interest rate schedule, and requires exclusion restrictions which would be hard to justify with the data on hand.

To circumvent this problem, the empirical implementation of the model divides the sample into formal sector borrowers and all other households. The probability of borrowing from the formal sector is given in Eq. (6), and the estimates of the informal reservation cost schedule so obtained are taken to refer to loans by relatives and friends. Provided that the least-cost source of informal loans is the same for all households, the empirical model recovers consistent estimates of the three equations, though there is a loss of efficiency associated with the fact that the information available from the set of informal borrowers is not utilized.

6. Empirical results from different models of sectoral choice

In this section, I present results from the estimation of various models of sectoral choice. The first set of results is obtained from a conventional model wherein the set of formal borrowers is determined by the bank's decision on access (Model I). The model yields estimates of the probability of access to the formal sector, as specified in Eq. (4) of the preceding section. The second model (Model II) generalizes the first by allowing the probability of borrowing from the formal sector to be jointly determined by the bank's decision on access as well as the household's demand for loans. The estimated joint probability density function recovers the parameters of the marginal probability of access and of demand for credit in Eq. (4), and allows a test of the hypothesis that a household's demand for credit significantly affects credit outcomes. The results from the estimation of these two models are the strongest empirical results of this paper, given the general specification of the error structure in the two models. These results and their implications are discussed in some details.

The third model (Model III) fully implements the econometric model of the previous section by introducing the informal sector, allowing for the possibility that some households choose this sector over the formal. Since the trivariate distributions of this model present computational difficulties, the model is estimated by putting additional structure on the error terms. The consistency of the estimates is conditional on the validity of this structure. However, as discussed below, this econometric model has been shown to yield accurate predictions. Accordingly, I focus most of the discussion of this model on the estimates of the probability of borrowing from the formal sector.

Table 3 describes the variables used in the empirical analysis. Exogenous household variables affecting farm profits and the demand for loans are the amount of land owned by the household (land), the amount of irrigated land (irr) at

Table 3
Description of variables used in regressions

Variable	Description	Mean (Standard deviation)
Household-level variables		
Interest rate	Predicted formal sector interest rate	12.72 (1.78)
Plots	Number of cultivated plots in the holding	4.52 (3.56)
Irr	Irrigated land (acre)	3.82 (5.30)
Land	Land owned (acre)	6.26 (8.01)
Males	Number of adult males	1.52 (1.13)
Security	Dummy variable = 1 if collateral offered on on informal loan. Predicted for the full sample of households.	0.52 (0.15)
Village-level variables		
V pop	Village population (10^3)	1.32 (1.50)
District-level variables		
Bkcred81	Per capita formal credit for all purposes (Rs per 100,000 population)	181.35 (196.17)
F yield	Foodgrain yield (100 kg ha^{-1})	13.63 (3.37)
Msoon79	Rainfall, monsoon season, 1979 (mm)	496.27 (170.90)
Msoon80	Rainfall, monsoon season, 1980 (mm)	1199.43 (398.07)
Road	Length of concrete road per 100 km^2	31.08 (9.91)

the start of the reference year, and the number of plots into which the cultivated holding is fragmented (plots). The set of regressors also includes the number of adult males in the household (males).

The demand for loans will also reflect regional variation in agricultural productivity and infrastructure. While such variation could be best accommodated by a set of dummy variables which allow the intercept to vary with the district in which the household resides, the many districts in the state (56) render such a treatment infeasible in the context of the empirical model of this paper. Instead, levels of infrastructure development and other regional variables affecting productivity are proxied by two variables, the length of concrete road in the district per 100 km^2 (road) and the yield of food grains in the district in the year prior to the survey year (*F* yield). Village-level variation in the availability of infrastructure is proxied by the village population level (*V* pop). Finally, since agrarian conditions are determined to a large extent by weather outcomes, the set of regressors include the amount of rainfall in the district in the monsoon seasons of the two years prior to the survey year (Msoon79 and Msoon80) [8].

The exogenous treatment of land ownership and the extent of plot fragmenta-

[8] If household expectations of rainfall follow an auto-regressive structure, lagged values provide better forecasts than a long term average.

tion is justified by the limited transactions in the land sales market observed in this and other parts of India [9]. However, the use of irrigated land as a measure of farm productivity, necessitated by the absence of data on other measures of land quality, introduces the possibility of bias if irrigation investments are financed by formal banks and if the household's debt history influences current loans. The extent of bias depends on the correlation between a household's irrigated land holdings and bank credit. This may be low as banks primarily finance investments in tubewell irrigation, whereas the measure of irrigated land used in this paper includes land irrigated from other sources such as canals and tanks.

Both the formal and the informal supply schedules are functions of the set of variables described earlier which determine farm productivity and the demand for loans. These two schedules are thus identified by variables which reflect sector-specific lending costs, which will be discussed later.

The formal sector supply schedule is primarily identified by a variable measuring the amount of formal loans for all purposes, agricultural and nonagricultural. This variable will affect the cost of loans to cultivators, given that bank lending for agriculture is required to be a fixed percentage of total formal credit. Since bank operations are generally monitored and evaluated at the level of the district [10], the variable used is the total credit advances in a district to all sectors in the survey year (Bkcred81). This information is available from Reserve Bank of India sources (Reserve Bank of India, 1987).

The 'developmental banking' procedures followed by the formal sector also provide an additional source of identification. These procedures required banks to assess the viability of a loan solely on the basis of the incremental income expected from the project financed. While the calculation of expected incremental income required an estimate of labor costs, these were estimated without making any allowance for the availability of family labor [11]. The variable males, the number of adult male workers in the household, therefore should not affect formal sector lending costs. The exclusion of this variable further serves to distinguish this schedule from the demand schedule and the informal sector access schedule [12].

Identification of the informal sector supply schedule is achieved on the basis of an indicator variable which takes the value 1 if borrowers provided 'personal

[9] For example, the study by Bliss and Stern (1982) of a village in the survey region notes that the distribution of village land in 1974–1975 closely reflected that before Independence (1947), and that land is rarely bought or sold.

[10] NABARD's monitoring of banks operates through a district-oriented monitoring scheme which monitors bank compliance with various targets at the level of the district.

[11] Details of banking operations are provided in the numerous evaluation studies conducted by banks of their agricultural lending schemes. See for example, Union Bank of India (1983) and National Bank for Agriculture and Rural Development (1987).

[12] This variable, however, is not necessary for identification, and its exclusion from the supply schedule is therefore testable. Reestimating the bivariate model (Table 5) with males included in the access equation yields a coefficient of 0.0097 with a standard error of 0.0446.

surety', a third party guarantee or other forms of collateral to secure the contract. The ability to offer such guarantees is assumed to increase the probability of access to informal credit. This indicator variable (security), however, is only available for informal borrowers and has to be predicted for the full sample of households. The conventional procedure is to use the sample of informal borrowers, further subdivided into those who provided security and those who did not, to estimate the probability that security or collateral is offered. Since the probability of being an informal borrower is endogenously determined, this procedure will likely yield biased results [13]. In order to recover unbiased estimates of the probability that collateral is required, it is thus necessary to explicitly account for the choice-based nature of the sample of informal borrowers by modeling the joint distribution of the probability of being an informal borrower and of the borrower providing collateral.

The estimation of this joint distribution requires specifying the underlying marginal distribution functions. The probability that collateral is offered is assumed to follow a normal marginal density function whose expected value is a function of the same set of regressors which determines the demand for credit. The specification of the probability of borrowing from the informal sector is, however, not so straightforward. Estimating this probability, in fact, is one of the major goals of this paper. The econometric model developed in Section 5 specifies the probability of borrowing from the informal sector, as a mixture of normals which reflect the reservation rate at which formal credit is demand, the reservation cost of formal credit and the reservation cost of informal credit which includes the variable security. Given this complicated structure, the exact form of the joint distribution to be estimated is not clear.

It is well known, however, that any marginal distribution can be approximated by a normal distribution by allowing for sufficient nonlinearity in its expected value (Lee, 1982). For the purpose of recovering consistent estimates of the probability that collateral is provided, I accordingly approximate the marginal distribution of borrowing from the informal sector by a normal distribution, whose expected value is a function of all the variables which affect demand and the cost of credit from both the formal and informal sectors, the squared value of all these variables, and a number of interaction terms [14]. This 'reduced form' equation serves to control for the choice-based nature of the sample used to predict the probability that collateral is provided. Since the set of regressors included in this equation affect the probability of being in the informal sector through the demand

[13] My thanks to an anonymous referee for pointing this out.

[14] The set of regressors in this equation is as follows: Formal interest rate, land, irr, plots, *V* pop, *F* yield, road, Msoon80, Msoon79, males, Bkcred81; squared values of all these variables; interactions of land with males, Bkcred81, road, *V* pop, interest rate; an interaction of *V* pop with road; interactions of interest rate with *F* yield, Bkcred81, irr; interactions of Bkcred81 with road, *F* yield, irr; and an interaction of irr with *F* yield.

for credit as well as the costs of both informal and formal credit, no attempt is made to interpret the coefficients in this equation, or to relate them to those of the underlying equations recovered in the 'full' empirical model, to be estimated later in this paper.

Given the two normal marginal distributions, the joint distribution of the probability of borrowing from the informal sector and the household offering security is then assumed to be bivariate normal and is estimated using data on the full sample of 2415 households [15]. Since the probability of borrowing from the informal sector reflects the costs of formal credit (besides variables affecting demand and the costs of informal credit), variables reflecting this cost (interest rate, Bkcred81), as well as the nonlinear terms required to approximate the 'true' distribution, serve to distinguish this equation from the equation specifying the probability that the contract requires collateral.

The unconditional probability that an informal contract requires collateral is then recovered from the estimates of the joint distribution. The estimates of this unconditional probability are used to generate estimates for the full set of sample households and these are included in the set of regressors in the specification of informal sector costs. Since the unconditional probability is estimated as a function of regressors which also directly enter the informal sector equation, the informal sector supply schedule is identified through nonlinearities alone. The inclusion of an estimated variable in the second stage regression requires a correction in the standard errors. This was done following standard procedures (Murphy and Topel, 1985).

A final issue which needs to be addressed relates to the measure of the formal sector interest rate (interest rate). As indicated in Eq. (4), the probability that a household demands formal credit, as well as the probability of access to such credit and the probability that formal credit costs less than informal credit, will depend on the formal sector interest rate. As noted earlier, this interest rate is fixed by the government. However, the stipulated rate varies across households primarily by geographic region, by the type of investment financed, and by farm size. The variable used in the empirical analysis is therefore the predicted interest rate from a regression of reported formal sector rates on a set of 82 dummy variables, reflecting the agroeconomic 'stratum' in which the household resides and the amount of land owned by the household [16]. This regression explains almost all the variability in the formal sector interest rate ($R^2 = 0.95$).

The sample used for this regression is the set of formal borrowers from among the full set of 7053 households in both the 'central' and the 'state' subsamples of

[15] In the interests of brevity, the results from this regression are not reported, but are available from the author by request. The log likelihood of the bivariate probit regression is −596.8 with 2368 degrees of freedom.

[16] Interest rate regressions (Kochar, 1991) reveal that the household's land holding is the only household-level variable which has a significant effect on formal sector interest rates.

the survey. Data from the full survey is used since in the 'central' subsample, which is used for the major empirical analysis of this paper, households in ten strata report no formal loans. Given that most of the variation in the interest rate is explained by the strata dummy variables, predicting interest rates for nonborrowers on the basis of observed interest rates in this smaller sample would require strong assumptions. In contrast, every stratum in the full survey has some households who report borrowing from the formal sector.

Since formal sector interest rates are set by the government and display little covariation with observed household characteristics, there is less possibility of biased estimates due to sample selection, than was the case in predicting the variable 'security'. Nevertheless, possible sample selection bias should properly be controlled for by modeling the probability of being in the formal sector. Such an analysis, however, is not possible since many of the variables which determine the demand and supply of credit, such as the extent of plot fragmentation and the amount of irrigated land, are not available for households in the 'state' subsample which are included in the interest rate equation. The need for such a correction can be gauged, however, by estimating a selectivity corrected regression equation on the interest rates reported by formal borrowers in the central sample [17]. This regression yielded an insignificant coefficient on the inverse Mills' ratio (coefficient value = 0.6147, t ratio = 1.2). This result suggests that sample selection bias in the estimation of the formal sector interest rate may be small, a finding which accords with the fact that interest rates are fixed by the government and vary little with observed household characteristics.

6.1. Univariate probit model of access to formal credit

The first model estimated (Model I) follows the conventional literature (Iqbal, 1981) by assuming the probability of borrowing from the formal sector to be determined exclusively by the bank's decision on access. This probability is represented by a univariate normal distribution representing the access equation in Eq. (4). This model assumes that all households demand formal credit at the existing interest rate, and that the formal sector is the cheapest source of credit for all households.

A possible reason for the popularity of Model I in the empirical literature is that this specification yields results which conform to theoretical predictions. This remains true of the estimates reported in Table 4. Since the probability of access is determined by the reservation cost of formal credit, variables affect this probability

[17] This selection correction term, the inverse Mills' ratio, is estimated on the basis of a probit regression on participation in the formal sector. The set of regressors is identical to that used to estimate the probability of being in the informal sector to correct selection bias in the security variable, as discussed earlier.

Table 4
Probit model of access to formal credit (model I)

Variable	Coefficient	Standard error
Constant	−0.8785[a]	0.0302
Interest rate	0.0929[a]	0.0362
Land	0.0740[a]	0.0333
Irr	0.1103[a]	0.0342
Plots	−0.0217	0.0319
V pop	0.0662[a]	0.0300
Bkcred81	0.0830[a]	0.0372
F yield	0.1060[a]	0.0474
Msoon79	0.0576[b]	0.0339
Msoon80	−0.1147[b]	0.0372
Road	−0.1508[a]	0.0405
Pr (access)	0.1900	0.0082
Log likelihood	−1152	
Sample size	2415	

[a]Significant at 5% level.
[b]Significant at 10% level.
Regressions are run on standardized data. Standard error for predicted probability is derived from a first order Taylor expansion of the relevant function around the estimated value.

in the same way as they affect loan supply. Thus, an increase in the formal sector rate increases the probability of access, or, equivalently, reduces the amount of rationing by this sector. Similarly, the household's ownership of land and its holdings of irrigated land increase the probability of access. Of district level variables, access is a positive function of total bank credit to all sectors (Bkcred81), thereby confirming that banks are effectively constrained by the requirement that they devote a stipulated percentage of their portfolio to the agricultural sector. Access also varies positively with levels of regional productivity (*F* yield), but negatively with the length of concrete road in the district (road). The latter may reflect levels of urbanization rather than differences in levels of rural infrastructure since highly urbanized districts have more concrete roads.

Estimates of the model predict a high degree of rationing by the formal sector. Evaluating the probability of access at the mean levels of the explanatory variables, 81% of rural cultivator households are estimated to be rationed out of the formal sector. The validity of this estimate, as well as the consistency of the coefficients of the access equation, however, are conditional on the validity of this simple selection rule which generates the sample of formal sector borrowers. I test this model against the more general bivariate model below.

6.2. Bivariate probit model of demand and access to formal credit

The second model (Model II) generalizes Model I by specifying the probability of borrowing from the formal sector as a bivariate normal, jointly determined by

the demand for credit and the bank's decision on access. The model relaxes one of the assumptions imposed in Model I, i.e., the assumption that all households demand formal credit. However, it maintains the assumption that the formal sector is a cheaper source of credit than the informal sector for all households.

The hypothesis that all households demand formal credit can be verified by testing Model II against Model I. Since the models are nonnested, conventional tests based on the value of the likelihood function cannot be used in selecting between the two [18]. Instead, I use nonparametric goodness-of-fit tests based on the ability of the models to predict the probability of borrowing from the formal sector. The two test statistics used are the χ^2 statistic, corrected for the error introduced by using estimated parameter values in its calculation (Heckman, 1984) and the Leamer-Schwarz metric. This metric, in contrast to a statistic based on the comparison of likelihood values, provides a means of model selection which penalizes the likelihood for the number of parameters that are estimated [19]. Both criteria support the selection of Model II over Model I, confirming the importance of demand considerations in the estimation of sectoral choice probabilities.

Estimates of the equations underlying the probability of demanding credit and access to formal credit generated by Model II are in Table 5. The separation of demand and supply yields considerable differences in the access equations generated under Model I assumptions and Model II. Interest rates have a marginally negative effect on demand probabilities, and allowing for this results in a stronger effect of interest rates on access than obtained in the simple probit model. The household's ownership of land and irrigated land increase the demand for loans, while their effect on access to bank credit is positive but statistically insignificant. In contrast to the estimates obtained from the simple probit model, the bivariate estimates suggest that access to bank loans is determined primarily by regional measures such as F yield, road and Bkcred81. Thus, the set of variables used by the formal sector in making its access decisions differs considerably from those determining the household's demand for credit.

This difference in the set of determinants of the household's demand for credit and the bank's decision on access suggests that some large farm households in backward regions where average productivity is low, who may nevertheless be viable borrowers, may have their loan applications rejected by the bank. Besides those households who are denied access to credit, nonborrowers will also include small farm households and farms with low levels of productivity (irr) who do not

[18] Model II is reduced to Model I at a correlation coefficient equal to 1. Conventional tests, however, cannot be applied at the boundary of the parameter space.

[19] The Leamer-Schwarz criterion is given by: [log likelihood-(ln N)k/2] where N is the sample size and k is the number of parameters estimated. This was estimated at -1171 for Model I and -1167 for Model II, whereas the corrected χ^2 statistic was 0.0026 for Model I and 9.72×10^{-5} for Model II. Imposing some of the exclusion restrictions suggested by the results in Table 5 considerably strengthens the case for Model II.

Table 5
Bivariate probit model of demand and access (model II)

Variable	Demand		Access	
	Coefficient	Standard error	Coefficient	Standard error
Constant	−0.2813	0.4765	−0.6414[a]	0.1101
Interest rate	−0.0045	0.1005	0.1224[a]	0.0559
Land	0.6986[a]	0.3562	0.0378	0.0396
Irr	0.4144[a]	0.2143	0.0121	0.0453
Plots	0.0224	0.1256	−0.0791[b]	0.0522
V pop	0.1470[b]	0.0951	0.0217	0.0488
F yield	−0.1893	0.2309	0.3165[a]	0.1074
Road	−0.0229	0.1095	−0.2565[a]	0.0743
Msoon80	−0.1323	0.1080	−0.1131[b]	0.0695
Msoon79	–	–	0.1308[a]	0.0612
Males	0.1364[b]	0.0873	–	–
Bkcred81	–	–	0.1192[a]	0.0674
Pr (demand)	0.3893	0.1827		
Pr (access)	0.2606	0.0358		
Pr (access|demand)	0.6042	0.1722		
Correlation coefficient	0.8736			
Log likelihood	−1130			
Sample size	2415			

[a]Significant at 5% level.
[b]Significant at 10% level.
Estimates of this model including the variable Msoon79 in the demand equation found the likelihood to be maximized with the coefficient on Msoon79 in the range of 0.005–0.08. Within this range, the likelihood equation was maximized at a correlation coefficient insignificantly different from 1, with the value of Msoon79 in the demand equation insignificantly different from zero. Convergence at $r = 1$ for certain parameter values is a common problem in such models (Goldfeld and Quandt, 1978). The model was therefore estimated by excluding Msoon79 from the demand equation. Standard errors are corrected for the use of an estimated variable. Standard errors on predicted probabilities are derived from a first order Taylor expansion of the relevant function around the estimated values.

apply for bank loans, yielding the heterogenous population of nonborrowers found in the data.

A major difference between the two models lies in their predictions of the extent of formal sector rationing and the demand for credit. Model II estimates the probability of borrowing from the formal sector, given by the joint probability of demand and access, to be 23.52%. The separate estimates of the demand and access equations suggest that access to the formal sector is more limited than demand for formal credit. The probability of access to the formal sector, evaluated at the mean levels of the explanatory variables, is only 26.06%. The probability of a household demanding formal sector credit, however, is also low at 38.93% (Table 5).

Due to this low demand for formal credit, the two models differ sharply in their predictions of the extent of effective rationing practiced by the formal sector.

Under Model II assumptions, such rationing is determined by the conditional probability of access, given that a household demands a loan. Evaluated at the mean value of variables, this is estimated at 60.42%, with the implication that of households that demand formal sector loans, the majority obtain them. Thus, while access to the formal sector is constrained, it is not as restrictive a constraint as suggested by a univariate probit model, which estimates that only 19% of the households which demand credit have access to the formal sector.

This difference in the extent of effective formal sector rationing carries important policy implications. It suggests that observed low levels of participation in the formal sector may primarily reflect a lack of demand for credit due to low agricultural productivity. Thus, policy interventions in other markets may increase credit disbursals to a greater extent than credit market interventions. For example, land reform which consolidates land holdings and increases farm size may substantially increase the demand for credit. The difference in the estimates of the reservation demand rate and the cost of formal credit also suggests that banks face significant informational problems and there is scope for increasing credit disbursals through the correct identification of viable borrowers.

6.3. Trivariate probit model of demand, access to formal credit and costs of informal credit

The theoretical model suggests that credit outcomes reflect not just household demand and formal sector supply decisions, but also the household's choice between the two sectors. The estimation of this model, specified in Section 5, presents significant computational problems, due to the combination of bivariate and trivariate distributions in the likelihood function. To circumvent such problems, in this section I use an alternative estimation strategy based on a one-factor specification of the error structure of the model.

A one-factor scheme specifies the correlation between the random variables u_i, $i = 1$ to 3, as a random variable v, which could be a vector, and is common to all three equations. Thus, the random error term u_i for household j is specified as:

$$u_{ij} = \Gamma_i v_j + e_{ij},\ i = 1 \text{ to } 3,\ j = 1 \text{ to } N, \tag{7}$$

where the e_{ij} are random variables which are independently and identically distributed across i and j. Instead of assuming a specific parametric functional form for the mixing distribution $f(v)$, this distribution is jointly estimated along with the parameters of the kernel distribution by maximum likelihood techniques. Heckman and Singer (1984a,b) show that for fixed parameters and a finite sample, when the kernel distribution is a bounded function of the unobservables v, the MLE of the mixing distribution is a finite mixture with relatively few points of support. Their empirical analysis showed the nonparametric MLE to produce good estimates of the structural parameters of the kernel distribution, though not of the unobservable v. However, the estimated values of the two distributions together

Table 6
One-factor estimation of model III

Variable	Demand	Formal access	Informal access
Interest rate	−1.4665[a] (0.3929)	0.6216[a] (0.2115)	2.3915[a] (1.0479)
Land	1.1826[a] (0.4748)	0.3668[b] (0.2417)	0.5899 (0.5278)
Irr	2.9364[a] (0.9366)	0.1390 (0.1574)	−0.2912 (0.4814)
Plots	−0.5186[a] (0.2038)	0.0253 (0.1043)	0.0506 (0.2576)
V pop	1.2912[a] (0.4909)	0.0275 (0.0794)	0.4111 (0.3069)
F yield	0.6840[a] (0.3376)	−0.5857[a] (0.3175)	−7.1424[a] (2.3709)
Road	0.6651[a] (0.3159)	−0.2525[a] (0.1272)	4.5539[a] (1.2306)
Msoon79	0.1588 (0.2075)	0.1647[b] (0.1217)	−1.1255 (1.3772)
Msoon80	0.4085[a] (0.2439)	−0.6629[a] (0.2515)	−1.6624[a] (0.7936)
Males	0.1942 (0.1933)	–	−0.6035[a] (0.2635)
Bkcred81	–	0.3782[a] (0.1413)	–
Security	–	–	3.7213[a] (1.3792)
Parameters of mixing distribution			
v_1	−6.4903[a] (2.1185)		
v_2	4.1548[a] (1.1629)		
Γ_2	0.1359 (0.1086)		
α_2	0.0902 (0.4908)		
Γ_3	−0.8981[a] (0.3996)		
α_3	−4.2913[a] (1.5438)		
p_1	0.6106[a] (0.1762)		
Pr (access)	0.4006 (0.2141)		
Pr (demand)	0.3519 (0.1762)		
Pr (formal cheaper)	0.3922 (0.1935)		
Pr (access|demand, formal cheaper)	0.7438 (0.1267)		
Log likelihood	−1080		
Sample size	2415		

[a]Significant at 5% level.
[b]Significant at 10% level.
Figures in brackets are standard errors. Standard errors are corrected for the use of estimated variables. Standard errors on predicted probabilities are derived from a first order Taylor expansion of the relevant function around the estimated values.

did produce good predicting equations. Additional Monte Carlo evidence supporting the performance of these estimators is in Mroz and Guilkey (1991).

The likelihood of this model (Model III) is in Appendix A, and estimates are in Table 6. The scaling factor on the coefficients is now given by the standard deviation of the random variable e_i in Eq. (7), which differs from the model specified in Section 5 where the parameters were scaled by the standard deviation of the error term u_i. Thus, while the predictions of this model are comparable to those of the previous two models, the coefficients differ from those obtained in the univariate and bivariate models discussed above.

Since this model differs from Model II in that it relaxes the assumption that the

formal sector is always the cheaper source of credit, a test of this model against Model II provides a test of this assumption. While there is no significant difference in the corrected χ^2 statistic, the Leamer-Schwarz statistic for Model III is -1145 as compared to -1167 for Model II [20]. Thus, there is evidence supporting the hypothesis that access to informal credit plays a role in determining participation in the formal sector.

The estimates of the model suggest that the majority of farm households (61%) face a lower reservation cost of credit in the informal sector [21]. While the demand for credit is still low at 35%, access to formal credit is estimated to be higher (40%). As a result, the probability of access to credit conditional on the household's demand for credit and choosing the formal over the informal sector increases to 74%, suggesting a considerable reduction in the degree of effective rationing.

6.4. Extending the empirical model to allow for an effect of formal loans on the cost of informal credit

As noted in Section 4, if informal lenders have priority over formal lenders, any formal loan the household acquire may lower the risk costs faced by informal lenders and, correspondingly, the cost of informal credit for such households. If so, the demand for formal credit will reflect, in part, the effect of formal loans on informal interest rates. This section considers the implications of such a link between the two sectors, should it exist, for the probability of borrowing from the formal sector and for the empirical results of the previous subsections.

As before, the probability of a household borrowing from the formal sector is determined by its demand for formal credit, its access to the formal sector, and the probability that the reservation cost of credit for the formal sector is less than that of the informal sector. Access to formal credit is unaffected by any effect of formal credit on informal sector costs. However, this is not true of either the demand for formal credit or the reservation cost of informal credit.

The household, in making its loan decisions, now distinguishes between the optimal informal loan (B_i^*) and the optimal formal loan (B_f^*), with the cost of informal credit varying not just with the amount of the informal loan but also with the formal loan amount. The informal interest rate is thus specified as $r_i(B_i, B_f)$, where r_i is a positive function of B_i, but a negative function of B_f. While the formal sector still offers credit at the fixed interest rate r_f, the effective cost of formal credit to the household is now reduced due to the negative effect of formal

[20] The one-factor estimation of Model II yields an even lower Leamer-Schwarz statistic of -1171.

[21] This does not imply that informal costs are consistently lower. Informal costs may be rising rapidly with loan amounts so that they exceed the formal interest rate at some relatively low amount. However, formal sector constraints will still bind only if the demand for credit is sufficiently high. Results from both Model II and Model III suggest that the demand for credit is low.

loans on informal credit. The household takes this effect into account, so that, corresponding to Eq. (4), it demands formal credit if:

$$\mathrm{MR}(B_f = 0, B_i^*) \leq r_f + \frac{\partial r_i}{\partial B_f}(B_i^*, B_f = 0) B_i^*. \tag{8}$$

Given the effect of formal loans on the cost of informal credit, the reservation cost of informal credit will also be a function of the formal loan obtained by the household (B_f^*). The probability that the reservation cost of formal credit is less than that of informal credit is thus given by:

$$\Pr(r_f < r_i(0, B_f^*)). \tag{9}$$

As Eqs. (8) and (9) made clear, the empirical implications of a link between formal credit and the cost of informal credit depend on whether formal sector borrowers demand informal credit. If formal sector borrowers choose not to borrow from the informal sector ($B_i^* = 0$), the major difference between this model and the empirical model of the paper is that the probability that the reservation cost of formal credit is less than that of informal credit in Eq. (9) will be a function of the household's formal loan. If this equation is specified in reduced form, as is done in this paper, it cannot be interpreted as the reservation cost of informal credit. It is also necessary to include all the determinants of the formal sector access equation, particularly the variable Bkcred81, in the informal sector equation. The reduced form system is still identified by the variables reflecting sector-specific costs. Thus, the indicator of the risk costs of informal credit (security) affects the household's choice of the formal sector over the informal sector (Eq. (9)), but not the demand for credit or access to the formal sector, while the bank's total credit disbursements to all sectors (Bkcred81) affect access but not demand. Conversely, if the optimal informal loan for formal borrowers (B_i^*) is strictly positive, and if formal credit reduces the cost of informal credit, the full empirical model cannot be identified. It would then be necessary to confine the analysis to the set of formal borrowers for whom $B_i^* = 0$.

In the AIDIS data used in this paper, the restriction that $B_i^* = 0$ holds for the majority of formal sector borrowers, with only 13% of formal borrowers (or 8% of all borrowers) also reporting informal loans. Given this, the econometric model can be extended to incorporate the possibility that formal credit affects the cost of informal credit as outlined above. The full model (Model III) was reestimated including the variable Bkcred81 in the informal sector equation. This estimation yielded a negative coefficient on Bkcred81 which is statistically insignificant at conventional testing levels (coefficient value = -0.72, t ratio = -1.4). A more thorough analysis of the relationship between formal and informal credit is, however, clearly warranted. This would require better data on the costs of informal credit than is currently available.

7. Conclusion

It is generally believed that the Indian government's policy of a fixed and relatively low interest rate has resulted in the considerable rationing of formal credit, with the majority of rural households being denied access to such credit despite their demand for it. While this assumption has influenced both academic research and government policy, it has not been rigorously tested. This paper calls into question the validity of these assumptions.

The empirical analysis of this paper is based on a model of credit market outcomes which yields the probability of borrowing from the formal sector as a function of the household's demand for credit as well as the reservation cost of borrowing from both the formal and informal credit sectors. It is worth emphasizing again that the interpretation of the coefficients of these equations as parameters of the underlying reservation cost schedules depends on the validity of the structural model and on the number of assumptions underlying the empirical model of this paper, particularly with respect to the informal sector. Better data on informal transactions than those currently available will allow some relaxation of these assumptions and may lend themselves more readily to structural interpretations.

Rather than concentrate on the structural interpretations of the estimated coefficients, I focus instead on the predictions of the model, particularly the estimates of the probability of demand and access to both formal and informal sources. The estimates of both the relatively general model which ignores the informal sector (Model II) and the model which allows households a choice between the two sectors (Model III) suggests that the demand for credit is low. Given this, the role of credit in enhancing levels of agricultural development may be limited. This hypothesis is increasingly suggested by other researchers (Bell, 1990). This paper provides empirical support for this claim.

The results of this paper also support the hypothesis that the reservation cost of informal credit may be less than that of formal credit for some households, further reducing the extent of effective formal sector rationing. However, additional data on informal credit transactions and on lender characteristics, in particular, are necessary to conclusively establish this hypothesis.

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Appendix A

A.1. The likelihood for the partial observability model of credit outcomes

The likelihood function for the model of Section 4 is specified here, with sectoral outcomes being generated according to Eq. (5). Since identification of all the elements of the variance matrix is not possible, this matrix is specified as:

$$\sum_u = \begin{bmatrix} 1 & \sigma_{12} & \sigma_{13} \\ \sigma_{12} & 1 & \sigma_{23} \\ \sigma_{13} & \sigma_{23} & \sigma_3^2 \end{bmatrix}.$$

Let $u_4 = u_1 + u_3$, so that $\sigma_4^2 = (1 + \sigma_2^3 + \sigma_{13})$. Define the random variable y_i, $i = 1$ to 3, as: $y_1 = 1$ if borrows from formal, otherwise 0; $y_2 = 1$ if borrows from informal, otherwise 0; and $y_3 = 1$ if nonborrower, otherwise 0.

Using Eq. (3) and assuming normally distributed error terms, the log likelihood of the sample is:

$$\begin{aligned} \ln L = \sum_1 \big[& y_{1i} \ln \Phi_{1,2,-3}(h_1, h_2, -h_3) + y_{2i} \ln\big(\Phi_{3,4} + \Phi_{2,3,-4} \\ & \times(-h_2, -h_3, h_4)\big) + y_{3i} \ln\big(1 - \Phi_{1,2,-3}(h_1, h_2, -h_3) \\ & - \Phi_{3,4}(h_3, h_4) - \Phi_{2,3,-4}(-h_2, -h_3, h_4)\big)\big], \end{aligned} \tag{A1}$$

where $\Phi_{i,j,-k}$ is the standardized multivariate normal distribution function of the random variables $(u_i, u_j, -u_k)$, and the h_i, $i = 1$ to 4, is defined: $h_1 = X_1 \beta_1 - r_f$, $h_2 = X_2 \beta_2 + r_f$, $h_3 = (X_3 \beta_3 + r_f)/\sigma_3$, and $h_4 = (X_1 \beta_1 + X_3 \beta_3)/\sigma_4$.

The likelihood function reflects the fact that observed outcomes are optimally chosen by some households, whereas others make constrained choices because of formal sector rationing.

A.2. The likelihood of the one-factor specification of the model

The distribution of the random variable v in Eq. (7) is specified as a discrete distribution, with v taking on one of k values with probability p_k. The probability of borrowing from the formal sector, conditional on X and v, is then given by [22]:

$$\begin{aligned} & f\big(e_1 > -(\alpha_1 + X_1 \beta_1 - r_f + \Gamma_1 v),\ e_2 > -(\alpha_2 + X_2 \beta_2 + r_f + \Gamma_2 v), \\ & \quad e_3 < -(\alpha_3 + X_3 \beta_3 + r_f + \Gamma_3 v)\big). \end{aligned} \tag{A2}$$

[22] Conditioning on X and v is suppressed for notational simplicity.

By integrating out the unobservable v, we obtain the probability conditional on the observables X alone. Recognizing that the random variables e_i are independently distributed, obtains:

$$\sum_k f(e_1 > -(\alpha_1 + X_1\beta_1 - r_f + \Gamma_1 v_k)) f(e_2 > -(\alpha_2 + X_2\beta_2 + r_f + \Gamma_2 v_k)) f(e_3 < -(\alpha_3 + X_3\beta_3 + r_f + \Gamma_3 v_k)) p_k. \quad \text{(A3)}$$

If the e_i are assumed to be normally distributed with variance covariance matrix:

$$\Sigma_e = \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & \sigma_3^2 \end{bmatrix},$$

the log likelihood of the model is given by:

$$\ln L = \sum_i y_{1i} \ln(\Phi_{21}) + y_{2i} \ln(\Phi_{22} + \Phi_{23}) + y_{3i} \ln(1 - \Phi_{21} - \Phi_{22} - \Phi_{23}), \quad \text{(A4)}$$

where y_i, $i = 1$ to 3, is as defined earlier, and:

$$\Phi_{21} = \sum_k \Phi(\alpha_1 + X_1\beta_1 - r_f + \Gamma_1 c_k)\, \Phi(\alpha_2 + X_2\beta_2 + r_f + \Gamma_2 v_k) \times \left(1 - \Phi \frac{(\alpha_3 + X_3\beta_3 + r_f + \Gamma_3 v_k)}{\sigma_3}\right) p_k,$$

$$\Phi_{22} = \sum_k \Phi\left(\frac{(\alpha_1 + \alpha_3) + X_1\beta_1 + X_3\beta_3 + (\Gamma_1 + \Gamma_3) v_k}{\sqrt{(1 + \sigma_3^2)}}\right) \times \Phi \frac{(\alpha_3 + X_3\beta_3 + r_f + \Gamma_3 v_k)}{\sigma_3} p_k,$$

$$\Phi_{23} = \sum_k \Phi\left(\frac{(\alpha_1 + \alpha_3) + X_1\beta_1 + X_3\beta_3 + (\Gamma_1 + \Gamma_3)}{\sqrt{(1 + \sigma_3^2)}} \times (1 - \Phi(\alpha_2 + X_2\beta_2 + r_f + \Gamma_2 v_k))\right) \times \left(1 - \Phi \frac{(\alpha_3 + X_3\beta_3 + r_f + \Gamma_3 v_k)}{\sigma_3}\right) p_k.$$

To achieve identification, Γ_1 is set equal to 1 and the constant in the first equation, α_1, equal to zero. Estimation of this model thus recovers nonlinear

functions of the parameters of the mixing distribution $f(v)$, while the parameters of the kernel distribution, β_i, are estimated up to a factor of proportionality.

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