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Risk, Credit Constraints and Financial Efficiency in Peruvian Agriculture

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ABSTRACT *Based on a panel data set, we use a two-stage analysis to evaluate the effects of access to formal credit on financial efficiency of farms in northern Peru. The first stage uses non-parametric data envelope analysis to estimate farm-specific measures of financial efficiency; 28 per cent of farmers are financially inefficient and credit constraints reduce profits of these farmers by an average of between 17 and 27 per cent. The second stage uses Tobit regression to evaluate the determinants of financial inefficiency; the results point to uninsured risk as a key determinant of financial inefficiency and suggest that policies to strengthen agricultural insurance markets would likely pay large dividends in rural Peru.*

I. Background

Expanding smallholder access to formal credit markets remains a high priority for policy makers in developing countries (World Bank, 2007: chap. 6). High yield and price risk, significant costs accruing from large distances and poor infrastructure, and long time lags between planting and harvest make the type of financial market deepening that has taken place in urban and semi-urban areas thanks to the microfinance 'revolution' much more challenging in rural areas. Just how severe are credit constraints facing smallholders? Unfortunately, empirical evidence quantifying the impacts of credit constraints on farm resource allocation is scarce. The evidence that does exist is troubling. Several recent papers have found that credit constraints among smallholder agriculture are widespread and indeed have significant adverse impacts on farm investment (Carter and Olinto, 2003), farm

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output (Feder et al., 1990; Sial and Carter, 1996; Petrick, 2004), farm profit (Carter, 1989; Foltz, 2004), and the efficiency of intra-household resource allocation (Fletschner, 2008).

This paper adds to the sparse empirical evidence by estimating the impact of credit constraints on farm profits using a panel data set of Peruvian farms. With the exception of Fletschner (2008), the authors cited above generate their impact estimates with parametric methods. In contrast, we follow the approach of Fare et al. (1990) and Blancard et al. (2006), and use non-parametric data envelope analysis (DEA) to estimate the size of foregone farm profits due to credit constraints. DEA offers two advantages. First, it does not impose a functional form on technology. This is especially important in our context of farmers with heterogeneous crop portfolios (Helfand and Levine, 2004). Second, it allows for a direct and intuitive measure of the impact of financial constraints on farm profits.

We proceed in two steps. In the first step, we use DEA to estimate a farmer-specific measure of financial efficiency. These estimates provide a direct measure of profit loss due to credit constraints. In the second step, we estimate a Tobit model of financial efficiency. We regress the first-stage financial efficiency measure against a set of variables hypothesised to affect the probability that farmers face a binding credit constraint, as well as their capacity to bring to bear resources when they face a binding credit constraint.

In our analysis, we incorporate recent innovations in the DEA literature to address the potential for biases due to influential outliers (Simar, 2003) and serial correlation across the efficiency measures (Simar and Wilson, 2007). Furthermore, we use a comprehensive definition of credit constraint that, following the theoretical argument of Boucher et al. (2008), includes demand-side manifestations of credit market imperfections. Specifically, we allow for three forms of non-price rationing in the credit market: quantity rationing, risk rationing and transaction cost rationing, each of which may reduce farmers' financial efficiency.

Finally, our survey permits us to directly observe the credit constraint status of each household and thereby avoid the overestimation of financial inefficiency characterising existing studies using the DEA approach. For example, since they do not observe the constraint status of individual farmers, Blancard et al. assume that 'the total expenditures over the accounting period indicate the maximum amount the farmer can spend on organizing production' (Blancard et al., 2006: 354). As acknowledged by the authors, this assumption is likely to overstate the degree of financial inefficiency: some farmers may be able to spend more but choose not to because they fail to identify the opportunity to enhance profit, perhaps due to lack of experience or managerial talent. We avoid this overestimation by classifying a farmer as financially inefficient only if he could have achieved higher profits by increasing expenditures *and* he was observed to be credit constrained.

The article is organised as follows. We start by presenting an expanded definition of non-price credit rationing and the methodology we use to identify farmers' credit rationing status. We then explain the approach we use to generate the farmer-specific efficiency measures and how it differs from current approaches in the literature. We describe the context in which rural farms operate in Peru, the data we employ, and how we specify our linear programming model. We discuss the results from the DEA analysis and our estimates of the profit loss associated with credit constraints.

We explore this further with a parametric analysis to identify factors associated with the extent of financial inefficiency. Finally, we conclude by providing policy recommendations.

II. Non-Price Rationing in Credit Markets: Definition and Measurement

The empirical analysis is based on a concept of *non-price rationing* that goes beyond conventional quantity rationing to include demand-induced withdrawal from credit markets as a result of transaction costs and risk, as explained below. The direct elicitation survey methodology is then briefly described, which permits us to directly distinguish farmers that are constrained from those that are unconstrained in the formal credit market.

Multiple Manifestations of Credit Constraints

High degrees of risk, combined with poorly defined property rights and lack of information infrastructure imply that rural credit markets in developing countries are likely to leave many farmers constrained. Beginning with the seminal work of Stiglitz and Weiss (1981), a long theoretical literature demonstrates that the moral hazard and adverse selection problems endemic to credit transactions may lead to quantity rationing, whereby lenders refuse to raise the interest rate to eliminate excess demand. In an agricultural context, a quantity rationed farmer is denied access to his desired amount of credit and, as a result, is unable to apply the profit maximising level of inputs.

Quantity constraints are thus a supply-side manifestation of asymmetric information. Several recent papers have pointed out that the same underlying information problems can also reduce participation in credit markets by restricting farmers' demand (Boucher et al., 2008; Guirkinger and Boucher, 2008). The key insight is that lenders' responses to asymmetric information go beyond the decision of whether or not and how much to lend. As described by Hoff and Stiglitz (1990), lenders have two additional means of responding to information asymmetries. On the one hand, they may directly attack information asymmetries by screening applicants and monitoring borrowers. While these actions may help lenders avoid granting loans to undesirable 'types' and provide borrowers with the incentives to avoid undesirable 'actions', they also may imply significant monetary and time costs for the borrower. A farmer is *transaction cost rationed* if the non-interest monetary and time costs associated with application for and administration of loans are sufficiently large that they lead a farmer to refrain from borrowing.

On the other hand, lenders may indirectly address incentive problems by requiring that borrowers post collateral. Perhaps the most obvious impact of collateral requirements is that they can lead to quantity rationing; farmers lacking assets of sufficient quantity or quality are excluded from collateral-based contracts. As demonstrated by Boucher et al. (2008), collateral requirements may lead to another form of non-price rationing that they call risk rationing. A farmer is *risk rationed* if he has access to an expected income enhancing credit contract but does not take it because the collateral requirement implies that he bear too much risk. Risk rationing in developing country agriculture may be particularly problematic because of the almost complete absence of formal risk management tools such as crop and health insurance.

Identifying Credit Rationing Status: The Direct Elicitation Approach

Each form of non-price rationing (quantity, transaction costs, and risk) has similar implications for farm resource allocation; namely that investment and expenditures are reduced and profits are foregone. Any empirical evaluation of the performance of the credit market should thus account for all forms of credit constraints, whether they derive from the supply side (quantity rationing) or the demand side (transaction cost and risk rationing). The Peru survey instrument employed a direct elicitation approach which allows us to directly observe whether or not a farmer is constrained and, if so, which non-price rationing mechanism is at play.[1] This approach utilises a combination of observed outcomes and qualitative questions. First, households are separated into those that applied versus those that did not apply for a loan. The rationing category of these households is determined based on the observed outcome of the application: rejected applicants are quantity rationed (constrained), while those whose application was approved are price-rationed (unconstrained).

Identifying the constraint status of non-applicants is more challenging because this group likely contains highly heterogeneous individuals including: (a) those who do not want a loan because they have no profitable project requiring external funds; (b) those who want the types of loans available to others but do not apply because they are certain to be rejected; and (c) those who believe they indeed qualify for a loan but are dissuaded from applying by either the transaction costs or risk associated with available contracts. Classification of these individuals thus requires an understanding of the reasons underlying their lack of effective demand. Non-applicants are first asked whether or not any lender would offer them a loan if they were to apply. If yes, they are then asked why they did not apply. Those saying they have sufficient liquidity or that the interest rate is too high (relative to their farm opportunities) are classified as price-rationed (unconstrained). Non-applicants who state that the time, paperwork and fees of applying are too costly are classified as transaction cost rationed (constrained); while those who cite fear of losing land pledged as collateral are classified as risk rationed (constrained). Finally, individuals who state that no lender would offer them a loan are asked whether or not they would apply for a loan if they were certain that a bank would approve their application. Those who say yes are classified as quantity rationed (constrained). Those who say no are then asked why not, and their answers are used to classify them as above.

The result of the direct elicitation methodology is that each household is classified as either constrained or unconstrained in the credit market. Farmers in the unconstrained group are assumed financially efficient; their terms of access to the formal credit market do not reduce their expenditures relative to the profit maximising level. Farmers in the constrained group, in contrast, are candidates for financial inefficiency. Members of this group are financially inefficient if the DEA framework described in the next section reveals that an increase in expenditures could increase their profit.

III. The Impacts of Credit Constraints on Farm Efficiency: DEA Framework

This section first reviews the various concepts of efficiency that we employ to evaluate the impacts of credit constraints and presents how DEA enables us to generate farmer-specific measures of efficiency. We also discuss how we incorporate farmers' directly elicited credit constraint status into the analysis.

Financial Efficiency: Conceptual Framework

Figure 1 gives a graphical representation of a simple technology with one input and one output. The points represent observed input-output mixes of five hypothetical farmers. The concave curve represents the production frontier, that is, the maximum level of output that can be reached with a given level of input. All points on or below the frontier are thus in the production set. The parallel lines, whose slope is the ratio of input to output price, represent iso-profit contours, with movements to the northwest corresponding to increasing profits. We draw on this figure to illustrate the various efficiency concepts used in our analysis.

Overall efficiency is the ratio of the farmer's observed profit to the maximum profit that is attainable given his endowments of productive factors. Assume that all farmers represented in Figure 1 have the same endowments. The farmer at point A earns $\pi_{\max}$, the highest attainable profit. Therefore, his overall efficiency is equal to 1. All farmers not at point A obtain a lower level of profits and are thus, overall, inefficient.

Since our goal is to identify the portion of each farmer's overall inefficiency attributable to credit constraints, we follow Fare et al. (1990) and decompose overall efficiency into *financial efficiency* and *actual efficiency*. Financial efficiency is defined as the ratio of a farmer's highest attainable profit given his observed credit constraint status to the highest attainable profit if he were unconstrained. Actual efficiency, in turn, is the ratio of observed profit to the highest attainable profit given his observed credit constraint status. Consider the farmer at D. This farmer is actually inefficient. With the same level of input he could have moved to point C and obtained π_1

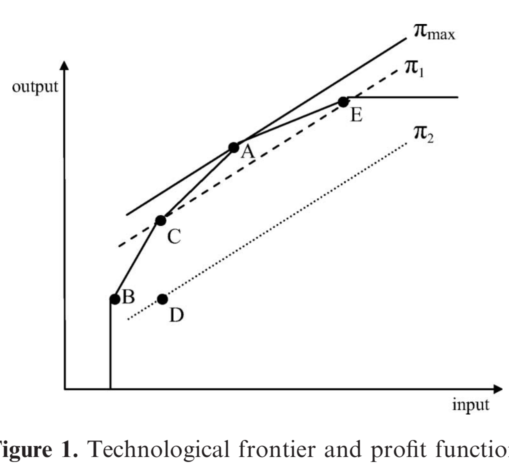

Figure 1. Technological frontier and profit function.

Increasing profits beyond π_1 requires additional expenditures. If credit constraints prevent him from realising these expenditures, the farmer at D is also financially inefficient. In this case, his financial, actual, and overall efficiency would be $\pi_1/\pi_{\max}$, π_2/π_1, and $\pi_2/\pi_{\max}$, respectively. It is important to note, however, that credit constraints are not the only potential explanation for why this farmer does not increase expenditures. Lack of experience or poor managerial skills may instead have led the farmer to erroneously identify the input level associated with point D as the profit maximising level. In this case, credit constraints are not the culprit of under-investment. As a result, actual efficiency would be equal to overall efficiency, both of which would equal $\pi_2/\pi_{\max}$.

Empirical Implementation

Generating the three efficiency indices described above for the j^{th} farmer requires calculating three profit levels: (1) the farmer's observed profit, π_j^O; (2) the farmer's highest attainable profit if he were unconstrained in the credit market, π_j^U; and (3) the farmer's highest attainable profit given his observed credit constraint status, π_j^C. If farmer j is unconstrained, π_j^U and π_j^C are the same. If, instead, farmer j is credit constrained, his expenditures are limited, and π_j^C will be lower than π_j^U. This can be the case if lenders refuse to lend to him or if he refrains from borrowing a larger amount because of the risk or transaction costs implied by the credit contract.

The first step in the analysis is to estimate the multivariate equivalent of the univariate input–output production set depicted in Figure 1. Recall that this production set gives all feasible production mixes for a farmer who is unconstrained in the credit market. Throughout the remainder of the analysis, vectors are denoted by bold type while scalars are denoted by italics. Suppose we have data from K farmers, each of whom has endowments of fixed inputs ($f^1 \ldots f^N$) and uses variable inputs ($x^1 \ldots x^M$) to produce outputs ($u^1 \ldots u^L$). Each of these observed input–output mixes belongs to the production set T, which is the set of input–output combinations that can be produced for a given level of endowments. Assuming the technology is convex, all linear combinations of the K farmers' observed input–output mixes also belong to the production set. The set of feasible input–output mixes for farmer j can thus be estimated as:

$$\hat{T}_j = \left\{ \begin{array}{l} (\boldsymbol{u}, \boldsymbol{x} | \boldsymbol{f}_j) \text{ such that} \\ \qquad \sum_{k=1}^{K} z_k u_k^l \geq u^l, \quad l = 1, \ldots, L; \\ \qquad \sum_{k=1}^{K} z_k x_k^m \leq x^m, \quad m = 1, \ldots, M; \\ \qquad \sum_{k=1}^{K} z_k f_k^n \leq f_j^n, \quad n = 1, \ldots, N; \\ \qquad \sum_{k=1}^{K} z_k = 1, \quad \mathbf{z} \in \Re_+^K \end{array} \right\}; \tag{1}$$

where the vector $\mathbf{z}$ is used to form linear combinations of the observed input–output mixes of all farmers. The linear program defined by Equation 1 gives the outputs, $\boldsymbol{u}$, that can be obtained (first constraint) with at least as many variable inputs as $\boldsymbol{x}$ (second constraint) given the j^{th} farmer's endowment of fixed inputs $\boldsymbol{f}_j$ (third constraint). The fourth constraint guarantees that the technology is convex and allows for constant, increasing and decreasing returns to scale.

Having estimated the unconstrained feasible set for each farmer, $\hat{T}_j$, we can now estimate the two remaining profit levels required for our efficiency measures. To do so, we first assume that all farmers face the same prices for outputs, $(p^1 \ldots p^L)$ and variable inputs, $(q^1 \ldots q^M)$. Our estimate of farmer j's maximum unconstrained profit, $\hat{\pi}_j^U$, is the solution to:

$$\hat{\pi}_j^U = \left\{ \begin{array}{ll} \max\limits_{u,x} \sum\limits_{l=1}^{L} p^l u^l - \sum\limits_{m=1}^{M} q^m x^m \\ \text{subject to} \quad (\boldsymbol{u}, \boldsymbol{x} | \boldsymbol{f}_j) \in \hat{T}_j \end{array} \right\} \tag{2}$$

Farmer j may not be able to attain this profit if the optimal unconstrained input–output mix implies expenditures greater than his observed expenditures. In order to generate $\hat{\pi}_j^C$, our estimate of farmer j's maximum attainable profit given his credit constraint status, we thus re-solve the optimisation programme in Equation 2 after adding the following constraint to Equation 1:

$$C_j * \sum_{m=1}^{M} q^m x_j^m \quad \leq \quad E_j, \tag{3}$$

where C_j takes value 1 if the farmer is observed to be credit constrained and zero otherwise. This additional constraint thus limits expenditures of constrained farmers to their observed level.

These three profit levels enable us to compute the following two efficiency measures for farmer j. We estimate his overall efficiency as:

$$\hat{O}_j = \frac{\hat{\pi}_j^O}{\hat{\pi}_j^U}. \tag{4}$$

His estimated financial efficiency is then:[2]

$$\hat{F}_j = \frac{\hat{\pi}_j^C}{\hat{\pi}_j^U}. \tag{5}$$

As such, farmer j is financially efficient if $\hat{F}_j = 1$.

The Value of Auxiliary Credit Market Information

As mentioned above, we address a limitation of existing DEA approaches by using the farmer's observed credit constraint status to estimate financial efficiency. Without this information, current approaches assume that a farmer's observed expenditures represent the maximum amount he could have spent. This assumption is likely to result in an overstatement of the impact of credit constraints on efficiency. To see this, consider a farmer at point C in Figure 1. The existing approach assumes that a binding credit constraint prevents this farmer from purchasing the additional inputs required to move to point A. Yet it is possible that this farmer was, in fact, unconstrained in the credit market but perhaps because of poor management skills, chose to produce at C. In this case, the assumption that observed expenditures equal maximum possible expenditures would incorrectly attribute the inefficiency to credit constraints. Our approach suggests instead that farmer j is financially inefficient only if he could have increased his profits by purchasing more inputs *and he was observed to be credit constrained*. If, for example, a farmer at C reports being non-price rationed, we estimate his financial efficiency as the ratio of π_1 to $\pi_{\max}$. If, instead, this farmer is unconstrained in the credit market, he would be financially efficient. In this case, the entire profit loss, $(\pi_{\max}-\pi_1)$, would be attributed to actual inefficiency.

In terms of Figure 1, use of directly elicited credit rationing information only affects the calculation of financial efficiency for farmers to the left of point A who report having adequate access to capital. For all other farmers, those who report being credit constrained or are to the right of point A, our efficiency estimates coincide with those calculated using existing approaches.

IV. Context, Data and DEA Model Specification

This section explains how we apply DEA to assess the efficiency of farmers in Peru. After describing our sample, we provide a general overview of credit markets in Piura and then specify the inputs and outputs used to characterise farmers in our model.

Sample Description

Our empirical analysis is based on a panel data set of 490 farmers interviewed in 2003 and 2004 in the department of Piura on Peru's north coast. The sample was drawn to be representative of farm households in Piura. This analysis focuses on households whose primary economic activity is growing crops. We thus exclude households with crop production of less than \$150 or which held more than five head of cattle in either survey year. Applying these criteria results in the exclusion of 118 households, leaving a potential sample of 372 households.[3]

Since the DEA methodology is sensitive to extreme values and outliers, it is important that the production frontier is not artificially 'pushed out' by farmers that are not comparable to the rest, either because they operate under a very different technology, not replicable by other farmers, or because of errors in the data. To address this issue, we follow the two-step, outlier detection methodology of Simar (2003). A detailed description of our implementation of this methodology is provided in the online appendix. The basic idea is as follows, in the first step, we use a bootstrap procedure to identify two types of potential outliers: (1) farmers who generate significantly higher profits than the next best farmer among those with equal or smaller endowments of fixed factors; and (2) farmers for whom there are very few sample farmers with equal or smaller endowments of fixed factors (and thus for whom we would have low confidence in the estimated technological frontier). In the second step, we examine the data associated with the farmers identified as potential outliers to check for inconsistencies that indicate data recording errors, data entry errors, or specificities in technology that make them non-comparable. Using this method, we detected nine outliers that we drop from the sample. The sample used in the remainder of this paper thus includes 363 farmers in each year.

Table 1 provides descriptive statistics of sample farmers for the two survey years. The mean farm size is just under four hectares. This relatively small farm size is typical of coastal Peru where the majority of irrigated land is controlled by *parceleros*, beneficiaries of the 1970s Agrarian Reform who subsequently disbanded and privatised the Agrarian Reform Cooperatives and *pequeños propietarios*, small landowners that historically co-existed alongside the *haciendas* and, subsequently, the Agrarian Reform Cooperatives. During the 1990s, the government implemented a large-scale land titling programme that significantly raised the fraction of farmers with a registered, private property title. In our sample, 68 per cent of farmers own at least one titled parcel. The majority of untitled parcels correspond to the *comunidades campesinas* (peasant communities) that only approved the move to private land in the late 1990s. At the time of the surveys, the titling programme had not yet reached all sectors within the *comunidades*. Farmers in Piura grow a mix of annual and perennial crops. Among sample farmers, rice, corn and cotton are the most common annuals, while bananas, lemons and mangos are the main perennials.

Description of Rural Credit Markets in Piura

The rural credit market in Peru has undergone significant changes in the last 15 years. Until 1992, the state-run Agrarian Development Bank (*Banco Agrario*) was the primary institutional source of agricultural credit. As part of a broader economic liberalisation programme, the government shut down the Agrarian Development

Table 1. Descriptive statistics of sample farmers

Characteristic	2003	2004
Mean farm size (ha.)	3.8	3.8
Percent with registered land title	68	68
Mean household size	5.4	5.5
Mean farmer age	56	57
Mean farmer education (completed years)	4.6	4.7
Per cent of households growing:		
Rice	59	57
Corn	30	38
Cotton	11	26
Other annual crop	15	20
Bananas	24	24
Lemons	14	14
Mangos	7	9
Other perennial crop	13	17

Bank in 1992, and eliminated interest rate controls. The government also promoted the establishment of rural banks (*cajas rurales*) and the strengthening of municipal banks (*cajas municipales*). These local banks are the primary formal financial intermediaries for small farmers in the post-liberalisation environment. Alongside this set of formal institutions, a vibrant informal credit sector coexists. Informal loans are primarily offered by local business owners, such as grain traders, rice mills and input supply stores.

The survey allows us to use the direct elicitation approach described above to classify each farmer as constrained or unconstrained in the formal credit market and, if constrained, to further identify whether the constraint derives from quantity, transaction cost or risk rationing. As a result, our empirical measure of financial inefficiency evaluates the profit loss due to the existence of constraints with respect to the *formal* credit sector.[4]

Table 2 gives the frequency of the credit constraints for each year. Approximately half of sample farmers were classified as unconstrained (price rationed) in the credit market in each year. Among unconstrained farmers, the fraction of borrowers increased slightly, from 28 to 31 per cent of the sample, while the fraction of non-borrowers fell from 26 to 15 per cent of the sample. Among the remaining half of sample farmers that were credit constrained, the relative frequencies of each type of non-price rationing was relatively stable. Risk rationing was the most common source of credit constraint in each year, increasing from 21 to 25 per cent of sample farmers. The fraction of farmers constrained by transactions costs also rose, from 12 to 18 per cent while the incidence of quantity rationing fell from 13 to 10 per cent of sample farmers.

Linear Programming Model Specification

We assume that all farmers in the sample face the same prices. This is a reasonable assumption given the good communication and transportation infrastructure of the region and the homogeneity of farm sizes. As shown by Fare et al. (1990), when farmers face the same prices the efficiency measures can de derived directly from revenues and costs. As suggested by Blancard et al. (2006), who also use panel data, we estimate a separate frontier for each year in order to allow for changes in technology, prices or climatic conditions between the two periods.

Table 2. Frequency of credit rationing outcomes

	Frequency	
Constraint status	2003 (%)	2004 (%)
Unconstrained	54	46
Borrowers	28	31
Non-borrowers	26	15
Constrained	46	54
Quantity rationed	13	10
Transaction cost rationed	12	18
Risk rationed	21	26

Each farmer is characterised by their production of three outputs and their use of 10 inputs, four variable and six fixed. The three outputs are: (1) annual crops; (2) tree-crops and bananas and; (3) land rental. The first two are measured as the value of production in the 12 months preceding the survey while the third is revenues received from renting out or sharecropping household land. The four variable inputs are: (1) hired labour; (2) irrigation; (3) chemical inputs; and (4) rented machinery. All variable inputs are measured as the total annual expenditure. The six fixed factors are: (1) owned area that is either under annual crop production or rented out; (2) owned area planted in fruit trees; (3) owned area planted in bananas; (4) whether or not the farmer has been certified to market bananas as organic; (5) family labour endowment; and (6) owned farm equipment. We separate total area owned into three categories because in the short-term, land cannot be easily converted across annuals, fruit trees and bananas. We include the organic certification as a fixed input because certification is a long process requiring outside verification of production techniques and soil tests over multiple seasons. Family labour endowment is measured in adult equivalents using weights defined by age and sex.[5] Farm equipment is measured as the value of agricultural machinery held by the household. All variables are expressed in 2004 Peruvian Soles. Table 3 presents means and standard deviations for the different categories of outputs, variable inputs and fixed inputs for the data pooled across the two survey years.

V. The Depth of Financial Inefficiency: Results from the DEA Analysis

Given the presence of fixed inputs, the reported financial efficiency coefficients are implicitly of a short run nature. They ignore longer term impacts of credit constraints on farmers' permanent crop planting decisions or investment in land and machinery.

Table 3. Descriptive statistics: inputs and outputs for pooled sample

Variables	Mean	Standard deviation
Outputs (u)		
Value of annual crops (soles)	11,735	14,632
Value of output of fruits and bananas (soles)	3,027	10,880
Revenue from land rental (soles)	75	342
Variable inputs (x)		
Expenditure on hired labour (soles)	1,601	2,178
Expenditure on irrigation (soles)	417	233
Expenditure on chemical inputs (soles)	2,676	3,307
Expenditure on machinery rental (soles)	907	1,364
Fixed inputs (f)		
Area in annual crop production or rented out (ha.)	2.8	2.4
Area in fruit trees (ha.)	0.60	2.2
Area in bananas (ha.)	0.51	4.2
Certificate for organic banana (1: yes)	0.08	0.28
Family labor endowment (days)	417	233
Value of farm equipment (soles)	787	1753

Note: All figures are in 2004 soles, with \$1 = 3.47 soles.

Two Estimates of Profit Loss Due to Credit Constraints

Table 4 summarises the efficiency measures obtained from the procedure described above.[6] Column (1) provides information for the full sample, while the remaining columns divide the sample between financially inefficient (columns (2)–(5)) and financially efficient farmers (column (6)). The average overall efficiency of the 726 farmer-year observations is 0.36, implying that actual and financial inefficiencies combine to limit farmers' profits to 36 per cent of their highest attainable level. The low level of overall efficiency should not be attributed solely to the developing country context. In their efficiency analysis of California rice farmers, for example, Fare et al. (1990) find an average overall efficiency of 0.42.

How much of the overall efficiency loss was due to financial constraints? Of the 726 pooled observations, 203 (28%) are financially inefficient. For these farmers, mean overall efficiency was 0.20. Given that average observed profits for this group were 1,723 Soles per hectare, this implies that eliminating *all* sources of inefficiency would allow these farmers to achieve profits averaging 8,614 Soles per hectare. If, instead, all non-financial inefficiencies were eliminated, these farmers would achieve an average profit of 6,158 Soles per hectare. The loss of potential profits per hectare deriving from financial constraints is thus 2,457 Soles per hectare, or 27 per cent of maximum attainable profits. Columns (3)–(5) further separate the financially inefficient according to the nature of the credit constraint they face: quantity, transaction cost or risk rationing. The estimates of financial efficiency and of profit loss due to credit constraints are remarkably similar across these three categories. Note also that the estimates of overall efficiency for farmers who are financially

Table 4. Efficiency measures

		Financially Inefficient				
	Pooled sample (1)	All (2)	Quantity rationed (3)	Transaction cost rationed (4)	Risk rationed (5)	Financially efficient (6)
Number of farms	726	203	49	59	95	523
Average overall efficiency (O)	0.36	0.20	0.20	0.24	0.18	0.42
Average financial efficiency (F)	0.93	0.73	0.72	0.74	0.74	1
Average observed profit per Ha. ($\pi^0/Area$)	2480	1723	1676	2114	1505	2773
Average profit loss per Ha. due to credit constraints						
Upper-bound estimate $((\pi^{\max} - \pi^C)/Area)$	687	2457	2628	2374	2412	0
Adjusted estimate $((0.86 * \pi^{\max} - \pi^C)/Area)$	413	1477	1487	1573	1412	0

inefficient are very similar regardless of the type of credit constraint they face, but they are noticeably smaller than the estimates of overall efficiency for farmers who are financially efficient. This suggests that transaction cost and risk rationed farmers indeed behave similarly to quantity rationed farmers and that ignoring these types of credit constraints would lead to an overly optimistic view of the health of credit markets.

The impact of credit constraints on farm profit reported above is significant. The average profit loss associated with financial inefficiency (2,457 Soles per hectare) actually exceeds average observed profits for financially inefficient farmers (1,723 Soles per hectare). This, in part, is an artefact of our empirical implementation of the DEA methodology, which attributes all allocative inefficiency of constrained households to credit constraints. Allocative inefficiency may, however, be due to poor decision making by farm managers. This concern can be illustrated with the aid of Figure 1. Assume the farmer at point C is credit constrained. The upper bound estimates reported in Table 4 assume that if the credit constraint were eliminated, the farmer would move from point C to point A and increase profits from π_1 to π_{max}, the maximum attainable profit. However, once the credit constraint is eliminated the farmer at C may, because of lack of managerial skill, choose a new production point between points C and A. Since our methodology attributes the entire profit loss ($\pi_{max} - \pi_1$) to credit constraints, we would overstate the impact of relaxing credit constraints. Our approach thus provides an upper bound on the impact of relaxing credit constraints. The greater is the component of allocative inefficiency due to poor management among constrained farmers, the larger is our over-statement of the true impact.

How large is this potential over-statement? Unfortunately, we cannot decompose allocative inefficiency into the portions attributable to credit constraints versus poor management for credit constrained households. If, however, we assume that credit constrained farmers, on average, have the same level of managerial skills as unconstrained farmers, we can generate an alternative estimate of the profit loss associated with credit constraints that is less subject to over-estimation. We generate these adjusted figures as follows. First, we calculate the profit that each farmer would earn if technical inefficiencies were eliminated. In terms of Figure 1, we bring farmers like the one at point D up to the frontier at point C. Next, we calculate the allocative efficiency for all unconstrained farmers. As they are unconstrained, any allocative inefficiency is due solely to poor management (as opposed to credit constraints). Mean allocative efficiency of unconstrained households is 86 per cent, implying that unconstrained households forfeit 14 per cent of potential profits due to poor management. Again, with reference to Figure 1, this implies that, for all unconstrained households, ratio π_1/π_{max} averaged 0.86. Finally, we assume that all constrained households have the same level of managerial skills as the mean unconstrained household, that is we lower their maximum attainable profit by 14 per cent. We then attribute any remaining allocative inefficiency to credit constraints.[7] As reported in the final row of Table 4, the average adjusted profit loss per hectare due to credit constraints is \$1,477 or 17 per cent of maximum attainable profits, for financially inefficient households. While smaller than the upper bound estimate, the adjusted profit loss attributable to credit constraints is still quite large, suggesting significant gains to improving the performance of rural credit markets.

The Impact of Using Directly Elicited Credit Constraint Information

It is worth considering how the incorporation of the directly elicited credit constraint information affects the efficiency analysis. Recall from Table 2 that nearly 50 per cent of farmers reported being credit constrained. Yet we find that only 28 per cent (203 out of 726) were financially inefficient; that is would have increased their profits if they had improved access to capital. This implies that some of the farmers who are non-price rationed in the credit market are financially efficient in the short run. There are at least two possible explanations for this. First, our efficiency analysis treats land and machinery as fixed production factors so that, as mentioned above, we are only capturing the short-term impact of credit constraints. The reported credit constraint status could instead reflect inadequate access to capital for long-term investments. If, for example, a farmer wishes to install fruit trees but because of his inadequate access to credit is unable and instead grows annual crops, he would still be considered efficient according to our short-term measures if he obtains the maximum possible profit that can be reached with annual crops. Second, we measure efficiency given the available technology which, in turn, reflects what other sample farmers are doing. Thus, if a farmer could increase his profit with a larger loan but nobody in the sample is doing better than him, the farmer would still be considered financially efficient. To put it more dramatically, if all farmers in the sample behave in the same way, they will all be financially efficient even if they all are credit constrained and could have increased their profits by increasing their expenditures.

Finally, we repeated the efficiency analysis (results not reported), ignoring the survey information on farmers' credit constraint status and assuming instead that observed expenditures represent the farmer's maximum possible expenditures. Without the credit constraint information, nearly twice as many (372 versus 203) farmers are classified as financially inefficient. This approach generates a larger estimate of the average financial efficiency of constrained farmers (0.77 versus 0.73) and thus a smaller estimate of the individual profit loss due to financial constraints. This is to be expected since this methodology includes as constrained some farmers that are, in fact, unconstrained in the credit market. In order to avoid this over-estimation of the incidence of financial inefficiency, we suggest that, when available, the direct measures of farmers' credit constraint status be utilised.

VI. Accounting for Financial Inefficiency: A Tobit Analysis

The previous section established that credit constraints reduce financial efficiency for an important fraction of sample farmers and that the profit loss attributable to financial inefficiencies is significant. In this section we carry out a parametric analysis to identify those factors that influence the depth of financial inefficiency.

Model Specification

A farmer's level of financial efficiency depends both on whether or not he is constrained in the credit market and, if constrained, on his ability to bring to bear alternative resources to finance farm expenditures. As credit constraints can derive from both the supply and demand side of the credit market, we include regressors that influence a farmer's access to and demand for credit. In addition, as the depth of financial inefficiency depends on the alternative sources of finance available to the farmer, we include variables related to his ability to mobilise other funds for agricultural investment. Table 5 presents definitions and summary statistics for all variables included in the estimation. The means and standard deviations are computed for the sample pooled across the two survey years. Variables with positive coefficients will be interpreted as reducing the inefficiencies associated with credit constraints while those with negative coefficients increase inefficiency.

The first six variables characterise the household's landholdings and farm technology. *FARMSIZE* is the household's endowment of irrigated land and is included to capture the potential bias against small farmers in access to formal credit found elsewhere in Latin America (Carter and Olinto, 2003; Boucher et al., 2005). *TITLE* indicates the possession of a registered property title, which should raise the collateral value of land and thus should also enhance credit access and financial efficiency. Farmers were asked to rank the soil quality of each of their plots on a scale from 1 (very bad) to 5 (very good). *LANDQUAL* is the area-weighted mean of this subjective assessment across a farmer's plots. *PUMP* is a dummy variable indicating whether or not the farmer has to pump water to irrigate any of his plots and is hypothesised to lower financial efficiency because of the greater expense implied by pumping compared to gravity irrigation. Finally, *CRSCALE* and *IRSCALE* are dummy variables indicating that the farm operates in a constant or increasing returns to scale portion of the technology, respectively. Profit loss due to credit constraints is expected to be greater for farmers in the constant and especially the increasing returns portion of the technological frontier compared to those in the decreasing returns portion, which is the omitted category.

The next three variables control for the household's stock of non-land capital and the transaction costs associated with loan application. *EDUC* is a measure of the

Table 5. Definitions and summary statistics of explanatory variables in Tobit

Variable name	Variable definition	Mean	Standard deviation
FARMSIZE	Total area owned (ha)	3.81	4.36
TITLE	1 if household land is titled	0.68	0.47
LANDQUAL	Average self-reported land quality on a scale of 1 to 5 (5 = best)	3.43	0.67
PUMP	1 if part of the irrigation is through pumping	0.11	0.32
CRSCALE	1 if technology exhibit constant return to scale	0.29	0.45
IRSCALE	1 if technology exhibit increasing return to scale	0.42	0.49
EDUC	Number years of education of household head	4.65	3.91
DURABLES	Value of durable goods (thousands of soles)	1.19	2.94
BUSINESS	1 if household has a business with more than $150 of assets	0.06	0.23
SALARY	1 if any household member has a permanent salaried job	0.50	0.50
DISTANCE	Distance to the closest local bank (in min)	25.01	24.57
CV	Coefficient of variation of yield in farmer's district	0.55	0.05
RISKAVERS	Measure of farmer's risk aversion	0.01	0.01
t	Year dummy = 1 if 2003, 0 if 2004		

household head's human capital, which is expected to have a positive impact on financial efficiency as it is expected to raise farm productivity and to reduce the transaction costs associated with loan application. *DURABLES* is the value of the household's holdings of non-farm consumer durables and is expected to reduce credit constraints and raise financial efficiency. Several local lenders indicated that they consider consumer durables as an indicator of repayment capacity; both because they can be liquidated and used for loan repayment if the household experiences a negative shock, and they reflect farmer skill via past performance. *BUSINESS* is a dummy variable indicating whether or not the household runs a non-farm enterprise with at least \$150 worth of assets; while *SALARY* is a dummy variable indicating whether or not any adult household member has a salaried non-farm job. These two variables indicate the existence of reliable non-farm income sources which are expected to raise financial efficiency by reducing the probability of credit rationing and facilitating increased expenditures for constrained farmers. *DISTANCE* gives the travel time in public transportation to the nearest formal lender. As the transaction costs associated with loan application increase with travel time, we expect this variable to lower financial efficiency.

Finally, we include two separate risk-related variables. *RISKAVERS* is a measure of each individual farmer's coefficient of relative risk aversion and was constructed based on the farmer's response to a series of hypothetical questions regarding their willingness to pay for different lotteries. *CV* is the coefficient of variation of yields in the farmer's district.[8] This variable is included to capture the severity of covariate risks such as water availability and pest infestations that simultaneously affect farmers within a region. Farmers that face greater risk and are more sensitive to a given risk are both more likely to be risk rationed and to commit fewer expenditures to production. These two risk variables are thus hypothesised to negatively affect financial efficiency.

Estimation Strategy

Recall that a farmer's financial efficiency is a relative measure bounded from above by one. As a result, we estimate the coefficients of the following random effects Tobit model:[9]

$$F_j^t = \min\{\alpha t + \beta X_j^t + \mu_j + \varepsilon_j^t, 1\} \tag{6}$$

Our dependent variable, F_j^t, is the financial efficiency of farmer j in year t. The explanatory variables include a year dummy t and a vector X which includes the explanatory variables discussed above and defined in Table 5. The error term has two components: μ_j is the random effect which is drawn from a farmer-specific mean-zero normal distribution, and ε_j^t which is a mean-zero error term also normally distributed, uncorrelated with the right-hand side variables and independent and identically distributed (i.i.d.) across farmers and over time.

The coefficients of Equation 6 were estimated via Maximum Likelihood using Stata's XT-Tobit command. As pointed out by Simar and Wilson (2007), the DEA efficiency indices are constructed based on the farmer's performance relative to others farmers in the sample, implying that the errors in the Tobit equation are serially correlated and also correlated with the explanatory variables. These correlations disappear asymptotically but at a very slow rate. As a result, while maximum likelihood estimates of the parameters are consistent, inference based on them will not be valid. To address this concern, we generate confidence intervals for the parameter estimates using the bootstrap procedure proposed by Simar and Wilson.

Results and Discussion

Columns A and B in Table 6 present the parameter estimates and their 95 per cent confidence intervals, while columns C and D present the marginal effects and their corresponding confidence intervals. Confidence intervals are based on 1000 bootstrap iterations. The marginal effect we calculate gives the change in the expected value of financial efficiency conditional on a farmer being financially inefficient and is computed at the median values of the explanatory variables.

First we comment on the model specification. In each of the 1000 bootstrap iterations, we calculated two additional statistics. First, we computed ρ, the percentage of overall variance of the residual attributable to the individual specific error component. The estimate for ρ is 16 per cent with a 95 per cent confidence interval ranging from 10–33 per cent. This result supports the random effects specification. Second, we computed the p-value associated with a Wald test for the joint significance of the right-hand side variables. The bottom row of Table 6 presents the

Table 6. Determinants of financial efficiency: parameter estimates and marginal effects from Tobit estimation

	Parameters			Marginal effects		
	(A) Coefficient	(B) 95% confidence interval		(C) $\frac{\partial E(F\mid F<1)}{\partial x}$	(D) 95% confidence interval	
FARMSIZE	−0.0014	−0.0144	0.0097	−0.0003	−0.0034	0.0019
TITLE	0.0724	−0.0169	0.1650	0.0164	−0.0044	0.0375
LANDQUAL	0.0889	0.0309	0.1487	0.0191	0.0051	0.0324
PUMP	−0.1326	−0.2546	−0.0092	−0.0314	−0.0618	0.0023
CRSCALE	−0.1813	−0.2888	−0.0687	−0.0328	−0.0562	−0.0075
IRSCALE	−0.1381	−0.2419	−0.0245	−0.0445	−0.0725	−0.0167
EDUC	0.0142	0.0015	0.0250	0.0031	0.0004	0.0056
DURABLES	0.0354	−0.0017	0.0607	0.0076	−0.0011	0.0129
BUSINESS	0.1838	−0.1775	0.3798	0.0349	−0.0099	0.0730
SALARY	0.0223	−0.0577	0.1104	0.0049	−0.0126	0.0231
DISTANCE	−0.0003	−0.0021	0.0013	−0.0001	−0.0004	0.0003
CV	−1.1669	−2.0387	−0.2792	−0.2510	−0.4423	−0.0533
RISKAVERSE	−8.4521	−14.1647	−1.6161	−1.8181	−3.1167	−0.3110
T	−0.1475	−0.2275	−0.0609	−0.0318	−0.0497	−0.0126
constant	1.7750	1.1981	2.3414			
p-value*	2.87E-10	4.29E-16	3.27E-7			
ρ**	0.17	0.10	0.33			

Notes: *p-values are for the Wald test of joint significance of all regressors. **ρ is the relative contribution of the variance of the individual-specific component of the error term to the overall variance of the residual.

p-value in the original data set and the 25th and 975th largest values of these 1000 p-values. The low values for the Wald test indicate that our right hand side variables indeed account for some variation of financial efficiency.

We now turn to the coefficient estimates. In general, the results are consistent with our theoretical expectations. We focus our discussion on the marginal effects as they provide a more intuitive interpretation. Conditional on being financially inefficient, higher levels of human capital, land quality, and consumer durables are associated with statistically significant, although small, increases in financial efficiency. Increasing the household head's completed education from four (the median) to five years, for example, raises financial efficiency by 0.3 percentage points. As expected, the higher expenditures associated with dependence on a pump for irrigation have a significant negative impact on financial efficiency. Similarly, conditional on being financially inefficient, farmers operating in the decreasing returns scale portion of technology have greater financial efficiency than those operating under constant or increasing returns to scale. A move from the decreasing to the constant returns portion of technology would lower the farmer's financial efficiency by 3.2 percentage points.

Interestingly, the *FARMSIZE* variable, although having the anticipated sign, had neither a significant parameter estimate nor marginal effect, suggesting that neither credit access nor the ability to finance per hectare expenditures are particularly sensitive to farm size for the range of farm sizes in our sample. Although the point estimate for the *TITLE* variable is positive and significant at a 10 per cent level of significance, the marginal impact is not significantly different from zero. In much of the study area, property titles were received relatively recently as part of the government's land titling programme of the late 1990s. Virtually all households possess alternative documents that establish strong tenure security over their land even in the absence of a registered title. In this context, receipt of a title is likely to relax credit constraints by making land more acceptable to lenders as collateral, but unlikely to raise investment demand via an increased tenure security effect. The positive and significant point estimate but insignificant marginal effect is thus not surprising as possession of a property title is expected to exert a greater impact on the probability of being constrained than on the level of efficiency reached by those who are constrained.

Our findings with regard to transaction costs are inconclusive. Distance does not seem to make a significant difference on the farm's financial efficiency and while more education is associated with higher financial efficiency, it is not clear how much of its impact is through transaction costs.

Perhaps the most interesting results are associated with the two risk variables. Both greater district-level yield variability and individual risk aversion have a significant and negative impact on financial efficiency, conditional on being inefficient. The marginal effect associated with the district-level coefficient of yield variation is –0.25, implying that an increase in the coefficient of variation from the median value of 0.5 to 0.6 (which corresponds to two standard deviations) results in a 2.5 percentage point reduction in financial efficiency. Similarly, an increase of risk aversion by two standard deviations (from 0.02 to 0.04) would lead to a 3.6 percentage point reduction in financial efficiency. These results suggest that uninsured risk has a significant adverse effect on farm productivity; exerting both a direct negative effect on farmers' willingness to invest in farm production and an indirect negative effect via a reduced willingness to take on risky credit contracts (increased probability of risk rationing). We will return to the role of risk and insurance in our policy discussion in the concluding section.

VII. Conclusion and Policy Implications

We used a non-parametric DEA approach to calculate financial efficiency indices for a panel of farms from Piura, Peru. We found that 28 per cent of farms were financially inefficient. Given the privileged infrastructure and relative prosperity of the Piura region, this is likely to be a lower bound estimate of financial inefficiency for the rest of the country.

Our approach built on existing DEA-based studies in two ways. First, we allowed for an expanded, and we believe conceptually more satisfying, definition of credit constraints by including risk and transaction cost rationing in addition to conventional quantity rationing. Second, we used survey data that directly identifies farmers' credit constraint status to avoid the over-estimation of financial efficiency inherent in existing studies. We found that utilisation of this additional information is important: incorporating additional information regarding farms' credit rationing status, the percentage of farms that are financially inefficient in our sample drops from 51 to 28 per cent.

The impact of credit market imperfections on farm profit is substantial. On average, farms that were financially inefficient attained a level of profit 27 per cent lower than those who had adequate access to capital. Our Tobit analysis reveals that the correlates of financial efficiency include household and farm characteristics, such as education, land quality and access to irrigation, but also risk preferences and exposure to risk. Expanding our conceptualisation of credit constraints beyond quantity rationing and incorporating the potential for risk rationing into empirical evaluations of the performance of rural credit markets and the efficiency loss due to credit constraints would thus appear crucial.

We conclude by using our parameter estimates to explore the potential gains to strengthening agricultural insurance markets in Peru. The two dotted curves in Figure 2 show how the probability of being financially inefficient changes as yield risk, measured by the district-level coefficient of variation of yields, increases. The upper dotted curve corresponds to a farmer with high risk aversion, while the lower dotted curve corresponds to a farmer with low risk aversion.[10] The two solid curves show how the expected level of financial inefficiency changes with yield variability for the same two levels of risk aversion. In this case, the upper of these two curves corresponds to a farmer with low risk aversion.

Consider a 20 per cent increase in the coefficient of variation, from 0.5 to 0.6. This increase in risk raises the probability of being financially inefficient from 7 to 11 per cent for the farmer with low risk aversion, and from 22 to 31 per cent for the farmer with high risk aversion. The same increase in yield variability lowers financial efficiency by 1 percentage point (from 81% to 80%) for farmers with low risk aversion and by 3 percentage points (from 76% to 73%) for highly risk averse farmers. As expected, the adverse impacts of risk are most severe for more risk averse households who, if risk aversion is decreasing in wealth, are also likely to be the

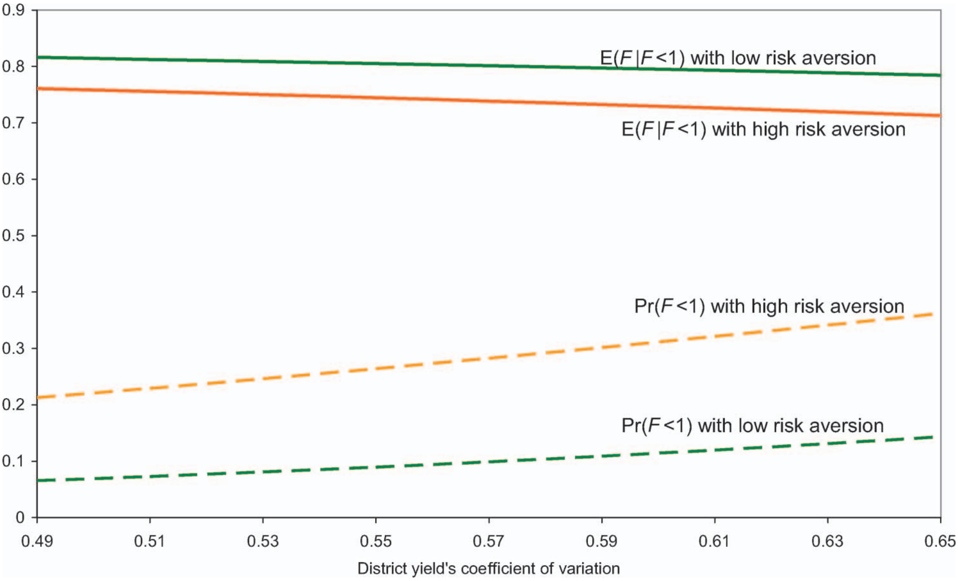

Figure 2. Impact of yield risk on the probability of being financially inefficient and on the size of inefficiency for two levels of risk aversion (low and high).

poorest. Reducing the risk to which farmers are exposed (that is, leftward movements in Figure 2) and raising farmers' willingness to bear risk (that is, a move from the curve of the more to the less risk averse farmer in Figure 2) would raise farm efficiency and equity.

While additional evidence on the impact of risk on access to and participation in credit markets as well as farm resource allocation is needed, our results suggest that strengthening agricultural insurance markets would have a positive impact on financial efficiency, primarily via overcoming risk rationing and stimulating credit demand. Governments such as Peru's are unlikely to have sufficient resources to promote conventional, multi-peril crop insurance which, based on evidence from the US, would be likely to require significant subsidies to compensate for moral hazard and adverse selection endemic to this product (Miranda, 1990). A particularly attractive and more feasible alternative would be to support the development of markets for index-based insurance products. Recent pilot programmes based on a rainfall index in India (Hess, 2003) and a livestock mortality index in Mongolia (Skees and Ayurzana, 2002) suggest that index insurance products can both provide small farmers significant risk reduction and be financially sustainable. In an ex-ante analysis, Carter et al. (2007) demonstrate that small farmers in Lambayeque, a coastal Peruvian valley similar to Piura, would have a high willingness to pay for an insurance product based on an area yield index. These findings, coupled with the findings reported here, suggest that strengthening agricultural insurance markets is a potentially fruitful policy direction. Government support, for example in facilitating the regulation of new insurance products and initial investment in the data collection and information infrastructure required for the measurement of potential indices, would represent a potential step in this direction.

Notes

1. See Boucher et al. (2009) for a detailed discussion of the direct elicitation methodology.
2. The estimated actual efficiency is then: $\hat{A}_j = \hat{\pi}_j^O \big/ \pi_j^C$.
3. The threshold of \$150 constitutes a breakpoint in the distribution of gross output. Households with a gross farm output of less than \$150 have production that resembles gardening. Seventy-seven households were excluded by this rule. Half of them had no production at all and half had very limited production. Forty-six farmers were excluded because they were heavily engaged in raising cattle. In our survey, significantly less detailed data are available on the cost structure of livestock operations so that we chose to exclude these farmers.
4. If the informal sector is a good substitute for an imperfect formal sector, then the profit loss due to *formal* credit constraint is likely to be small. We have reason to believe that the informal market offers less favourable terms than the formal market, as interest rates are much higher, loan sizes are smaller and maturity shorter.
5. Children under 10 years old are given a weight of zero while those between 10–15 years are given a weight of 0.5. Men are given a weight of 1 and women a weight of 0.75.
6. In the DEA literature, there has been increasing attention paid to an inherent bias of this method that can lead to overestimating farm efficiency. Specifically, since the production frontier is constructed from a sample of farms, it is possible that the most efficient farms are not selected into the sample and, as a result, the estimated frontier may be below the true frontier. Simar and Wilson (1999) show that this bias could be substantial. It is, therefore, reasonable to expect that the measures of overall and actual efficiency we obtain may be biased upward. This concern may be especially relevant in developing country agriculture because the dispersion of 'true' efficiency is likely to be larger than in developed countries. However, the measures of financial efficiency that are the centre of our analysis are less likely to be affected by this problem because they are the ratio of two measures (π^c and π). If the two measures are biased, the bias will be in the same direction and of the same magnitude, resulting in a smaller bias in the ratio.
7. Our procedure implies that any constrained household with allocative efficiency greater than 86 per cent would be financially efficient. That is, we would not attribute any profit loss due to credit constraints.
8. The coefficient of variation variable was constructed using annual data published by the Ministry of Agriculture from 1996–2005.
9. Simar and Wilson (2007) use a truncated regression in their analysis of the determinants of DEA-based efficiency measures. Our case differs from theirs however, as we use a financial efficiency index instead of a classic DEA distance estimate. Recall that a farmer is considered financially inefficient only if he could have increased his profits by purchasing more inputs *and he was observed to be credit constrained*. Thus, in contrast with Simar and Wilson's setting, the fact that we have a probability mass at 1 is not an artifact of having a small sample. Due to the binary variable we use to identify credit rationing status, all unconstrained farmers in our sample have a financial efficiency of 1.
10. High and low risk aversions correspond to the 95th and fifth percentiles, respectively, of the relative risk aversion coefficient of sample farmers. All other variables are held at the sample median.

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