ABSTRACT
Rural households in developing countries typically grow multiple crops each season. They do so for many reasons, but because agriculture in such settings is characterized by high risk, the portfolio diversification motive remains popular among researchers. Oftentimes, however, the observed year-to-year allocation patterns are driven by crop rotation patterns. The premise of crop rotation is that the choice of crop in one season affects the yield of the next season's crop (yield effects). By rotating crops over multiple fields, farmers clearly benefit from yield effects and, if they are risk averse, from portfolio effects as well. But it remains unclear what role, if any, risk aversion plays in the farmer's decision-making process. This paper models cropping choices as dynamic decisions made on a plot-by-plot basis, rather than over the entire farm. It then tests whether risk aversion and yield variance influence cropping choices. It concludes that a model of farmers making decisions to maximize certainty equivalent can still outperform one in which farmers maximize expected profit, even after taking into account rotation effects.

1 Introduction

Rural households in developing countries typically grow multiple crops each season. They do so for many reasons, including protecting consumption in the face of imperfect markets (Fafchamps, 1992), high transaction costs (Omamo, 1998; Key et al., 2000), the seasonal allocative efficiency of inputs (Alderman & Paxson, 1982), but perhaps most importantly, the avoidance of risk. Agriculture is a risky enterprise. Agriculture in developing countries, where irrigation is infrequently used and crops are grown under marginal conditions, is even riskier. For this reason, common wisdom links cropping choices to households' willingness to tolerate risk, and the portfolio diversification motive, in particular, has gained traction (e.g. Ellis, 2000). When risk arises from prices or host-specific pests, revenue is arguably idiosyncratic across crops; in such a setting, a diversified crop portfolio will reduce the variability in crop returns. However, when the primary source of risk is insufficient rainfall, a diversified crop portfolio theoretically does little to reduce total income variability, as all crops are negatively affected. Yet crop diversification is the norm, and especially so in areas characterized by high rainfall variability.

Oftentimes the observed year-to-year crop allocation patterns are driven by crop rotation choices. The ancient practice of crop rotation is common in both developing- and developed-country settings, and it is based on the knowledge that the state of the soil affects yields, and that the history of preceding crops affects that state. Crop rotations commonly include leguminous crops such as beans and peas, as well as forage crops such as alfalfa and clover. Such crops have the well-known property of biologically fixing atmospheric nitrogen into a form that plants can utilize. Additionally, planting dissimilar crops from one year to the next disrupts the reproductive cycles of pests and diseases, reducing the soil pest load. In arid areas, farmers are thought to include a fallow in the crop cycle to build up soil moisture for the benefit of successive crops (Swearingen & Bencherifa, 2000). The crop choice in one season may affect not only the mean of the following crop's yield, but also its variance (the *yield effect*). Households in hazard-prone areas with few mechanisms for coping with income shocks may be concerned with yield stability as well as yield maximization.

But households that rotate crops over multiple plots automatically benefit from the income-stabilizing effects of a more diversified crop portfolio. Such households can stagger rotation patterns over time and grow multiple crops each year, thereby experiencing portfolio effects. Farmers clearly benefit from the yield effect, and if households are risk averse, from portfolio effects as well.

Little is known about the decision-making mechanism behind observed cropping patterns, especially in developing countries. It is unclear if households *choose* crop diversity at the farm level in order to stabilize total crop income, or if households decide what to plant each year on a plot-by-plot basis. If cropping decisions are made on a plot-by-plot basis, does yield variance concern farmers? As changes in global climate increase rainfall variance in many parts of the world, it is crucial that we understand its effect on yield variance, and how this could affect farmer decision making.

In developing-country contexts, farmers are typically modeled as choosing optimal levels of crop diversification in the form of diversity over space[1], rather than diversity over time. Such treatments ignore the yield effects (both variance and mean) of rotating crops. Studies using long-term agronomic data from developed countries are able to account for yield effects, but by modeling farmers as choosing optimal, steady-state rotation patterns, they assume that farmers optimize dynamically over infinite horizons (e.g. El-Nazer and McCarl, 1986, Maynard et al., 1997, Pannell and Nordblom, 1998). These models to do not permit behavior to change from year to year. Furthermore, these latter studies are unable to empirically link observed cropping choices with individuals risk attitudes.

This paper uses two years of plot-level data from a cross-section of farm households in North-Central Morocco and asks whether risk (in the form of yield variance) matters to households in their cropping decisions. It uses a plot-by-plot decision model of crop choice that is motivated by the observation that cropping patterns vary not only from farmer-to-farmer, but also from season-to-season. It then estimates household-specific means and variances of yield for six major crops using this data. Combined with risk aversion

[1]Two commonly used indices are the Simpson and Shannon indices. Both are based on the relative portions of land that are observed to be allocated to different crops in a given year.

data from choice experiments, this permits a comparison of expected-profit-maximization and expected utility maximization in explaining cropping patterns observed over four years.

2 Theoretical Model

An Expected Profit-Maximizing Producer
We consider a farmer whose objective is to maximize expected profit from her fixed land endowment. Each season, she can choose one crop (k) to plant on her land and how much fertilizer to apply (m) at cost ρ. Yields (y_k) are a function of fertilizer, soil productivity (n), and rainfall (r). At the time of the choice, rainfall and therefore yield are unknown, but the farmer considers rainfall to be a random draw from a known distribution. If the farmer chooses crop k, she can expect revenue $p_k \cdot y_k$, given the output price p_k. Her objective is

$$\max_{k,m} E[p_k \cdot \tilde{y}(m, k, n, \tilde{r}) - \rho \cdot m]. \tag{1}$$

Soil productivity depends on demands made on the soil in the previous season, which are a function of the previous season's crop (k_0) and that crop's yield (y_0).[2]

$$n = f(k_0, y_{k0}) \tag{2}$$

To solve (1) the farmer chooses, for every possible crop choice k, the optimal fertilizer level m_k^*. These crop-specific optimal fertilizer levels are a function of the past season's crop, its yield, and the farmer's expectation of

[2]It is widely understood that different crops have differing nutrient demands; it is also possible that the *amount* of a crop taken off of a plot matters. Good rains make for good harvests, and good harvests may deplete more soil nutrients. Conversely, a poor harvest, or the extreme case of crop abandonment, may result in little or no nutrient depletion.

rainfall, as well as the prices of output and fertilizer.[3]

$$m_k^* = g(k_0, y_0, k, \rho, p_k) \tag{3}$$

and m_k^* is such that

$$\begin{array}{l} p_k \frac{dE[y_k^*]}{dm_k^*} < \rho \text{ if } m_k^* < 0 \\ p_k \frac{dE[y_k^*]}{dm_k^*} = \rho \text{ if } m_k^* = 0. \end{array} \tag{4}$$

From among all possible crop-and-optimal-fertilizer combinations, she chooses that which yields the highest expected profit. The dummy variable D_k denotes that the k-th crop is selected if $D_k = 1$.

$$D_k = \begin{cases} 1 & \text{if } \bar{\pi}_k > 0 \text{ and } \bar{\pi}_k = \max(\bar{\pi}_1, \ldots, \bar{\pi}_K) \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

In the following season, the farmer will solve the same fertilizer-crop problem, but will be faced with different parameter values k_0, y_0 and p_k. The farmer is modeled not as a dynamic optimizer, but as a myopic agent who makes choices from season to season. Myopic behavior is may be plausible in settings where decisions in one period result in highly uncertain consequences in the future.

In this model, differences in both cropping choices and fertilizer application rates can be explained by differences in past decisions and fertilizer access. But mightn't attitudes toward risk also influence these two choices? If fertilizer increases yield variance (as is generally assumed) and the previous cropping choice affects not only current yield but also variance, then a risk-averse farmer may choose a different fertilizer-crop combination.

An Expected Utility-Maximizing Producer

We now allow the possibility for a preference for certainty. The farmer max-

[3]Farmers have differing access to fertilizer (whether due to transportation and transaction costs or to limited liquidity). The price of fertilizer ρ is therefore farmer-specific.

imizes her expected utility from profit.

$$\max_{k,m} E[u(p_k \cdot \tilde{y}(m,k,n,\tilde{r}) - \rho \cdot m)] \tag{6}$$

Solving (6) is equivalent to maximizing the certainty equivalent

$$E[p_k \cdot \tilde{y}(m,k,n,\tilde{r}) - \rho \cdot m] - R, \text{ or } E[\pi] - R, \tag{7}$$

where R if the risk premium. In the neighborhood of $E[\pi]$ we can approximate R as a function of the variance of π and the farmers' Arrow-Pratt risk aversion coefficient α, and the problem becomes one of maximizing the certainty equivalent

$$C^e = E[\pi] - \frac{\alpha}{2} \cdot Var(\pi). \tag{8}$$

As in the previous model, the household chooses an optimal crop-fertilization combination given past decisions and access to fertilizer. In evaluating all possible crop-fertilizer combinations, however, the farmer now receives disutility from variance. The necessary conditions for the optimal fertilizer choice, conditional on choosing crop k, reflect that:

$$\begin{array}{ll} p_k \cdot \frac{dE[y_k^*]}{dm_k^*} - \rho - \frac{\alpha}{2} \cdot p_k^2 \cdot \frac{dVar(y_k^*)}{dm_k^*} = 0 & \text{if } N > 0 \\ p_k \cdot \frac{dE[y_k^*]}{dm_k^*} - \rho - \frac{\alpha}{2} \cdot p_k^2 \cdot \frac{dVar(y_k^*)}{dm_k^*} < 0 & \text{if } N = 0 \end{array} \tag{9}$$

If fertilizer increases yield variance and farmers are risk averse, the optimal application level will be less than would be prescribed by expected-profit maximizing behavior. The optimal crop choice may also deviate from the expected profit-maximizing choice, a result of the variance effects from both the fertilizer level and the past crop.

$$D_k = \begin{cases} 1 & \text{if } C_k^e > 0 \text{ and } C_k^e = \max(C_1^e, \ldots, C_K^e) \\ 0 & \text{otherwise} \end{cases} \tag{10}$$

3 Estimation of Crop Choice Model

Our objective is to compare the two models of crop choice. There are possibly two components to a farmer's certainty equivalent profit from a plot: her expected profit and her risk premium. If the data show that year-to-year cropping choices could arise from expected-profit-maximizing behavior, then risk, while having serious consequences, may not drive farmer choices. If, on the other hand, including the farmer's risk premium could better explain cropping decisions, then we can think of farmers as maximizing expected utility from profit from each plot.

Rewriting the certainty equivalent equation 8 in terms of the mean and variance of the crop yield,

$$C_k^e = p_k \bar{y}_k - c_k - \frac{\alpha}{2} \cdot p_k^2 \cdot Var(y_k), \tag{11}$$

where c_k is the cost of growing crop k. While the above equation suppresses all notation other than the crop k, each farmer has his own level of risk aversion, and may make decisions that would rationalize his personal α_i. Furthermore, given the diverse, dynamic cropping patterns observed in the data, there is reason to believe that mean yield and yield variance are also farmer-, plot-, and time specific. Crop rotation is, after all, the strategic ordering of crops in order to boost and/or stabilize yields.

Before the two models can be compared, two task are at hand: estimating farmer-specific coefficients of absolute risk aversion, and estimating a yield function that allows inputs to condition the variance. For the first task, we use choice experiment data and rely on Lybbert and Just's (2007) true probabilities approach. For the second, we apply Just and Pope's (1979) model of stochastic production to plot-level data on yield, inputs, and cropping histories.

3.1 Study Site and Data

In the summer of 2007, and again in 2008, a collaborative team comprising researchers from the Moroccan National Institute of Agronomic Research (INRA), ICARDA, CIMMYT, and UC Davis implemented a survey of wheat-growing households in the Meknès-Tafilalet administrative region. The same households were interviewed in both years, with 282 participating in 2007 and 253 following up in 2008. The households were chosen to represnt four rural districts: Ain Jemaa, Sidi Slimane, Ait Ouikhalféne/Sebt Jehjouh, and Ben Smim. Together, they form an altinudinal transect running nothwest-southeast through the jurisdiction of the Meknès Regional Agricultural Research Center, our Moroccan partner institution. The four districts separately represent lowlands(300 to 400 masl), plateau (500 to 600 masl), foothills (700 to 900 masl), and mountains (1,200 to 1,500 masl). Households in this area depend on income from rain-fed annual crops (wheat, barley, oats and pulses), livestock, wage labor, and remittances.

Annual crops account for a significant portion of total household income, and excepting one district (Ben Smim), comprise the single most important source of household income. Table 1 summarizes responses to a survey module in which farmers stated the degree of risk that they associated with cereal income, non-cereal income, fruits/olives, livestock, and non-agricultural income, and then indicated the percentage contribution of each to total household income in an 'average' year. A risk rating of 1 indicates that the farmer considers income from an activity 'very risky' and 4 indicates that the farmer associates no income risk with an activity. We conclude that farmers consider annual crops ('cereal crops' and 'non-cereal crops') to be the riskiest income sources, and within annual crops, cereal crops are particularly risky.

This study relies on two unique types of data: plot-level rotation data and risk attitudes. In both 2007 and 2008, we recorded the cropping history (that is, which crop preceded the current crop), in addition to yield, inputs, soil type and land quality data for all of the farmers' plots. Additionally, the 2007 survey round asked farmers to recall the crops grown in the previous two years on each of the plots. The fate of each plot mentioned in the 2007 round was tracked in the subsequent round. This allowed us to record, for any given plot, the crops grown in 2004-2005, 2005-2006, 2006-2007 and 2007-2008, with input and yield data for the last two seasons. The data show that, while nearly all households avoid planting the same crop repeatedly on the same plot, household cropping patterns can vary from year to year.

In 2007, farmers participated in a series of choice experiments designed by Travis Lybbert. Farmers were presented with four possible rainfall outcomes ('drought,' 'poor rains,' 'good rains,' and 'very good rains'), and three hypothetical wheat seeds for purchase: a low-risk/low-return seed; a medium-risk/medium-return seed; and a high-risk/high-return seed. In the first of these choice experiments, farmers were asked how much money they would entrust with a friend to purchase each of the three seed types, given that the price of each is unknown. The farmer's return after each round depended on how much money he decided he would send with his friend, the random seed price, and the random weather outcome. If the farmer sent sufficient money to purchase the seed, then his return would be his yield less the seed price. Otherwise, his return would be zero. The experiments are describedl in Lybbert (2009).

3.2 Estimating farmers' risk aversion

We use Lybbert and Just's (2007) *true probabilities approach* to find a local approximation of absolute risk aversion from each farmer. It utilizes farmers' willingness-to-pay for three seed types s of varying yield risk. Each seed yields payoff $x_{\omega s}$ with probability $\pi_{\omega s}$. Our experiment presented four possible payoffs depending on the rainfall outcome ω. Lybbert and Just's approach is to find the seed-specific parameters β_{is} for each farmer i that are consistent with the expected utility relationship

$$1 = \sum_{\omega=1}^{4} \pi_{\omega s}[1 + (-WTP_{is} + x_{\omega s}) - \beta_{is}(-WTP_{is} + x_{\omega s})^2] \tag{12}$$

We use the average of the three seed-specific curvature parameters as the farmer's coefficient of absolute local risk aversion.The risk aversion coefficients range from -.0154 to .0155. Figure 1 shows a trimodal distribution of risk coefficients, with just over half of the sample being risk averse.

3.3 Estimating the stochastic production function

We estimate yield for bread wheat, durum wheat, barley, oats, faba beans and chick peas as functions of rainfall, fertilizer, preceding crop, and plot characteristics.[4] Cropping patterns appear in each of the production functions in the form of dummy variables that take the value of one if crop k_0 was planted on the plot in the preceding year (D_{k_0}). Fertilizer M is also represented using a dummy variable, since a significant portion of households reported using no fertilizer. $\mathbf{D_p}$ if a vector of plot characteristics. For each crop k on plot p

$$y_{pk} = f_k(\mathbf{X_p}) + u_{pk} \tag{13}$$

$$f_k(\mathbf{X_p}) = exp(\beta_{R_t} R_t + \beta_{R_t-1} R_{t-1} + \beta_M M_p + \sum_{k_0=1}^{K_0} \beta_{k_0} D_{k_0} + \beta_{\mathbf{p}}' \mathbf{D_p}) \tag{14}$$

The effects of a household's choice of crop rotations and inputs may show up in the yield variance, as well as in its expectation. The effectiveness of synthetic fertilizers in non-irrigated agriculture depends heavily on natural precipitation; when rainfall is insufficient, fertilizers have been shown to do more harm than good. In such places, irrigation may stabilize yields, as may soil moisture captured through previous fallowing. If inputs systematically

[4] Combined, these crops account for 80% of all plots and XX% of cultivated land.

affect the variance, then the original specification in (13) would no longer be efficient. Following Just and Pope's (1979) method, the error term u_{pk} in the yield function is modeled as a function of the same parameters in the yield equation:

$$u_{pk} = \epsilon_{pk} h_k^{1/2}(\mathbf{X_p}) \tag{15}$$

where $E[u_{pk}] = 0$ and $E[u_{pk}u_{qk}] = 0$ for $p \neq q$.

The farmers' decision of which crop to grow on each plot may depend on observed and unobserved characteristics of the farmer, the plot, and the year. These characteristics could also introduce bias to the yield coefficients. We control for selectivity in crop choice using Dubin and McFadden's (1994) bias correction. In deciding which crop to grown on plot p at time t, farmer i chooses crop k over crop l if $C^e_{iptk} \geq C^e_{iptl}$. Let us assume that C^e_{iptk} is the sum of a deterministic component V_{iptk} and some unobserved component ϵ_{iptk}. Suppressing the notation for time and plot,

$$C^e_{ik} = V_{ik} + \epsilon_{ik} \tag{16}$$

It follows that

$$\begin{aligned} Pr(D_{ik} = 1) &= Pr(C^e_{ik} \geq C^e_{il}) && \text{for all } l \neq k \\ &= Pr(V_{ik} - V_{il} \geq \epsilon_{ik} - \epsilon_{il}) && \text{for all } l \neq k \end{aligned} \tag{17}$$

The farmer's choice to grow crop k is the result of a comparison between the expected utility of growing k and that of all other alternatives l. According to our model, V_{ik} (V_{il}) comprises farmer i's expectation of net revenue from growing crop k (l), and, if she is risk averse, it will also include the variance of crop k (l)'s net revenue and the farmer's risk parameter.

Assuming independence of irrelevant alternatives, we use multinomial logistic regression to estimate the probability that a farmer will choose crop k on plot p at time t. We assume that the deterministic component is linear in parameters. If, further, we assume that the error on the observed yield y_{kpt} is a linear function of the unobserved components of the unobserved crops ϵ_{lpt}, for all $l \neq k$, then Dubin and McFadden's bias correction term (*Conditional Expectation Correction Method*) permits a consistent estimation of parameters. In summary, we do the following:

1. Use a multinomial logistic regression to estimate the crop selection equation parameters. Predict the probabilities of each crop k being grown on each plot p in season t ($\hat{P}_{kpt}$).

2. For each crop k, estimate the production function

$$y_{pt}^{k} = f_k(X_{pt}, \beta) + \sum_{l \neq k}^{K} \gamma_l \Big[\frac{\hat{P}_{lpt} ln \hat{P}_{lpt}}{1 - \hat{P}_{lpt}} + ln \hat{P}_{lpt} \Big] + \mu_{pt} \tag{18}$$

   using non-linear least squares.

3. Use the residuals $\hat{\mu}_p t$ from step 2 to estimate the conditional variance function $h_k(X_{pt}, \alpha)$ where the α parameters are estimated via the following OLS regression: $ln|\hat{\mu}_{pt}| = \alpha_0 + \frac{1}{2}(lnX_{pt})'\alpha + v_{pt}$.

4. Estimate the function $y_{kpt}^{*} = f_k^{*}(X_{pt}, \beta) + \epsilon_{pt}$ using non-linear least squares, where $y_{pt}^{k*} = y_{pt^{k*}} h_k^{-1/2}(X_{pt}, \hat{\alpha})$ and

$$f_k^{*}(X_{pt}, \beta) = \Big(f_k(X_{pt}, \beta) + \sum_{l \neq k}^{K} \gamma_l \Big[\frac{\hat{P}_{lpt} ln \hat{P}_{lpt}}{1 - \hat{P}_{lpt}} + ln \hat{P}_{lpt} \Big] \Big) h_k^{-1/2}(X_{pt}, \hat{\alpha}). \tag{19}$$

3.4 Estimation results

In the crop choice estimation, we used three years of cropping data (2005-2006, 2006-2007, and 2007-2008) yielding 2,541 plot × year observations. Farmers faced the following crop choices: bread wheat, durum wheat, barley, oats, truck crops[5], chick peas, faba beans, sunflower, onions. Additionally, farmers had the option of fallowing their plot for a year. Choice variables included the previous year's crop (to capture 'soil' effects); last season's rainfall as a proxy for last year's price (and/or last year's nutrient offtake); plot characteristic dummies; and farmer characteristics such as distance to market, the average risk premium (from from the experiment), wealth, and livestock ownership.

The logistic regression was highly significant with a likelihood ratio 2950 and a pseudo-R^2 of .27. Table 2 shows the marginal effects of each of the variables, with wheat as the excluded category for the previous crop dummies. Households were less likely to grow wheat following feed/food crops such as oats and barley, but more likely to do so following fallow, leguminous crops, onion, and truck crops. Leguminous crops or fallow typically followed wheat crops. Irrigated plots were less likely to be fallowed or planted in wheat. Greater rainfall in the previous season significantly increased the likelihood of fallowing a plot.[6] These results show the highly non-random nature of cropping choices.

Farmers appear to be strategic in their cropping sequences. Of particular interest are the effects of 'lower-value' activities such as fallow and legumes on the 'important' wheat crops. Tables 3 and 4 respectively show the results from the yield mean- and the yield variance regressions. Previously fallowing or growing chick peas increase the conditional variance, while also modestly increasing the expected yield. The effect of faba bean on bread wheat, however, is the opposite: a previous faba bean crop lowers yield while also possibly decreasing the vriance. The effect of a previous fallow increases

[5] This general crop category denotes higher-labor, irrigated crops such as potatoes, carrots, eggplants, and squash.

[6] This can be interpreted two ways: Higher rainfall results in a greater yield, necessitating that the soil 'rest.' Or, higher rainfall means lower prices, giving farmers less incentive to plant in the following season.

the yield variance of bread wheat. Fertilizer also has a negative effect on bread wheat yield, but it lowers the yield variance as well. In the case of durum wheat, however, fertilizer has a positive effect on variance. The significance of the coefficients in tables 4 and 5, however, is unknown as of this writing. The author intends to bootstrap the standard errors.

3.5 Expected profit maximization v. expected utility maximization

Finally, we use the coefficients from above to predict the yield and variance of each possible crop for each plot $\times$ year observation, based on the plot's characteristics and cropping history; the last season's rainfall and a district-level mean rainfall [7]; and predicted fertilizer use. Fertilizer use for each crop is predicted using probit estimation based on transportation cost (distance to market, owning a vehicle), liquidity (a wealth index), soil productivity (soil quality, past crop, and the previous season's rainfall). [I would like to also include prices in the these fertilizer-use prediction equations.] Transforming these values of expected yield into expected profits further requires expectations of output prices and input costs. For the output prices, we rely on the mean of 'average' prices reported at the village level. For expected costs, we assume one set of crop-specific per-hectare cost estimates when fertilizer use is predicted, and another set of costs otherwise. These estimates are the median total reported cash costs, using the entire sample. Figure 2 shows the distribution of predicted yields for bread wheat (estimated for every plot $\times$ year observation), alongside actual yields reported in 2007 and 2008. The dotted vertical line indicates the 'break-even' yield when no fertilizer is used (3.5 quintals), and the dashed line indicates the break-even yield

[7] Since we are modeling the farmer's decision at planting time, we assume that the farmer expects 'average' rainfall.

when fertilizer is applied (6.5 quintals).

For each observation, the crop yielding the highest { expected profit, certainty equivalent profit } is the { expected profit-, certainty equivalent profit- } model's optimal crop. We compare the performance of the two models using observations in Districts 3 and 4, where nearly all households are observed sowing their plots in the five predicted crops or fallow. As can be seen from the diagonal squares in Tables 6 and 7, the predictive performance of both models is poor, but especially so for the expected profit maximization model. Notably, the profit-maximization model would never have a farmer choosing to fallow. While neither model is successful in 'picking' the observed cropping activities, perhaps one model is more capable of ranking the choices? Table 5 compares the means for the calculated expected profit and certainty equivalent, based on whether the farmer had picked that particular crop. The better model would predict higher values for the chosen crop, and lower values for the crops that were ultimately not planted. Again, the certainty equivalent model modestly outperforms the expected profit model.

4 Conclusion

This study makes the case for a more nuanced treatment of farmers' cropping choices. It uses a unique dataset on Moroccan dryland wheat farmers to investigate the received wisdom that, "risk averse farmers in risky environments respond by diversifying their crop portfolios." In particular, it proposes a dynamic model of plot-by-plot crop choice that is based on past cropping patterns and estimated values of absolute local risk aversion. It tests whether risk (in the form of yield variance) and risk aversion play a role in these choices. It concludes that a model of farmers making decisions to maximize certainty equivalent can still outperform one in which farmers maximize expected profit, even after taking into account rotation effects.

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Figure 1: (Local) Absolute Risk Aversion Coefficients

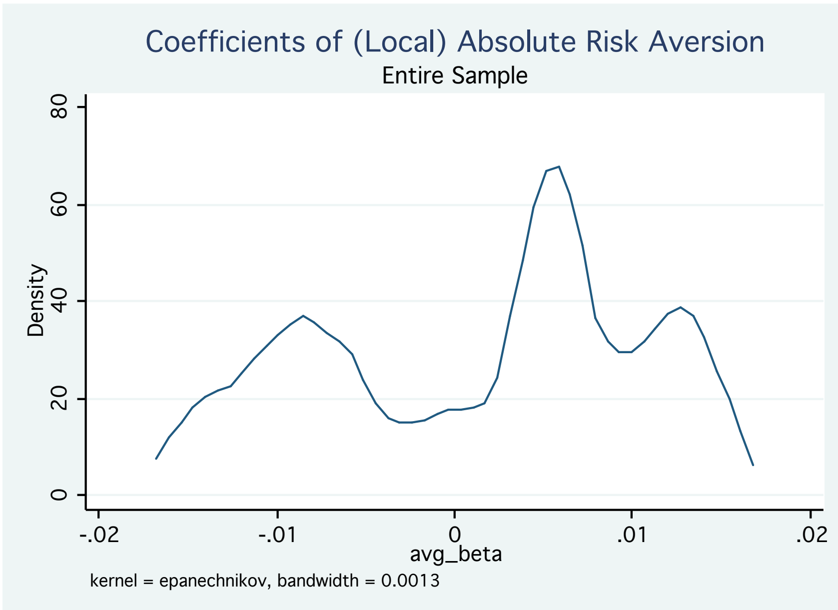

Figure 2: Predicted and Observed Bread Wheat Yields

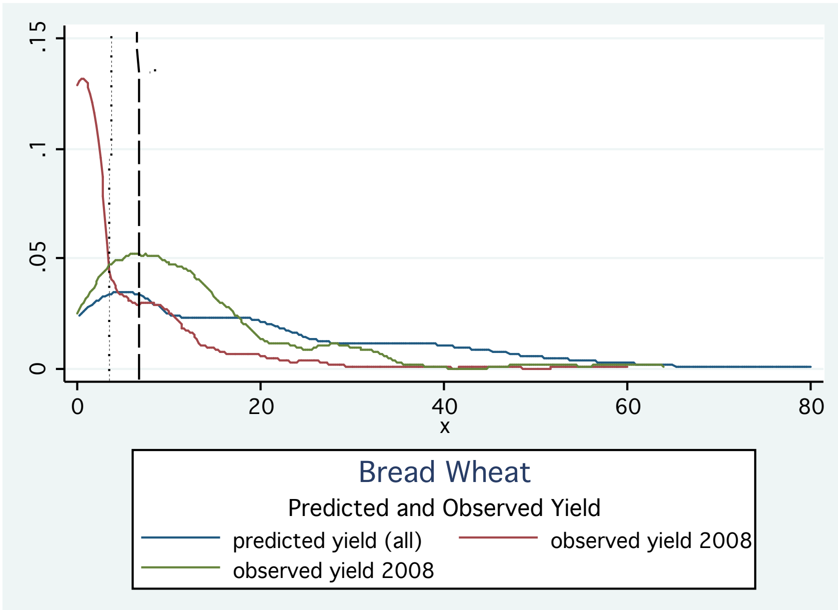

Table 1. Perceived Risk and Contribution of Income Categories by District

		Sidi Slimane	Ain Jemaa	Sebt Jehjouh	Ben Smim
Cereal Crops	*perceived risk*	1.58	1.42	1.24	1.62
	contribution (%)	32	46	39	18
Non-cereal Crops	*perceived risk*	2.35	1.97	1.73	2.09
	contribution (%)	19	24	11	12
Olives/Orchards	*perceived risk*	3.03	2.75	2.37	1.89
	contribution (%)	13	6	5	9
Livestock	*perceived risk*	2.64	2.42	2.21	2.20
	contribution (%)	23	20	43	47
Non-agricultural	*perceived risk*	3.33	3.77	3.36	3.28
	contribution (%)	12	4	3	14
Total Income	*perceived risk*	2.37	1.95	1.84	2.15
N		66	77	80	54

Table 2. Marginal Effects from Crop Choice Regression

	br. wheat	dur. wheat	barley	oats	fallow	truck crop	chick pea	faba	sunflower	onion
Chosen Prob.	0.392	0.075	0.164	0.133	0.129	0.043	0.038	0.0239	#####	#####
Prev. Crop Dummy										
forage	-0.216 **	-0.032	0.175	0.146	0.023	-0.024 **	-0.050 **	-0.021 **	0.000	0.000
fallow	0.088	0.067	0.073	0.004	-0.122 **	-0.041 **	-0.043 **	-0.027 **	0.000	0.000
legumious	0.269	0.106	-0.019	-0.091 **	-0.154 **	-0.040 **	-0.050 **	-0.020 **	0.000	0.000
onion	0.283	0.121	-0.113 *	-0.084 **	-0.090 **	-0.022 *	-0.021	-0.073 **	0.000	0.000
truck crop	0.210	0.081	-0.098 **	-0.019	-0.121 **	-0.015	-0.028 **	-0.009	0.000	0.000
rain last season	0.000	0.000	0.000	0.000	0.000 **	0.000	0.000	0.000	0.000	0.000
dist. to mkt.	-0.010 *	0.000	-0.002	0.003	0.005	0.003	0.000	0.000	0.000	0.000
risk premium	-0.072	-0.009	-0.036	-0.034	0.118	0.013	0.012	0.009	0.000	0.000
wealth	0.007	-0.002	0.002	-0.009	0.010	-0.003	0.002	-0.007 *	0.000	0.000
large animals	0.049	-0.018	0.016	-0.021	0.014	-0.009	-0.019	-0.013	0.000	0.000
small animals	-0.042	0.008	0.028	0.013	0.034	-0.038 *	-0.007	0.004	0.000	0.000
plot w/ irrig.	-0.141 **	-0.006	0.004	0.016	-0.057 **	0.153	-0.007	0.037	0.000	0.000
flat	0.066	0.004	-0.054 *	0.027	-0.027	-0.015	-0.004	0.003	0.000	0.000
soil: tirs	0.149	-0.010	-0.036	-0.076 **	-0.023	-0.005	-0.002	0.003	0.000	0.000
soil: hamri	0.012	0.051	0.010	-0.079 **	0.005	-0.006	0.016	-0.007	0.000	0.000
district 2	-0.079	0.094	0.171	-0.222 **	-0.119 **	-0.011	0.079	0.087	0.000	0.000
district 3	-0.142 *	0.057	0.134	-0.107 **	0.044	-0.048 *	-0.042 *	0.104	0.000	0.000
district 4	-0.334 **	0.101	0.199	-0.068	0.091	0.029	-0.029	0.012	0.000	0.000

** significant at 1%
* significant at 5%

Table 3. Coefficients from Mean Yield Estimation

	br. wheat	dur. wheat	barley	oats	chick pea	faba
Previous Crop Dummy						
br. wheat	excl.	excl.	-1.87	-0.19	excl.	excl.
dur. wheat	-0.10	-0.06	-0.03		15.93	
barley	-0.28	-0.58	excl.	-0.01		-0.13
oats	0.26	-0.43		excl.		0.00
fallow	0.35	-0.73	-4.33	0.41		
chick pea	0.33	-0.13	0.00			
faba	-0.64	-0.22	0.84	0.00		1.10
sunflower	-0.46					
onion	0.19					
rain this season	0.01	0.00	0.00	0.00	-0.05	0.00
rain last season	0.00	0.00	0.00	0.00	0.00	0.00
plot w/ irrigation	0.10	0.20	1.03	-0.50	17.64	-0.44
used fertilizer	-0.64	0.08	-0.27	-0.01	-0.05	0.38
flat	0.00	-0.06	0.46	0.10	1.23	0.05
soil: tirs	0.22	-0.03	1.03	0.37	0.97	0.72
soil: hamri	0.61	-0.09		0.78	1.67	0.00
constant	1.87	3.42	2.28	3.15	-1.37	2.76
N	406	102	191	146	93	45
Adj. R-sq	0.46	0.62	0.45	0.34	0.17	0.56

Table 4. Coefficients from Yield Variance Estimation

	br. wheat	dur. wheat	barley	oats	chick pea	faba
Previous Crop Dummy						
br. wheat	excl.	excl.	-0.67	-2.14	excl.	excl.
dur. wheat	0.48	0.87	0.95		0.47	
barley	0.19	0.63	excl.	-1.23		0.36
oats	0.48	0.43		excl.		-1.21
fallow	1.52	-0.04	-0.26	-1.29		
chick pea	1.04	-1.13	-2.92			
faba	-0.41	-0.59	-0.52	-1.47		1.48
sunflower	0.67					
onion	0.55					
truck crops	0.91					
rain this season	0.01	0.00	0.00	0.00	-0.06	0.00
rain last season	0.00	0.00	0.00	0.00	0.00	0.00
plot w/ irrigation	0.88	-0.21	1.37	-0.75		1.62
used fertilizer	-1.09	2.35	-0.15	1.17	-0.70	-0.66
flat	-0.24	0.04	-0.17	0.34	0.12	-0.49
soil: tirs	0.56	0.16	0.67	-0.81	-0.08	0.30
soil: hamri	0.78	0.44		-1.37	0.18	-1.20
constant	0.01	0.32	2.20	4.72	16.77	1.08
N	410	105	198	146	98	105
Adj. R-sq	0.53	0.59	0.46	0.69	0.37	0.15

Table 5. Expected Profit v. Certainty Equivalent

	Expected Profit		Certainty Equivalent	
	chosen	not chosen	chosen	not chosen
bread wheat	-638	**3237**	-2732	**2587**
durum wheat	125	**6210**	**-119**	-6037
barley	2393	**2419**	**-2322**	-2608
oats	-430	**2534**	**197174**	-87216
faba	3352	**6778**	111	**4548**

Using Districts 3 and 4

Table 6. Comparison of Expected-Profit-Maximizing Crop with Observed Crop

	Observed Crop					
Predicted Crop	*oats*	*dur. wheat*	*bread wheat*	*faba bean*	*fallow*	*barley*
oats	**0**	84	0	0	5	2
dur. wheat	0	**0**	1	120	281	16
bread wheat	0	0	**0**	0	53	113
faba bean	226	0	273	**0**	3	68
barley	11	1	13	0	12	**14**

Using Districts 3 and 4

Table 7. Comparison of Certainty-Equivalent-Maximizing Crop with Observed Crops

	Observed Crop					
Predicted Crop	*oats*	*dur. wheat*	*bread wheat*	*faba bean*	*fallow*	*barley*
oats	**63**	37	86	15	114	56
dur. wheat	16	**6**	8	62	79	17
bread wheat	0	0	**1**	8	72	64
faba bean	115	0	148	**10**	24	39
fallow	11	24	4	7	**29**	6
barley	0	5	6	5	5	**10**

Using Districts 3 and 4