SMOOTHING CONSUMPTION BY SMOOTHING INCOME: HOURS-OF-WORK RESPONSES TO IDIOSYNCRATIC AGRICULTURAL SHOCKS IN RURAL INDIA

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Abstract—While research has demonstrated that farm households in developing economies are able to protect consumption from idiosyncratic crop shocks, little evidence shows how this is achieved. This paper examines the extent to which labor markets allow households to shift labor from farm to off-farm employment, and the extent to which such a shift explains the observed lack of correlation between consumption and idiosyncratic crop shocks. The empirical analysis uses a novel measure of the idiosyncratic crop income shock which utilizes information on start-of-season cropping choices to more accurately estimate household expectations of weather.

I. Introduction

This paper estimates the responsiveness of the market hours of work of Indian farm households to idiosyncratic or household-specific shocks to crop income. The motivation for this research stems from a literature that finds that household consumption appears to be relatively well protected from such forecast errors, despite the absence of formal insurance markets in the rural Indian economy (Townsend, 1994). It is widely believed that this is achieved through asset transactions, yielding a high cost of uncertainty due to both ex ante portfolio choices that favor more-liquid but less-productive assets and to the ex post sale of assets at a possible loss (Eswaran & Kotwal, 1989; Morduch, 1994). There may, however, be little need to use assets to mitigate the effects of crop shocks if labor markets are flexible enough to accommodate a reallocation of labor from the family farm to the wage labor market. Evidence on whether such a reallocation is possible thus informs models of savings that maintain that a significant share of the savings of farm households in developing economies represents a precautionary response to uncertain crop incomes (Deaton, 1989).

Despite the recognized importance of idiosyncratic crop income shocks in developing economies, research on their effects is scant. This may reflect the fact that most data sets do not provide measures of such shocks, necessitating the use of estimated measures. One contribution of this study is the measure it provides of farm-specific crop shocks. Using the longitudinal data collected by the International Crop Research Institute of the Semi-arid Tropics (ICRISAT) for farm households in central India, I devise a measure that exploits the information contained in the farmer's cropping choices at the start of the season to estimate household expectations of weather in the season to come. As with any estimate of the shock in household incomes, the possibility of measurement error remains. The ICRISAT data, however, also record any crop failure reported by the farmer in any given season. This reported ordinal measure serves as an instrument to consistently estimate the effect of crop income shocks and also provides a check on the robustness of the results.

To summarize the results of this paper, I find that household males increase their market hours of work in response to unanticipated variations in crop profits. This need not reflect the desire of households to smooth consumption; with well-functioning labor markets, farm-specific shocks would result in a shift from own farm production to the labor market even if households had access to insurance markets. This paper thus also proposes a test of the hypothesis that labor market allocations explain the lack of observed correlation between consumption and farm income shocks. Supporting the results of earlier research (Townsend, 1994), a reduced-form regression of consumption on crop shocks reveals no significant effect of the latter. Conditional on hours of work, however, crop income shocks have a negative effect on consumption, confirming that the ability to protect consumption from crop income shocks reflects, in large part, adjustments in hours of work.

The empirical results of this paper are tempered, however, by the very small cross-sectional component of the ICRISAT data, which reduces the efficiency of the estimates and which may also explain some of the anomalies in the regression results noted in the body of this paper. Thus, while the results suggest the importance of labor decisions in explaining the smoothness of consumption profiles, these findings need to be confirmed with alternative larger data sets.

This paper is organized as follows. Section II describes the survey region and the nature of fluctuations in agricultural incomes. Section III discusses the literature and evidence on household responses to income fluctuations. Section IV outlines the theoretical model that underlies the empirical work, while section V develops the measure of crop shocks used in this paper. Empirical issues are discussed in section VI and the results in section VII. My conclusions are set forth in section VIII.

II. The Survey Region

The empirical work of this paper uses the panel data set of Indian farm households collected by ICRISAT. This widely

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used data set is discussed in detail, as are the villages surveyed, by Walker and Ryan (1990). The sample used in this paper is drawn from three villages in central India: Aurepalle in the state of Karnataka, and Shirapur and Kanzara in the state of Maharashtra. The data set provides details of consumption, crop production, income, and savings for thirty cultivator households and ten noncultivators over a ten-year period (1975–1984) in each of these villages. Detailed data on labor income are, however, available only for the period 1979 to 1984. The analysis of this paper is accordingly based on this period. Since this paper focuses on the effects of idiosyncratic crop income shocks, the analysis is further restricted to the sample of cultivator households.

TABLE 1.—IMPORTANCE OF LABOR INCOME IN THE SAMPLE

	Sample Means in Constant Rupees (1983)			% of Households Reporting Labor Income
	Total Profit (1)	Labor Income (2)	(2) as % to (1)	
Full Sample	4,179	1,049	25.10	70.0
By Village				
Aurepalle	2,782	479	17.22	59.5
Shirapur	4,853	1,690	34.82	93.6
Kanzara	4,943	1,982	40.10	56.9
By Farm Size				
Small farm	892	1,994	223.54	87.5
Medium farm	1,971	1,377	69.86	76.0
Large farm	9,109	712	7.82	46.4

Note: Profits are the sum of profits over all seasons and from perinnial crops.

A. *The Labor Market in the Survey Villages*

The labor market in all three villages is large and active, with farm households relying heavily on hired labor which accounts for 60% to 80% of total farm labor in the villages of Aurepalle and Kanzara, and slightly less in Shirapur. The size of the labor market is reflected in the importance of wage income in the total income of farm households (table 1). The majority of sample households (70%) report earning wage income. While almost all small farm households (87.5%) report such income, so do a significant number of large farms (46.4%). Household wage income amounts, on average, to 25% of crop profits, although its importance varies by farm size. For small farms, wage income exceeds crop income by 224%.

The labor market functions primarily as a spot market wherein daily contracts dominate. Most cultivator households, irrespective of farm size, participate in this market as both buyers and sellers of labor. Employees generally work for a number of different employers in any given season, and personal relationships between employers and employees are rare, as are links between labor contracts and land or credit contracts. Labor markets in all three villages are, however, segmented by gender, with women being barred by social taboos from tasks involving the use of the plow or bullocks. The considerable segmentation of tasks has resulted in the quite distinct operation of the labor market for men and women (Walker & Ryan, 1990).

B. *The Nature of Crop Income Uncertainty*

Crop incomes in the Indian economy are dependent on the monsoons and hence are highly variable, particularly in the *kharif,* or rainy season. This is evidenced by the high coefficient of variation in kharif profits for sample households (0.59).[1] Rainfall patterns do, however, vary across villages; rainfall levels are lower and the variability in rainfall is greater in Aurepalle and Shirapur relative to Kanzara. Correspondingly, the coefficient of variation in kharif crop profits varies across villages, being highest in Shirapur (2.01), but lower in Aurepalle (0.67) and Kanzara (0.65). The coefficient of variation in kharif profits also varies by farm sizes, reflecting differences across farms in their vulnerability to rainfall levels. The smallest farms exhibit the greatest coefficient of variation (2.12) followed by medium-sized farms (1.45) and large farms (1.1).

An analysis of the variation in crop incomes reveals that most of it is farm specific or idiosyncratic, with little comovement in crop incomes across farm households in any given village. A regression analysis of kharif profits on village-year dummies yields generally low R^2 statistics; aggregate variables explain only 40% of the variation in kharif profits in real Rupees (Rs.) in Aurepalle, while the corresponding figures for Shirapur and Kanzara are 5% and 33%, respectively. Research by Morduch (1991) and Townsend (1994) using the ICRISAT data also reveal the relative importance of idiosyncratic variations in income.

While some of the idiosyncratic variation in income may result from farm-specific adverse events such as the trampling of fields by stray cattle, commonly experienced events such as rainfall may also affect farms differently, contributing to the observed lack of comovement of crop incomes in the village economy. This results from the considerable diversity in soil characteristics—such as groundwater retention, groundwater recharge, and surface runoff in India's semiarid tropic—even across adjoining plots. These factors in turn determine the effect of any given level of rainfall on standing crops.

III. Evidence on Household Responses to Income Shocks

The low level of covariance in farm incomes within a village implies that households potentially have available to them a wide variety of mechanisms to deal with risk, including village-based institutions. Of such mechanisms, credit transactions have received the most attention in both the theoretical and empirical literature (Morduch, 1990;

[1] The coefficient of variation is calculated by averaging the coefficient of variation for each household (over the years of the survey) across the sample as a whole.

Eswaran & Kotwal, 1989; Rosenzweig, 1988). There has been relatively little work on the extent to which households mitigate the effects of farm-specific crop shocks by shifting their labor from the family farm to the market.[2] This may reflect the widespread belief that labor markets in developing economies are characterized by unemployment and wage rigidity, factors which render such shifts difficult (Dasgupta & Ray, 1986, 1987; Stiglitz, 1976; Datt & Ravallion, 1994). Evidence that farm households increase their hours of market work in response to regionwide shocks such as droughts (Jodha, 1978) suggests, however, that corresponding increases should also be possible in the event of idiosyncratic crop income shocks.

An analysis of the correlation of household income by source (table 2) suggests that such reallocations between self-employment and the wage market do occur. The only significant correlation for the sample as a whole is the negative correlation between kharif profits and wage income. This negative correlation exists across all three villages and across farms of different sizes. By contrast, there is no significant correlation between profits and either net remittances or net informal borrowing. Reflecting the negative covariance between wage income and profits, the variability of profits for the sample as a whole ($\sigma = 14{,}295$) exceeds that of the sum of profits and wage income ($\sigma = 11{,}736$). This result holds for all three villages and for large farms. However, despite the negative covariance of wage income and profits for small and medium farms, the larger variability in wage income for these two groups results in the variability of the sum of profits and wage income exceeding that of profits alone.[3]

Since the variability in income reflects both anticipated and unanticipated variation in response to aggregate and idiosyncratic factors, this evidence need not imply that the shift from own-farm to off-farm work reflects idiosyncratic crop shocks. Moreover, wage income is aggregated over households and within the household, ignoring nonparticipation by some households in the labor market as well as possible differences in the labor-supply response of females and males. Such factors necessitate the use of regression techniques to deal with participation decisions and to control for variables that cause anticipated (life-cycle) fluctuations in labor income. Prior to such an analysis, I first sketch a dynamic model of household behavior that clarifies the means whereby income shocks affect households, and that suggests a methodology for estimating the surprise in incomes, a topic which I discuss in section V.

TABLE 2.—CORRELATION BETWEEN CROP PROFITS AND OTHER SOURCES OF INCOME (CONSTANT RS. 1983)

	Correlation with Profit Income			
	Profits	Labor Income	Remittances	Informal Borrowing
Full Sample	1.00	−0.09*	−0.02	−0.003
By Village				
Aurepalle	1.00	−0.37*	0.01	0.05
Shirapur	1.00	−0.01	−0.004	0.002
Kanzara	1.00	−0.24*	−0.19*	−0.07
By Farm Size				
Small farm	1.00	−0.19*	−0.15*	0.01
Medium farm	1.00	−0.15*	0.08	−0.17*
Large farm	1.00	−0.05	−0.01	−0.02

Notes: Profits are real kharif profits in constant (1983) Rupees, excluding the cost of family labor. Total income includes crop income, real net informal borrowing, real net remittances, and real labor income. Labor income is real wage income received by family members.

IV. Theoretical Framework

An analysis of the effects of the forecast error or surprise in income on household decisions requires the specification of a dynamic model whereby observed choices reflect the household's expectation of future income. Since expectations are formed by incorporating the new information contained in the forecast error in current incomes into the household's information set, this forecast error will directly influence current decisions. In contrast, the forecast error in income plays no role in static models, since household decisions in such models depend only on current income and prices and, hence, on the realization of the income shock.

The dynamic model that underlies the empirical work of this paper divides the agricultural season into two stages, that are linked not just by savings decisions (as in a standard intertemporal model) but also because decisions regarding agricultural inputs in the first stage affect output in the next (Antle, 1983; Skoufias, 1993). The first stage is the planning or planting stage, when households make and implement their planting decisions for the upcoming season on the basis of all currently available information including the realization of any start-of-season income shocks, using labor and other first-stage inputs. Let h^o_{m1} and h^o_{f1} represent male and female family labor hours in the first stage, x_1 represent all other first-stage inputs including hired labor, and θ_1 be the realization of start-of-period shocks. The cultivated or sown land then represents the output or profits from the first stage:

$$\pi_1 = \pi(p_1, \theta_1, h^o_{m1}, h^o_{f1}, x_1). \tag{1}$$

Since farmers incur costs without realizing any marketable output, first-stage profits will typically be negative.

The level of output or farm profits in the second stage reflects the output of the first stage, $\pi_1(.)$, as well as second-stage inputs and the realization of second-stage

[2] In related research, Haurin (1989) uses U.S. data to examine the effects of unanticipated changes in a husband's earnings on women's hours of work, using hours of work in previous years to estimate expected current hours. In research using data from developing economies, Rose (1992) assesses labor market responses to aggregate shocks in the Indian economy, while Kanwar (1995) employs a static model to estimate the effect of expected revenue on female labor supply.

[3] The standard deviation of profits is 3,619, 25,435, and 8,463 for the villages of Aurepalle, Shirapur, and Kanzara, respectively, while that of the sum of profits and wage income is 3,129, 18,370, and 7,638. By farm size, the standard deviation of profits is 1,737, 2,067, and 23,895 for small, medium, and large farms, respectively, while that of the sum of profits and wage income is 1,888, 2,294 and 23,881.

weather or other income shocks:

$$\pi_2 = \pi(p_2, \theta_2, h^o_{m2}, h^o_{f2}, x_2, \pi_1(\cdot)). \quad (2)$$

Moving to the household's maximization problem, I take the household's relevant planning period, t, to correspond to a stage of the agricultural season, and assume a stage-specific instantaneous utility function which is nonseparable in consumption and hours of work:

$$U = U(c(t), h^o_m(t), h^w_m(t), h^o_f(t), h^w_f(t), Z(t)) \quad (3)$$

The household is assumed to distinguish the labor hours of its members by gender only, with $h_i(t)$ (i = males, females) representing the aggregate labor supply of all members of gender i. To reduce any biases caused by aggregating labor across ages, I assume that the household values the labor hours of its members of ages 15 to 45 only. Following the treatment of family labor in the profit function, I allow the time spent on own-farm production, $h^o(t)$, to be valued differently from time spent on the wage labor market ($h^w(t)$). $c(t)$ is aggregate household consumption, and $Z(t)$ is a vector of observed and unobserved factors affecting preferences. Assuming that utility functions are additively separable over time, the household maximizes the expected value of time and preference discounted total utility subject to the intertemporal budget constraint,

$$\begin{aligned} A(t+1) = (1 + r(t+1)[A(t) + \pi_s(t) \\ + \textstyle\sum_i w_i(t) h_i^m(t) - c(t)] \\ i = m, f; \quad s = 1, 2, \end{aligned} \quad (4)$$

the time allocation constraint,

$$h^o_i(t) + h^w_i(t) + l_i(t) = \Omega(t) \qquad i = m, f, \quad (5)$$

and the non-negativity constraints,

$$c(t) \geq 0, \qquad l_i(t) \geq 0 \qquad i = m, f \quad (6)$$

$$h^o_i(t) \geq 0, \qquad h^w_i(t) \geq 0 \qquad i = m, f. \quad (7)$$

In the intertemporal budget constraint, $A(t)$ is the household's assets at the beginning of period t. Profits are given by equation (1) or (2), depending on whether the current period is the planning stage or the harvest stage. In the time constraint, $\Omega(t)$ is the household's labor endowment, while $l_i(t)$ is "leisure" time or time spent in activities other than own-farm and off-farm work. I assume that preferences are such that the nonnegativity constraints (equation (6)) on consumption and leisure are never binding.

Maximization of expected utility subject to the constraints (equations (4), (5), and (7)) yields the standard first order conditions for intertemporal and intratemporal maximization:

$$U_c(c(t), h^0_m(t), h^w_m(t), h^0_f(t), h^w_f(t), Z(t)) = \lambda(t) \quad 8(i)$$

$$\begin{aligned} &U_{h_i^w}(c(t), h^0_m(t), h^w_m(t), h^0_f(t), h^w_f(t), Z(t)) \\ &\quad \geq \lambda(t) w_i(t) \qquad i = m, f \end{aligned} \quad (ii)$$

$$\begin{aligned} &U_{h_i^0}(c(t), h^0_m(t), h^w_m(t), h^0_f(t), h^w_f(t), Z(t)) \\ &\quad \geq \lambda(t) \frac{\partial \Pi}{\partial h_i^0}(t) \qquad i = m, f \end{aligned} \quad (iii)$$

$$\lambda(t) = \beta E_t(\lambda(t+1)(1 + r(t+1))). \quad (iv)$$

These conditions reveal that the forecast error or the surprise in incomes affects households primarily through its effects on $\lambda(t)$, the marginal utility of wealth in period t. As noted by MaCurdy (1985), under uncertainty $\lambda(t)$ varies across periods as households use the "surprise" in current income to update their expectations of future income. As a consequence, consumption and labor decisions in a dynamic setting will reflect both the realization of income shocks and also, separately, the surprise in incomes. In contrast, intratemporal choices regarding consumption and labor—as reflected in the marginal rate of substitution derived by dividing equation 8(iii) or 8(ii) by equation 8(i)—are affected by the realization of stage-specific income shocks through their effect on farm profits, but not directly by the forecast error in incomes. In this two-stage model, however, intratemporal choices in the second stage will also reflect expectations of income through first-stage inputs. This may yield an additional source of correlation between the forecast error in income and hours of work since, empirically, a regression of hours of work on the realization and the expectation of the shock is equivalent to a regression on the forecast error and the expectation of the shock. This effect of the forecast error through endogenous wages is, however, not the primary justification for the analysis of income shocks. Instead, the justification comes from the intertemporal model.

The model, as specified, does not accommodate credit constraints in the form of a nonnegativity constraint on assets in any given period. If such a constraint exists for some households, equation 8(iv) will not hold as an equality. There is, however, little evidence in the data that households draw their assets down to zero.[4] A more realistic framework allows credit constraints to take the form of household-specific credit supply schedules that are increasing in the loan amount, yielding interest rates that vary systematically with household characteristics. I do not explicitly model

[4] Even small farmers report average assets of Rs. 7,000, and, while dis-savings are common (42% of small farmers and 43% of the sample), no household reports zero assets.

interest rates in the empirical model, assuming their effect to be captured through household-fixed factors and time-varying household variables. The joint modeling of credit and labor decisions is beyond the scope of this paper, but it remains an important area for future research.

In addition to the first-order conditions above, a separate set of first-order conditions describe household choices regarding stage-specific production inputs, $x(t)$. For first-stage inputs this condition is

$$\lambda(t)\frac{\partial \pi_1(t)}{\partial x_1(t)} = \frac{E_t\lambda(t+1)(1+r(t+2))\dfrac{\partial \pi_2(t+1)}{\partial x_2(t+1)}}{E_t(1+r(t+1))} \tag{9}$$

Thus, decisions regarding first-stage inputs reflect household expectations of future shocks, an observation I use in the estimation of the surprise in crop incomes, as described in section V.

V. Estimating the Surprise in Crop Incomes

This paper focuses on the effect of the surprise in second-stage or harvest incomes, restricting attention further to income shocks in the kharif season only. Household labor responses to such shocks are considered for the entire cropping year. Second-stage kharif shocks may reflect only part of the income shocks that households are subject to, and it may also be the case that the methods used by households to mitigate the consumption consequences of such shocks differ from those used to mitigate the effects of shocks at other stages of the agricultural cycle. Several factors motivate my focus on second-stage kharif shocks. Unlike the rabi (or post-rainy) season, kharif profits are so heavily dependent on weather realizations that much of the variation in kharif profits is weather related. This yields a set of instruments for correcting for measurement errors in estimated values of the crop shock. The problems inherent in estimating the surprise in incomes motivate the focus on second-stage income shocks. As I describe below, credible estimates of such shocks can be obtained by using the information contained in first-stage input choices.

Since household expectations of farm profits are unlikely to be time-invariant, I define the surprise in incomes, θ_{it}, as the deviation of period t profits from the household's $(t-1)$ expectation of profits as determined by the household's $(t-1)$ information set, $I(t-1)$: $\theta_{it} = \pi_{it} - E(\pi_{it}|I_{\,i,t-1})$. This forecast error can then be estimated as the residual from a regression of crop profits on variables determining the household's $(t-1)$ expectations of profits. A conventional set of regressors to measure such expectations include a set of household dummy variables, reflecting all time-invariant factors, and a set of time-varying demographic variables: the number of males and females of ages 15 to 45; the age, squared age, and level of education of members of these two demographic groups; the number of males and females of ages 15 to 55; the number of young children of ages less than 5; and the total number of family members. To separate out the aggregate component of the surprise in income, the regression also includes a set of village-year dummy variables, so that the regression residual is orthogonal to the aggregate or common shock in farm incomes.

The residual from this regression, in addition to the idiosyncratic shock in crop incomes, also contains unobserved $(t-1)$ variables that determine household expectations, as well as any measurement error in profits. Moreover, since I measure crop profits as the value of output net of all costs excluding those of family labor (so as to avoid the difficulties inherent in imputing a value to family labor), farm profits reflect the return to family labor as well as other family-owned farm inputs. The regression residual thus also contains any unobserved preference shocks that determine leisure choices. All these components of the residual will likely be correlated with unobserved variables determining market hours of work, yielding biased estimates of the effect of idiosyncratic crop shocks on hours of work. I describe below the methodology used to minimize the bias caused by the inclusion of unobserved $(t-1)$ variables. The bias due to measurement error and preference shocks is dealt with by instrumental variable procedures, also described below.

The major difficulty in estimating income shocks stems from the fact that household expectations of income are based on far more information than the researcher can access. This problem of the household's "superior" information can be circumvented if there exists a variable, known to the researcher, that serves as a sufficient statistic in that it reflects the household's expectation of future income. For example, household savings can serve this function if savings reflect expectations of future income (Deaton, 1992). In developing economies in which savings are low and held mainly in illiquid forms that do not typically vary from season to season, savings may only weakly reflect household expectations of profits in the coming season. Additionally, liquidity constraints may prevent households from adjusting savings to fully reflect their expectations of future output, particularly when such expectations are negative.

The sequential nature of farming and the fact that farmers must make production plans in the first stage before weather outcomes are fully realized provide an alternative control for household expectations of weather. In particular, if planting decisions reflect expectations of weather in the coming season, then including the acreage under specific crops amongst the set of regressors provides a control for expectations of weather in the second stage, and, hence, improves on estimates of crop income shocks that make no allowance for the household's superior information. The Walker and Ryan (1990) study of the survey villages notes that cropping choices are sensitive to expectations of weather. Thus, farmers commonly increase the acreage of drought-resistant crops relative to that of water-intensive crops when they expect poor rainfall.

A household's choice of crops, however, yields an effective instrument for its expectations of weather only if a restrictive set of conditions is met. First, the crops considered need to be commonly cultivated, so that variations in acreage do not primarily reflect farm-specific agronomic factors. More importantly, it is necessary to restrict attention to crops whose adoption is known to be sensitive to expectations of weather and which are planted early enough so that the area under the crop does not reflect any ex post adjustment to weather outcomes. This also means that inputs such as labor or fertilizers that are used throughout the season cannot be used to measure household expectations, since the level of their use will reflect realizations of weather outcomes as they occur. A number of crops meet these conditions. One crop, cultivated by almost all farms in the three villages, is pigeon pea, a drought-resistant pulse that farmers are known to plant relatively more of when they expect a bad monsoon. Planting is completed by the third week of June, which coincides with the onset of the monsoons. I also include the area under a second major crop, with the choice of crop varying from village to village: local varieties of pearl millet in Aurepalle, minor pulses in Shirapur, and local varieties of cotton in Kanzara. The regressors in the profit regressions additionally include start-of-period cultivated acreage and capital, interactions of cultivated acreage and capital with each other and with the household's endowment of male and female labor of ages 15 to 45, and the conventional set of household and village-year dummy variables and demographic variables described above.

Table 3 reports the results of this regression. For all three villages, the set of regressors significantly explains current profits, indicating that profits are not randomly distributed around their mean value. The results reveal considerable intervillage differences in the extent to which we can predict the variation in profits around its mean. The unexplained variance of income is only 7% in Kanzara, but 19% in Aurepalle and 47% in Shirapur, reflecting the high levels of uncertainty associated with crop production in Shirapur.

While the inclusion of first-stage crop choices reduces the possibility that the regression residual contains unobserved $(t-1)$ variables, there remains the possibility that the residual includes both current preference shocks and measurement error in profits. Conventional instrumental variable techniques can control for this bias, provided there exists an instrument that is correlated with the "true" idiosyncratic crop shock but not with preference shocks or the random measurement error in crop profits. Since crop shocks in the kharif season are primarily weather related, I use interactions of village-level rainfall in the monsoon months of June, July, August, and September with the first-stage cultivated acreage and capital, the number of household males and females of ages 15 to 45, and the amount of land under pigeon pea, local sorghum, cotton and other pulses as instruments.

TABLE 3.—CROP PROFIT REGRESSION (DEPENDENT VARIABLE: REAL KHARIF PROFITS, 1983 RS.)

Variables	Village: Aurepalle	Shirapur	Kanzara
Area under			
Pigeon pea	110.82*	129.41*	−119.29*
	(59.13)	(58.40)	(51.40)
Local pearl millet	−200.22*	—	—
	(81.68)		
Minor pulses	—	−9.32	—
		(47.41)	
Local cotton	—	—	192.53*
			(62.63)
Start-of-period cultivated area	125.52	−98.82*	100.89
	(97.55)	(54.53)	(73.78)
Start-of-period capital	0.65*	0.15	1.07*
	(0.23)	(0.24)	(0.33)
Area*Capital	−0.03*	0.06*	0.005
	(0.01)	(0.01)	(0.006)
Area*Males	−8.00	42.53*	−28.36
	(52.86)	(23.06)	(34.49)
Area*Females	15.21	−14.70	−10.88
	(24.08)	(18.67)	(25.32)
Capital*Males	−0.11	−0.21*	−0.07
	(0.15)	(0.08)	(0.27)
Capital*Females	−0.05	−0.04	−0.23*
	(0.16)	(0.09)	(0.11)
R^2	0.82	0.53	0.93
Sample size	283	203	285

Notes: All regressions include household-fixed effects, a set of village-year dummies, and the following demographic variables: the number of males and females of ages 15 to 45, their average age and squared age, the number of males and females of ages 15 to 55, the number of children of ages 0 to 5, and family size. The total number of regressors in each equation is approximately 65. Method of estimation: Fixed effects OLS.

* significant at 5% level † significant at 10% level.

The ICRISAT data also provide another effective instrument for idiosyncratic crop shocks in that they record any incident of crop failure reported by the farmer on a plot- and crop-specific basis. To allow for differences in the severity of crop failures across households, I construct a weighted average of the number of episodes of crop failure reported in each of the household's plots in that season using the size of the plot relative to the household's total landholding and the number of crops that failed relative to the total number of crops on that plot as weights. This "reported" ordinal measure of idiosyncratic crop income shocks serves as an instrument for the cardinal "residual" measure recovered from the profit regressions. It also generates additional support for the empirical results of this paper in that the response of hours-of-work to this indicator should compare to those obtained using the residual measure. The self-reported ordinal indicator, however, does not measure the magnitude of the shock (as does the residual measure) and, hence, cannot be used to evaluate the economic significance of any particular method of mitigating the effects of crop income shocks.

VI. Empirical Issues

A. *The Market Hours-of-Work Equation*

The equation determining the household's market hours of work is derived from equation 8(ii). This specification yields separate hours of work equations for males and females, with the market hours of males (females) being a function of aggregate consumption, own farm hours ($h_m^o(t)$, $h_f^o(t)$), male and female wages, $\lambda(t)$ and $Z(t)$, in addition to the market hours of work of females (males). Corner solutions in market hours are significant, with approximately 30% and 34% of sample households reporting no such hours by males and females, respectively. Market hours of work are thus estimated using tobit regressions, whereby observed hours ($h^w(.)$) equal notational or desired hours ($h^*(.)$) when the latter are positive, and are zero otherwise.

From equation 8(ii), male (female) market hours of work are also a function of hours supplied to own-farm production by both males and females, as well as female (male) market hours, so that corner solutions in all these variables also need to be addressed. If, for example, a significant percentage of households record no own-farm hours, the reduced-form specification of market hours of work will differ for such households and those with strictly positive hours. Corner solutions in own-farm hours are, however, not significant amongst cultivator households, with 89% of households reporting strictly positive hours by both males and females. Further, 86% of households that report positive hours of market work for males also report positive market hours for females, and, of households that report positive market hours of work by females, 88% also report positive market hours for males. Given these high percentages, I neglect corner solutions for both own-farm hours and market hours by members of the opposite sex. Substituting in for the determinants of own-farm hours, the desired market hours-of-work equation is

$$\begin{aligned} h^*_{ijt} = \alpha_o + x'_{ijt}\alpha_1 + Z'_{ijt}\alpha_2 + V'_{jt}\alpha_3 + \alpha_4 w_{ijt} \\ + \alpha_5 r_{ijt} + \alpha_6 \lambda_{ijt} + \alpha_7 \theta_{ijt} + \eta_{ijt}. \end{aligned} \tag{10}$$

where x_{ijt} and Z_{ijt} are vectors of production and demographic shift variables determining the marginal product of own-farm labor and preferences in period t; V_{jt} is a vector of village-level variables affecting hours of work such as aggregate income and preference shocks and village prices; r_{ijt} is a household-specific interest rate; θ_{ijt} is the current idiosyncratic crop income shock; λ_{ijt} is the household's marginal utility of wealth in period t; and w_{ijt} is the period t market wage rate for household i.

The empirical treatment of these latter two variables is discussed in more detail below.

B. *The Life-Cycle Component, $\lambda(t)$*

The intertemporal framework yields consumption and labor-supply decisions that are a function of the household's marginal utility of wealth, $\lambda(t)$. As noted earlier, under uncertainty $\lambda(t)$ can be specified as a linear function of the household's initial marginal utility of wealth, $\lambda(0)$, the sequence of past forecast errors in shocks, and the current shock to income and preferences. The empirical equation thus includes $\lambda(0)$ and the estimate of the current crop income shock amongst the regressors. The history of forecast errors and current preference shocks are relegated to the regression error term.

Following Heckman and MaCurdy (1980), $\lambda(0)$ can be incorporated through a set of household-fixed effects. As they note, however, tobit fixed-effect regressions may yield biased estimates in short panels of data. They, however, report Monte Carlo results from previous research which found that a multivariate probit model with fixed effects performed well with eight years of data and suggest that the fixed-effect tobit model is likely to perform even better. The ICRISAT panel, however, contains only six years of data on labor hours, so that inconsistent estimates is a distinct possibility. An alternative estimator, suggested by Honoré (1992) to overcome the limitations of a short panel, is however also ill suited to this data, since its consistency requires the regression error term to be independently and identically distributed across time. This condition is rejected by the data; the variance of the error term is found to be household specific and time varying. Given the known inconsistency of the Honoré estimator in this application, I therefore report results from a fixed-effect tobit regression. As a check on the results, I also report results from a regression that—instead of using household-fixed effects to incorporate the time-invariant $\lambda(0)$ term—does so by including a set of household-specific, time-invariant variables. These variables include details of the household's inherited land from a supplementary retrospective survey of ICRISAT households, as well as the educational status of the household head and his wife. It is difficult to judge, however, how well these variables approximate $\lambda(0)$, so that the possibility of inconsistent regression coefficients remains a concern.

C. *Market Wage Rates for Multiple Worker Households*

A final issue relates to the relevant market wage for the household. While data on the wage income of individual household members is available, the considerable variability in the number of adult family members across households in economies such as India's renders difficult an empirical analysis that takes the individual as the unit of observation. The conventional approach to this problem has been to consider broad aggregates of household labor (Rose, 1992; Skoufias, 1994), and to take the gender- and year-specific village average wage as the wage applicable to this aggregate commodity. Such a procedure inputes a common wage to all households in the village.

An alternative approach developed in Kochar (1997) follows the literature on the aggregation of consumption goods, defining household preferences over an aggregate labor good with a price given by the weighted average of the price of each individual labor activity. This approach justifies aggregating the labor of household members in the utility function and also yields a well-defined, household-specific wage rate. It builds on the observation that total labor hours in agriculture comprise the sum of hours spent in distinct agricultural tasks, and that wages in the Indian rural economy show little variation across individuals engaged in the same task (Bardhan & Rudra, 1981; Binswanger et al., 1984). Wage rates for aggregate household labor can then be calculated as the weighted average of village-year-gender- and task-specific wages, with the proportion of household time devoted to individual tasks serving as weights.

The data provide strong support for the hypothesis that task-specific wages show little variation across individuals, so that much of the observed variation in wage rates in any given cross-section of data primarily reflects variation in the individual choice of activities. Regressions of these wage rates on a set of season-year-village- and task-specific dummy variables reveals that the set of village average task-specific wages in any given season-year explains almost all the variation in wage rates. Thus, the R^2 in the regression of *kharif* season wages is 98% for Aurepalle and Shirapur, and 96% for Kanzara.

Since observed wages reflect household choices regarding the proportion of time devoted to each activity, wages estimated by this procedure will be endogenous and correlated with unobserved variables determining market hours. The objectives of this paper, however, do not require an explicit measure of wages, and I accordingly circumvent the problems inherent in including an endogenous measure by estimating a reduced-form regression that includes, instead, their exogenous determinants, namely interactions of village-gender-year- and task-specific wages with exogenous variables determining the household's choice of market activities. These are taken to be the average age of females of ages 15 to 45, and the levels of education (literate, primary, middle, and higher) of males of the same age group. The tasks for which wages are considered are those for which hired labor use is the greatest: harvesting for both males and females, in addition to sowing and field preparation for males.

D. *Estimating Equation for Hours-of-Work*

Substituting in for wages and interest rates, the estimating equation for hours of work is:

$$\begin{aligned} h^*_{ijt} &= \beta_o + \gamma'_{ij}\beta_1 + x'_{ijt}\beta_2 + Z'_{ijt}\beta_3 + \zeta'_{jt}\beta_4 + \beta_5\theta^+_{ijt} \\ &\quad + \beta_6\theta^-_{ijt} + \mu_{ijt} \\ h^w_{ijt} &= h^*_{ijt} \qquad \text{if } h^*_{ijt} > 0 \\ &\quad 0 \qquad \text{otherwise.} \end{aligned} \tag{11}$$

γ_{ij} represents a vector of household dummy variables that incorporate the effect of all fixed factors affecting hours of work, including those that determine preferences as well as farm production. This vector also incorporates the effect of the household's initial marginal utility of wealth, $\lambda(0)$. ζ_{jt} is a set of village-year dummies. The vector x_{ijt} includes the time-varying household specific variables that determine farm production. From the profit regressions, these include the household's start-of-period cultivated acreage and capital, the acreage under particular crops, and interactions of these terms. The vector of household-specific variables, Z_{ijt}, is redefined to include both the set of variables determining wages (described above), as well as observed time-varying variables that affect preferences in period t. These latter variables are assumed to be primarily demographic variables: the number of male and female able-bodied adults of ages 15 to 45, their average age and age squared, as well as their levels of education, family size, the number of children in the household less than 5 years of age, and the number of male and female members of the household of ages 15 to 55 (excluding those with any significant disability).

The error term in equation (11), μ_{ijt}, includes the error term from equation (10), η_{ijt}, as well as unobserved determinants of interest rates and wages and the history of past forecast errors. This history forms part of the household's information set in each period, so that, if the current forecast error is correctly estimated, it will be orthogonal to lagged errors. η_{ijt}, however, includes other current shocks such as preference shocks as well as measurement error in profits, terms which are likely to be correlated with the residual in crop profits, θ_{ijt}. I control for bias by using a two-stage tobit method (Nelson & Olsen, 1978), replacing the crop income shock by its predictor from an ordinary-least-squares (OLS) regression of such shocks on the set of instruments described in section V, as well as the other exogenous variables in the hours-of-work equation (11). Given imperfect credit markets, positive and negative shocks will differ in their affect on household savings and, correspondingly,labor supply. I therefore separately predict positive ($\theta_{ijt}{}^+$) and negative ($\theta_{ijt}{}^-$) crop shocks, and allow them to affect hours of work differentially. The explanatory power of the set of instruments in these first-stage regressions on positive and negative shocks is confirmed through F tests; the relevant F statistics, $F(33, 194)$, are 3.67 and 4.20 for positive and negative shocks, respectively. The likelihood function also allows for heterosedasticity in the form of variances that depend linearly on family size.

VII. Results

This paper presents two sets of results. I first consider the effects of the residual measure of crop income shocks and, separately, the effects of the self-reported indicator of crop failure on the market hours-of-work of male and female members of the household. The second set of results considers the effect of crops shocks on household consumption: first in its reduced form, and, second, conditional on hours of work. Table 4 provides descriptive statistics on hours of work and consumption, as well as on other important variables.

TABLE 4.—DESCRIPTIVE STATISTICS

Variable	Mean	Std. Deviation
Market days, males	134.60	142.33
Market days, females	82.60	103.12
Own-farm days, males	84.55	91.84
Own-farm days, females	46.70	55.97
Consumption (Rs)	4,476.82	3,293.84
Positive residual shock	547.64	1,216.11
Negative residual shock (abs. value)	550.74	936.02
Reported shock	1.02	2.11
Males 15–45:		
number	1.72	0.96
average age	28.96	8.08
number literate	1.15	1.03
with primary education	0.39	0.64
with middle education	0.28	0.56
with higher education	0.38	0.75
Females 15–45:		
number	1.71	0.93
average age	28.65	6.41
number literate	0.70	1.07
with primary education	0.29	0.59
with middle education	0.26	0.65
with higher education	0.11	0.38

Note: These statistics are for the sample of 381 cultivator households with at least one male and one female of age 15 to 45.

A. *Market Hours-of-Work by Gender*

Tables 5 and 6 present regression results for the market hours of work of household males and females, respectively. Each table reports three sets of regressions. The first two utilize two-stage, fixed-effect tobit procedures, but differ in that the first regression uses the cardinal residual measure of shocks whereas the second uses the ordinal self-reported index. The third regression uses a set of household-specific, time-invariant variables (a partial list of which is included in the table) instead of the set of household dummy variables. All three regressions yield approximately the same result: households increase the market hours of work of their male members in response to negative crop income shocks, although there is little significant effect on the market hours of work of females.

Since the data in this analysis are standardized to have a mean of zero and a unit variance, converting the parameter estimates into slope coefficients ($\beta\Phi(X\beta)$) and evaluating the responses at the standard deviations for the mean shock and mean market days of work for males yields magnitudes of the effects of crop income shocks on market days of work. Multiplying these by the mean market wage allows an assessment of the extent to which the wage market participation of males compensates for crop income shocks.[5] These calculations, based on the coefficients from the fixed-effect tobit specification, yield significant responses of wage income to crop shocks: male wage income compensates for as much as 30% and 33% of the negative crop income shock for small and medium farms, respectively, and 7% for large farms. By village, male wage labor compensates for 19% of crop income shocks in Kanzara, 11% in Aurepalle, and as much as 55% in Shirapur.

The conclusions that can be drawn from the positive effect of (adverse) income shocks on market hours are tempered, however, by the fact that higher-than-expected crop incomes also appear to result in an increase in market hours. While this may be so, one cannot rule out the possibility that the regression results are biased, either as a consequence of the treatment of $\lambda(0)$ or on account of difficulties in estimating the pure effect of the income shock.

B. *Analyzing the Effects of Idiosyncratic Crop Income Shocks on Household Consumption*

The ability to shift from own-farm to off-farm work in response to idiosyncratic crop income shocks reduces the variability in household income and, hence, the need to rely on savings to smooth consumption in response to such shocks. However, if labor markets function well, such a shift would occur even if households had access to full insurance markets. In order to assess whether such reallocations of labor serve an insurance function, this section analyzes their effect on the correlation between consumption and income shocks. To do so, I first assess the overall effect of income shocks on household consumption by running a reduced-form regression of consumption on a set of covariates that includes the idiosyncratic crop shock. The role of hours of work is then examined through a structural regression that conditions on hours of work. If households primarily buffer consumption through wage income, conditioning on hours of work should yield a significant negative effect of crop shocks on consumption, even while the overall effect on consumption (as reflected in the reduced-form regression coefficients) will be low.

Since the first-order condition (equation 8(i)) holds as an equality for all households, regardless of their market hours of work decision, the structural consumption regression that conditions on hours of work does not require a correction for corner solutions in hours of work.[6] I distinguish between own-farm ($h_m^o(t)$, $h_f^o(t)$) and market hours of work ($h_m^w(t)$, $h_f^w(t)$), allowing households to value these two uses of their time differentially. This distinction is supported by the regression results, which yield very different effects of own-farm and market hours on consumption for both males and females.

Own-farm and market hours of work are clearly endogenous variables; and hence, the structural regression is estimated using instrumental variable procedures. From the set of first-order conditions (equation (8)), a valid set of

[5] The standard deviation of mean market days for small, medium, and large farms is 118, 117, and 81, respectively. The mean (real) daily wage is Rs. 8 for males in small and medium farms and Rs. 9 for those in large farms. By village, the standard deviation in mean market days is 93, 125, and 108, in Aurepalle, Shirapur, and Kanzara, respectively, while the mean wage is Rs. 7, Rs. 8, and Rs. 9, respectively.

[6] Conditioning on hours of work is preferred to conditioning on wage income, since it is unclear how wage income will affect consumption. Under the permanent-income hypothesis or in a full-insurance economy, one would in fact not expect wage income to affect consumption in a regression that controls for household wealth and aggregate consumption (through fixed effects and village year dummies).

TABLE 5.—MARKET HOURS OF WORK, MALES AGES 15–45

	Fixed-Effect Tobit				Tobit with Time-Invariant Regressors	
	Regression 1		Regression 2		Regression 3	
Shock Measures						
Residual shock						
positive	0.2615*	(0.1206)	—	—	0.2728*	(0.1303)
negative	0.2012*	(0.0922)	—	—	0.1736	(0.1089)
Reported shock	—	—	0.0875†	(0.0558)	—	—
Males 15–45						
number	0.8409*	(0.2312)	0.8239*	(0.2344)	0.8008†	(0.1790)
average age	1.4637	(1.0988)	2.0091*	(1.0663)	1.5712*	(0.7788)
average age sq.	−1.4025*	(0.7619)	−1.7164*	(0.7454)	−1.2483*	(0.5526)
number literate	−1.4400	(0.9425)	−0.7768	(0.9146)	−1.0866*	(0.6265)
with primary education	0.8588*	(0.4574)	0.7571†	(0.4636)	0.5604*	(0.3421)
with middle education	0.8617*	(0.4981)	0.9310*	(0.4955)	0.8902*	(0.3516)
with higher education	−1.3179	(20.4544)	−0.3714	(34.1365)	0.9790*	(0.4824)
Females 15–45						
number	0.1395	(0.2135)	0.1212	(0.2144)	0.3783	(0.1530)
average age	−1.0316	(1.2009)	−0.9116	(1.2021)	1.5430*	(0.9605)
average age sq.	1.0425	(0.9545)	0.8855	(0.9562)	−0.5316	(0.6982)
number literate	0.3474	(0.5170)	−0.0441	(0.5084)	−0.1078	(0.2894)
with primary education	0.6108†	(0.3628)	0.7012*	(0.3624)	−0.0532)	(0.1789)
with middle education	2.6626	(1.3209)	2.5704*	(1.3120)	0.4187*	(0.2520)
with higher education	0.5697	(0.4128)	0.6552	(0.4141)	0.2941†	(0.1964)
Fixed Factors						
inherited land	—	—	—	—	−0.5702*	(0.1733)
head literature	—	—	—	—	−0.0361	(0.3237)
head primary education	—	—	—	—	−0.3062*	(0.1430)
head middle education	—	—	—	—	−0.7609*	(0.2530)
head higher education	—	—	—	—	−0.2844	(0.3503)
Log Likelihood	−169.58		−171.33		−253.18	
Sample Size	371		371		371	

Notes: Regressions are run on the sample of cultivator households with at least one male and one female of ages 15 to 45. Coefficients on the full set of regressors are not reported in this table, but are available on request. The additional regressors include a set of household and village-year dummy variables, family size, the number of children ages 0 to 5, interactions of village-gender-year and task-specific wages with age and education variables, cultivated acreage, capital, area under specific crops, and interaction terms in these variables. Instruments for the residual shock are interacted terms in monthly rainfall levels with cultivated acreage, capital, acreage under specific crops, and the number of household males and females of ages 15 to 45, as well as the self-reported measure of shocks, as instruments for the residual shock measures. Regression 3 drops the set of household-fixed effects but includes, in addition to reported regressors, data on the education of the head's wife.

instruments for market and own-farm hours of work are the determinants of market wages and own-farm labor productivity, respectively. Following the discussion of the determinants of market wages in section VI(C), interactions of village-gender-year- and task-specific wages with age and education variables are used as instruments for market hours. While age and education variables may independently affect preferences (and hence are included amongst the regressors), the identifying assumption is that preferences are not directly affected by the interaction of these demographic variables with village-year- and gender dummy variables. The variables reflecting own-farm productivity that are used to instrument own-farm hours are taken from the profit regression. These are start-of-period cultivated area, capital, and area under specific crops, as well as interactions of these variables with each other and with the household's endowment of male and female labor of ages 15 to 45. Both the reduced-form and the structural regressions also treat the residual shock measures as endogenous, instrumenting them by interaction terms in monthly rainfall levels and by the self-reported shock measure.

Since the structural consumption equation is overidentified the validity of the instruments can be tested by standard Basmann overidentification tests. The F statistic from this test, F(60, 261), equals 1.16, and hence fails to reject the hypothesis of valid instruments. The explanatory power of the instruments in the first-stage regressions is also confirmed through F tests. Thus, the relevant F(66, 252) statistics are 4.20 and 1.42 for own-farm and market hours of males, and 2.85 and 1.40 for own-farm and market hours of females.

Due to corner solutions in market hours of work, a reduced-form consumption regression that does not condition on hours of work will differ across households that report positive market hours and those that do not. Accordingly, I restrict the regression sample to households that report positive market hours by males and females, controlling for sample selection bias through the inclusion of the inverse Mill's ratio, calculated from the tobit regression of wage market participation by male workers. This results in a considerable loss of precision, both because of the reduction in sample size and because of the need to correct standard errors for the inclusion of an estimated variable (the inverse Mill's ratio). Nevertheless, corner solutions in market hours of work necessitate such controls on the regression sample.

In addition to the forecast errors in income and Mill's ratio, the covariates in the reduced-form regression include a set of household dummy variables, a set of village-year dummy variables, demographic variables influencing preferences, and all the variables used to instrument market and own-farm hours as previously described. The regression results (table 7) reveal that the time profile of household

TABLE 6.—MARKET HOURS OF WORK, FEMALES AGES 15–45

	Fixed-Effect Tobit				Tobit with Time-Invariant Regressors	
	Regression 1		Regression 2		Regression 3	
Shock Measures						
Residual shock						
positive	0.0608	(0.1402)	—	—	0.0904	(0.1513)
negative	−0.1987	(0.1311)	—	—	−0.526	(0.1511)
Reported shock	—	—	−0.1950*	(0.0870)	—	—
Males 15–45						
number	0.8050*	(0.2525)	0.8062*	(0.2510)	0.5934*	(0.2126)
average age	1.4704	(1.3281)	1.3101*	(1.2907)	−1.5147	(0.9473)
average age sq.	−1.4928†	(0.9265)	−1.4281†	(0.8968)	0.9002	(0.6788)
number literate	−1.4847	(1.4242)	−2.1050	(0.4812)	−0.9501*	(0.8079)
with primary education	0.5661	(0.7258)	0.9522	(0.7423)	0.7428*	(0.4286)
with middle education	0.3767	(0.8792)	0.4911	(0.8778)	0.5316	(0.4851)
with higher education	−7.5294	(11.1154)	−8.5199	(10.4250)	0.4468	(0.6022)
Females 15–45						
number	0.5938*	(0.2305)	0.6303*	(0.2365)	0.6972†	(0.1769)
average age	−1.8902	(1.6520)	−1.4469	(1.6372)	−0.5009	(0.1425)
average age sq.	1.0113	(0.2907)	0.6856	(1.2797)	0.1375	(0.8226)
number literate	−2.7963*	(0.2664)	−2.4354	(1.3328)	0.0844	(0.3869)
with primary education	0.7815*	(0.6213)	1.6620*	(0.6452)	−0.1721	(0.2235)
with middle education	0.3033	(1.9827)	−0.1300	(2.1985)	0.0320	(0.3217)
with higher education	0.3399	(0.5678)	0.2071	(0.6153)	−0.3534	(0.3642)
Fixed Factors						
inherited land	—	—	—	—	−0.7857*	(0.2433)
head literature	—	—	—	—	0.2892	(0.4218)
head primary education	—	—	—	—	−0.1511	(0.1689)
head middle education	—	—	—	—	−1.4387*	(0.3881)
head higher education	—	—	—	—	−2.1178*	(0.5420)
Log Likelihood	−188.55		−189.02		−280.33	
Sample Size	371		371		371	

Note: Details regarding additional regressors and the set of instruments are in the note to table 5.

consumption is relatively smooth; much of the sample variation in consumption is explained by the set of household-fixed effects, the district-year dummy variables, and a relatively small set of demographic preference shifters. In particular, idiosyncratic crop income shocks have an insignificant effect on consumption. While this suggests that household consumption is protected from such shocks, this interpretation, as noted above, is weakened by the small sample size and the consequent overall loss in efficiency. However, it is noteworthy that, even in economic magnitudes, crop income shocks have little effect on consumption. Converting the standardized coefficients into elasticities, a 10% increase in adverse income shocks reduces consumption by only 0.2%.

In contrast to the results from the reduced-form regression, the "structural" consumption regression reveals that consumption falls with unexpected declines in crop incomes, suggesting that the overall insignificant effect of crop shocks on consumption reflects adjustments in hours of work. The quite different effects of the market and own-farm hours of males on household consumption again, however, suggests the fragility of the estimates and the need for caution in interpreting the results.

The results from the structural regression imply that an increase of one standard deviation in negative crop shocks reduces consumption by 0.20 standard deviations. Evaluated at the standard deviations of the mean shock and level of consumption, this amounts to a reduction in consumption equal to 44% of the income shock suffered by small farms, and 74% and 83% of that experienced by medium and large farms, respectively. By village, the fall in consumption amounts to 81%, 112%, and 96% of the loss in crop profits in Aurepalle, Shirapur, and Kanzara, respectively. This considerable decline in consumption in the absence of adjustments in family hours of work is in contrast to the estimated effect of income shocks on the market hours of males (table 5), which indicate that wage income earned by male members of the household compensates, on average, for 30% of the crop income shortfall of small farms, and 33% and 7% of that of medium and large farms, respectively. The structural consumption equation, however, controls not just for the market hours of work of males and females, but also for their own-farm hours. Male own-farm hours have a positive and statistically significant effect on consumption. One explanation for the large effects of income shocks on consumption in the absence of adjustments in hours of work could thus be that households that experience crop income shocks at the start of the season adjust not just male market hours but also their own-farm hours.

VII. Conclusion

This paper reports evidence that suggests that the smoothness of household consumption in the presence of farm-specific crop income shocks reflects the ability of households to smooth income directly, by increasing their market

TABLE 7.—CONSUMPTION REGRESSION

Variable	Reduced Form Method: OLS with Selection Correction		Structural Equation Method: Two-Stage Least Squares	
	Coeff.	Std. Error	Coeff.	Std. Error
Shock measures:				
Residual shock				
Positive	0.0169	(0.0748)	0.0719	(0.0735)
Negative (abs value)	−0.0575	(0.0770)	−0.1960*	(0.0778)
Endogenous variables:				
market hrs-males	—	—	−0.2287*	(0.1153)
farm hrs-males	—	—	0.1919*	(0.0958)
market hrs-females	—	—	0.0528	(0.1170)
farm hrs-females	—	—	−0.0457	(0.1028)
Males 15–45:				
number	−0.0857	(0.2401)	0.1142	(0.2343)
aveage age	0.5503	(0.9850)	0.0137	(0.3210)
average age sq.	−0.6609	(0.7046)	−0.1231	(0.3161)
number literate	−0.9182	(0.8388)	0.0940	(0.3744)
with primary education	0.1029	(0.4535)	0.0020	(0.2137)
with middle education	1.3050†	(0.7276)	−0.0265	(0.2252)
with higher education	2.5809	(2.0696)	−0.0794	(0.2511)
Females 15–45:				
number	−0.0857	(0.1947)	0.0469	(0.1917)
average age	2.1498†	(1.4254)	0.1353	(0.2997)
average age sq.	−1.6783	(1.1252)	−0.1804	(0.2703)
number literate	−1.2718	(2.3136)	0.8991*	(0.3101)
with primary education	1.6876	(1.1709)	−0.5648*	(0.1873)
with middle education	−0.4824	(1.5333)	−0.5350*	(0.2227)
with higher education	1.5530*	(0.7940)	−0.5806*	(0.1185)
Mill's ratio	0.1691*	(0.1179)	—	—
Sample size	205		435	
Over-identification test statistic	—		1.16	
F(60,251)				

Notes: The reduced-form regression is run on the sample of households reporting positive hours of market work by males and females. The Mills' ratio is calculated from the tobit results of participation by males in the labor market. Standard errors are corrected for the use of an estimated variable. Both regressions additionally include a set of household and village-year dummy variables. The reduced-form regression also includes the instruments for market hours (interactions of village-gender-year and task-specific wages with age and education variables), as well as those for own-farm hours (cultivated land, capital, and area under specific crops, and interaction terms in these variables). The residual measures of shock in both regressions are instrumented by interactions of this latter set of variables with month-specific rainfall levels as well as the reported shock measure.

hours of work. Due to data limitations, legitimate concerns regarding the reliability of the results remain. If, however, they are confirmed through analyses of other data sets, they carry important implications for research on the costs of income uncertainty on farm households. Much of the research in this area has assumed that households primarily use assets to smooth consumption, and has consequently sought to establish the costs of income uncertainty through analyzing its effect on savings. If, however, household labor is more important in this regard, the costs of income uncertainty may primarily be reflected in decisions that affect the household's labor endowment, including educational and fertility outcomes and decisions regarding migration. The results of this paper also suggest that interventions in labor markets—either directly through public works programs or indirectly through health programs that enhance the ability of individuals to engage in agricultural tasks—may significantly improve the economic security of households.

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