# More empirical evidence on the adoption of chick peas in Western Australia.·
# or:
# *Different ways of thinking about nothing.*

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This paper presents various econometric models of the adoption of chick peas in Western Australia. Data are available on both whether farmers intend to adopt, and the intensity of adoption, defined by the area planted. Traditionally, analysis of such data has focussed on the probability of adoption (using Probit/Logit models), or assumed that intensity and adoption are determined by a single process (Tobit models). However, an alternative specification, which is not commonly used in adoption studies, is to allow for two processes, one determining adoption, the second intensity, and estimate these jointly (i.e. Double Hurdle models). The implications of using these alternative specifications for inferences about the causes of adoption are explored.

## 1. Introduction

The analysis of the adoption of an agricultural technology can be conceptualized in 3 different ways: who adopts, when do they adopt and how much do they adopt. They are clearly interrelated, although asymmetrically. Thus, the standard bivariate approach simply identifies which individuals within a sample have adopted, and tries to explain this difference in behavior in terms of producer characteristics. It does not consider at which point in time they adopted, although the fact that adoption is conditioned upon a particular sampling date introduces a temporal aspect to the problem that is not often recognized. The explicit consideration of *when* adoption occurs clearly nests the first question of *who*, and one can model the process as a simple extension of the bivariate model. The data are set up as a panel, with each producer contributing as many observations as periods in which they potentially could have adopted (see Jenkins (1995) for a formal exposition of this and Burton et al. (1998) for an application).

It is possible to model the degree of adoption (measured, for example, as the proportion of a crop sown to a new variety) without having to deal with the explanation of *who* adopts. Under very limited circumstances it is possible to restrict attention to the sub-sample of those who have adopted. However, application of this model in inappropriate circumstances leads to biased estimates. A more common approach is to combine the *who* and *how much* into a single model, such as the Tobit.

These different models can be characterized by different rationalizations of the process underlying the observed non-adoption of a technology (the zeros). We present a number of different models of

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adoption, each of which treat the non-adopters, the 'zeros', in a different way, and as the results indicate, lead to quite different interpretations of the determinants of the probability of adoption and intensity of adoption. In theory, it should be possible to develop a model which encompasses all three issues. This would involve integrating a duration model (which generalizes the adoption decision across time) with a model of intensity (such as a standard Tobit model). This ambitious task is not attempted here, and instead we concentrate on the adoption and intensity aspects of the problem.

The presentation abstracts from a number of issues: there is no formal presentation of the utility maximization problem facing the producer, the solution of which presumably has led to the observed behavior. Instead we follow the precedent of using an ad hoc, reduced form specification for a latent variable which is assumed to capture the relevant features of the problem. In the model development section (section 2) the definition of 'adoption' is not expanded upon: it could be at any of the 3 stages of adoption identified by Lindner et al. (1982): discovery, evaluation or full adoption. It assumes that the innovation being considered is well defined, and those producers who adopt can be unambiguously classified as such (avoiding problems which may arise in situations where the technology under consideration is multifaceted, such as those related to 'sustainable' agriculture, or integrated pest management). Instead we focus on alternative models that could rationalize the observed zeros, and their econometric implementation.

Some of these broader issues are touched on when considering the particular empirical case study: the adoption of chick peas in Western Australia. Section 3 outlines the data series available, which implicitly represent a model of the underlying economic process. Section 4 presents and compares the results from 4 different models of adoption, and 5 concludes.

## 2. The Models

### *Probit*

The initial model considered is that of binary choice, which ignores any information on the intensity of adoption that is available. However, it is a convenient starting point, as it becomes a component of some of the later models, and is one of the most widely used empirical models of adoption (Feder et al., 1985, Feder and Umali, 1993)

Consider an index variable, Y which takes a value of 1 if a producer adopts the technology and 0 otherwise. We believe that a set of technical and socioeconomic factors ($x$), loosely derived from an underlying theory, explain that decision, so that

$$\text{Prob}(Y=1)=F(\beta x)$$

The function F should be defined such that the probabilities generated are well behaved, and the normal distribution provides that restriction, giving the Probit model:

$$\text{Prob}(Y = 1) = \int_{-\infty}^{\beta x} \phi(t)dt \qquad (1)$$

$$= \Phi(\beta x)$$

where $\phi$ and $\Phi$ are the standard normal density and distribution functions respectively.

***Tobit***

The Tobit model explicitly accounts for the level of intensity of adoption, and assumes that the zeros are corner solutions to the underlying process: in deciding on the optimal level of intensity of adoption the exogenous variables have taken a particular set of values that lead to non-adoption. A (possibly marginal) change in any of those variables may cause a revision in that decision. There are a number of applications of this model to agricultural technology adoption (e.g. Akinola and Young, 1985, Lin, 1991; Abadi Ghadim and Pannell, 1998, Goodwin and Schroeder, 1994).

Formally, a latent variable ($y^*$) is defined which governs both the adoption and intensity decision.

$$\begin{aligned} y_i^* &= \beta x_i + \varepsilon_i \\ y_i &= 0 \quad if \quad y_i^* \leq 0 \\ y_i &= y_i^* \quad if \quad y_i^* > 0 \end{aligned} \qquad (2)$$

where $\varepsilon \sim N(0,\sigma)$.

Thus, $y^*$ is unobserved, and the observed variable, y, is censored at zero. The limitation of this model is that both the probability of adoption and the level of intensity are linked by the same latent index, i.e.

$$\begin{aligned} \Pr ob(Y_i = 1) &= \Phi(\beta x_i / \sigma) \\ E[y_i | x_{i,} Y_i = 1] &= \beta x_i + \sigma \lambda_i \end{aligned} \qquad (3)$$

where

$$\lambda_i = \frac{\phi(\beta x_i / \sigma)}{\Phi(\beta x_i / \sigma)}.$$

There is no reason, a priori, why this should be the case. Thus education, acting as a proxy for human capital, may have strong positive marginal impacts on the probability of adoption, due to farmers being more aware of the innovation and how it can be incorporated profitably into their farming system, and yet have very minor marginal impacts on the level of intensity (measured as e.g. application rate per hectare) due to the nature of the technology being adopted. Alternatively, farm size may act positively on the probability of adoption in early adopters, as larger farms are better placed to absorb the risks associated with trialing the crop, and yet farm size may be negatively correlated with intensity of those adopting (measured as % of farm planted to the crop) if there significant economies of size associated with the trialing of the innovation. If such possibilities exist in the processes generating the observed data then (2) will be an inappropriate modeling framework, and will lead to biased estimates of the determination of both the probability and intensity of adoption.

***Heckman***

The alternative is to provide separate mechanisms for the two activities within the same model. This the Heckman model does, but again with some severe restrictions on the interpretation of the process generating the zero observations. We now have two decisions, adoption and intensity which are modeled separately.

The adoption decision is governed by a wholly unobserved latent variable, $z_i$

$$
\begin{aligned}
z_i &= \alpha q_i + u_i \\
Y_i &= 1 \;\; if \;\; z_i > 0 \\
Y_i &= 0 \;\; otherwise
\end{aligned}
\tag{4}
$$

where $q$ is a vector of explanatory variables.

The intensity level is governed by a separate latent variable ( $y^*_i$) which is truncated normal at zero:

$$
\begin{aligned}
y_i^* &= \beta x_i + \varepsilon_i, \; y^* > 0 \\
y_i &= Y_i \; * y_i^*
\end{aligned}
\tag{5}
$$

$$
(u, \varepsilon) \sim BVN\begin{pmatrix} 0, & 1 & \sigma\rho \\ & \sigma\rho & \sigma^2 \end{pmatrix}
$$

where BVN indicates a bivariate normal and $\rho$ is the correlation coefficient between the two residuals, which is to be estimated.

This is termed a first hurdle dominance model, because once the first hurdle is cleared one is guaranteed a positive level of adoption: none of the observed zeros are due to corner solutions in the intensity equation. Although preferable to the Tobit model, this still imposes restrictions on behavior. In particular, if a variable appears in the vector x, determining intensity of adoption, it is not possible for changes in that variable to sequentially lead to reduced and then zero intensity, although if it appears in the first hurdle it may have that effect.

Imposing the restriction that ρ=0 implies that the adoption and intensity decisions are independent, leading to the complete dominance model which can be estimated as two separate equations: a Probit for the adoption decision and then estimation of the intensity over the positive observations using only truncated regression (Greene, 1993).

***Double hurdle***

A more general specification is the double hurdle model, which allows for two processes to potentially generate zero observations. The 'participation' decision (adopting the terminology of the demand studies) can be interpreted as a decision as to whether the technology is even feasible for a particular farmer, and potentially could be determined by availability, knowledge of the technique etc. There is then a subsequent 'intensity' decision which allows for the possibility of setting the level of use to zero, and hence non-adoption even if the participation decision is positive.

Formally, this can be specified by a participation equation:

$$
\begin{aligned}
& z_i^* = \alpha q_i + u_i \\
& Y_i = 1 \;\; if \;\; z_i^* > 0 \\
& Y_i = 0 \;\; otherwise
\end{aligned}
\qquad (6)
$$

where $z$ is again an unobserved latent variable and $q$ vector of explanatory variables. The indicator variable Y is also strictly unobserved. There is also an intensity equation, which can generate corner solutions:

$$
\begin{aligned}
& y_i^{**} = \beta x_i + \varepsilon_i \\
& y_i^* = 0 \;\; if \;\; y_i^{**} \le 0 \\
& y_i^* = y_i^{**} \;\; if \;\; y_i^{**} > 0
\end{aligned}
\qquad (7)
$$

The observed outcome is given by:

$$y_i = Y_i y_i^* . \qquad (8)$$

where

$$(u, \varepsilon) \sim BVN\left(0, \begin{matrix} 1 & \sigma\rho \\ \sigma\rho & \sigma^2 \end{matrix}\right).$$

Initially developed by Cragg (1971) this model has been extensively applied in the consumer demand literature (e.g. Jones, 1989; Burton et al. 1994; Blaylock and Blisard, 1992; Yen, 1993) but there is apparently only one application in the agricultural adoption literature (Coady, 1995). There it is applied to the use of fertilizer in Pakistan, where there were clear indications that both availability of fertilizer, and economic (non-)profitability of applying fertilizer were both generating zero adoption responses in the data.

This general model nests a number of others. If the estimate of $\rho$ is constrained to equal 0 then the model collapses to the independent Cragg (which is what is estimated in Coady (1995)). If the vector q is restricted to a constant (so that there is a constant probability of participation, unaffected by individual characteristics) then one has the p-Tobit of Deaton and Irish (1982). If both $\rho=0$ and $\Phi(\alpha q)=1$ then one has the standard Tobit model[1].

## 3. Data

The empirical analysis reported here builds on a previous study of the adoption of chick peas in Western Australia (Abadi Ghadim and Pannell, 1997, 1998). Based on Lindner's (1987) approach to the theory of adoption of innovations, Abadi Ghadim and Pannell (1997) develop a formal framework to evaluate how perceptions of risk, and attitudes to risk, affect adoption behavior. There the adoption process of a farmer considering a new crop is modeled as a dynamic decision problem spanning a number of years. The model allows for generation of potentially valuable information from trials of the crop. The value of such trials is due to development of skills in agronomic management of the crop as well as due to reduction in uncertainty about its long term profitability. The former of these appears not to have been adequately recognized in previous literature and even the latter has often been neglected. In order to properly represent the process, the framework must include the farmer's personal perceptions, managerial abilities and risk preferences.

The data set used to implement this model was generated from a longitudinal survey of 136 farmers selected at random from the wheatbelt of Western Australia. The surveys were administered through personal interviews spanning three years from 1994-97, but the dependent variable under consideration is the area of chick peas planned for planting in 1997, expressed as a proportion of the total area of the farm suitable for chick peas. The sample of farmers used in the analysis reported in this study contained 114 farmers. The 22 farmers whose responses were not used showed either inconsistencies in their answers or did not complete the interview process.

The fact that only 16 farmers had grown chick peas for 3 or more years and the relatively small percentages of the total suitable area of the farm being cropped with chick peas (an average of 11%) indicates that most of the farmers were either in the non-trial evaluation or trial evaluation phase (Lindner, 1987).

[1] Further generalizations are possible. A Box-Cox double hurdle model relaxes the assumption of bivariate normality (Yen, 1993), and it is possible to relax the assumption of homoscedasticity in the error terms. However, in the empirical application neither of these generalizations led to significant improvements in fit, and hence are not elaborated on here.

An earlier analysis of this data is reported in Abadi Ghadim and Pannell (1998), using Tobit, Probit and OLS techniques. The approach employed there is to generate an ad hoc index equation, with the definition of the variable set guided by the underlying theory. Thus, adoption and intensity of adoption is assumed to depend upon a wide range of factors:

- farmer's past experience with the crop, represented by the cumulative sum of the chick pea area grown by the farmer in previous years;
- perception of scale of relevance, represented by the total area of the farm considered to be suitable for chick peas;
- relative profitability, represented by the difference between the gross margin of chick peas and the best alternative enterprise;
- relative riskiness of chick peas, represented by the difference in the variance of the revenue from chick peas and variance of the revenue from wheat;
- farmer's personal risk preferences;
- farmer's innovativeness, represented by their past behaviour in adoption of wheat and lupin varieties;
- availability of resources such as machinery and labour to facilitate adoption of chick peas;
- factors that influence a farmer's ability to learn from a trial in order to revise their estimate of the profitability of the crop and to improve grower's skill in managing the crop to obtain higher yields and prices. Those factors include the covariance between the yield of wheat and chick peas, perception of the difference between the gross margin of chick peas with full knowledge and the gross margin at the time of the interview, the value of the first trial with chick peas relative to later trials, the ability to predict the yield of the crop and the time required for the farmer to develop sufficient skill for full adoption of chick peas; and
- interactions between the above factors, particularly between risk factors and the scale of relevance.

Table 1 below gives a full listing of variables employed. The approach of the current study is to take this set of variables as given, and explore the implications of the alternative modeling frameworks outlined in section 2 above.

**Table 1**. Definitions of the variables used in the regression analyses of survey data.

| Variable | Description |
|---|---|
| RP | Risk Preference - Pratt-Arrow - Constant Absolute Risk Aversion Coefficient |
| $A_T$ | Scale of relevance - total area of the farm suitable to chick peas - (ha); |
| $\overline{G}_C^L$ | Expected long run average gross margin of chick peas with complete knowledge ($/ha) *(only used in constructed variables)* |
| $\overline{G}_A$ | Expected gross margin of the alternative enterprise ($/ha) *(only used in constructed variables)* |
| $\overline{G}_C^C$ | Expected gross margin of chick peas with the level of knowledge at the time of the interview ($/ha) *(only used in constructed variables)* |
| $Cov_{WC}$ | Covariance of yield of wheat and chick peas $(kg\ /ha)^2$ |
| $A_{Cs}$ | Area of chick pea crop(s) previously grown by the farmer (ha) |
| $Rf$ | Long term annual average rainfall of the farm (mm) |
| $L_f$ | Number of family labour available for cropping (integer); |
| $L_h$ | Number of hired labour available for cropping (integer); |
| $T_w$ | Years taken to adopt the most recent wheat variety being grown by the farmer (years); |
| $T_l$ | Years taken to adopt the most recent lupin variety being grown by the farmer (years); |
| $Rr$ | Rate of return required to invest surplus cash funds in a term deposit account for one year (%); |
| $Spd$ | Duration of the crop seeding program (days) |
| $Sc$ | Seeding capacity (ha/day); |
| $Ap$ | Ability to predict the yield of chick pea after seeding compared to wheat expressed as odds out of ten (%); |
| $Sk$ | Time to acquire 95% of the skill for growing chick peas as compared to a new wheat variety (years); |
| $Efa$ | Time to develop enough confidence for full adoption of chick peas (years); |
| $Vt$ | Value of first trial with chick peas compared to a new wheat variety (%); |
| $\sigma_C^2$ | Variance of the net revenue of chick peas $(t/ha)^2$ |
| $\sigma_A^2$ | Variance of the net revenue of alternative enterprise $(t/ha)^2$ |
| $\overline{G}_C^L - \overline{G}_A$ | |
| $\overline{G}_C^L - \overline{G}_C^C$ | |
| $A_{Cs}$ (Dum) = 1 if $A_{Cs}$ >0, 0 otherwise. | |
| $A_T$ *RP | |
| $Cov_{WC}$ *RP | |
| $Cov_{WC}$ * $A_T$ | |
| $\sigma_C^2 - \sigma_A^2$ | |
| $(\sigma_C^2 - \sigma_A^2)$*RP | |
| $(\sigma_C^2 - \sigma_A^2)$* $A_T$ | |
| $(\sigma_C^2 - \sigma_A^2)$* $A_T$ *RP | |

## 4. Estimation results

*Double hurdle*

The estimation results[2] are presented in the reverse order to that of the models outlined in section 2, thereby moving from the general to the restricted. For brevity not all possible specifications are reported. The full dependant double hurdle model was estimated, but a log likelihood test on the significance of the covariance term (ρ) indicates that the independent double hurdle model is appropriate (this restriction was accepted on the basis of a log likelihood ratio (LLR) test statistic of 0.066 compared to a critical value of the $\chi^2$ distribution of 3.84). Our starting point (Table 2) reports the results of this independent double hurdle model. It is usually thought necessary to impose some exclusion restrictions across the two vectors of explanatory variables in order to adequately identify the parameter estimates. However, theory seldom allows one to be precise as to which variables should appear in which vector. The final choice of variables was arrived at after an extensive search across the variable space (as defined in Table 1 above), constrained by poor convergence properties when a large number of variables are used in both equations. A subsequent test of the p-Tobit model (where only a constant is employed in the 'participation' equation) was rejected (LLR test statistic of 22 compared to a critical value of 7.82).

The economic interpretation of these results is aided by the calculation of elasticities with respect to each of the exogenous variables. The 'intensity' equation is essentially a tobit model, and the elasticity is decomposed into the separate impacts on the probability of adoption and the intensity of adoption, using the McDonald and Moffat framework (McDonald and Moffat, 1980). The marginal impact on the observed outcome is given by:

$$\frac{\partial Ey}{\partial x_i} = \Phi\left(\beta x_i / \sigma\right)\frac{\partial E\overline{y}}{\partial x_i} + E\overline{y}\,\frac{\partial \Phi\left(\beta x_i / \sigma\right)}{\partial x_i} \qquad (9)$$

$$\textit{where} \quad E\overline{y} = E(y \mid y > 0)$$

Thus, the marginal impact is split into the change in y of those who have a positive level of intensity, weighted by the probability of it being positive (the first term), and the change in the probability of there being a positive level of adoption, weighted by the expected level of intensity if it is positive (the second term). It is important to note that in the double hurdle model these marginal effects are themselves conditioned upon the first, participation, hurdle i.e. E(Y)=1.

In Table 2 these two parts underpin the Intensity and Adoption elasticity's reported for the intensity equation. The elasticity's reported for the participation equation simply report the impact of changes in the variables on the probability of clearing the first hurdle.

[2] All estimation was undertaken using Stata 5.0 (Statacorp, 1997).

Table 2 Independent Double Hurdle Model (*equations 6-8, $\rho$=0*)

| Variable | Coef. | Std. Err. | Z | P>\|z | Elasticities: Intensity | Elasticities: Adoption |
|---|---|---|---|---|---|---|
| **Intensity equation** | | | | | | |
| $G_C^L$-$G_A$ | 0.229 | 0.070 | 3.252 | 0.001 | 1.428 | 0.729 |
| $G_C^L$-$G_C^C$ | -0.211 | 0.083 | -2.552 | 0.011 | -0.565 | -0.288 |
| $T_w$ | -0.203 | 0.092 | -2.209 | 0.027 | -0.465 | -0.237 |
| $A_T$ | -0.196 | 0.050 | -3.951 | 0.000 | -0.440 | -0.224 |
| $S_{pd}$ | 0.092 | 0.038 | 2.423 | 0.015 | 0.417 | 0.213 |
| $S_c$ | 0.200 | 0.061 | 3.262 | 0.001 | 0.512 | 0.262 |
| $L_f$ | 0.158 | 0.043 | 3.718 | 0.000 | 0.703 | 0.359 |
| $R_r$ | 0.205 | 0.057 | 3.581 | 0.000 | 0.504 | 0.257 |
| RP | -0.736 | 0.938 | -0.784 | 0.433 | -5.591 | -2.853 |
| $Cov_{WC}$ | 0.049 | 0.084 | 0.584 | 0.559 | 0.189 | 0.097 |
| $\sigma_C^2$-$\sigma_A^2$ | -0.206 | 0.074 | -2.800 | 0.005 | -1.524 | -0.778 |
| $Cov_{WC}$*RP | 0.456 | 0.355 | 1.284 | 0.199 | 3.077 | 1.570 |
| ($\sigma_C^2$-$\sigma_A^2$) *RP | -1.260 | 0.531 | -2.375 | 0.018 | -1.724 | -0.880 |
| Intercept | 0.323 | 0.395 | 0.818 | 0.413 | | |
| $\sigma$ | 0.039 | 0.006 | | | | |
| **Participation equation** | | | | | | |
| $A_{CS}$(Dum) | 3.227 | 1.352 | 2.388 | 0.017 | | 0.04/0.93* |
| $V_t$ | 0.982 | 0.324 | 3.025 | 0.002 | | 0.902 |
| Intercept | -2.163 | 0.661 | -3.272 | 0.001 | | |

Log Likelihood =17.116

$R^2$=0.430

$\sigma_n$ =0.518

The z statistic is given by the ratio of coefficient to standard error. P>|z reports the significance level of the coefficient.
* $A_{cs}$(Dum) is a 0-1 dummy variable. The values reported here are the probabilities of adoption as this value switches from 0 to 1, with $V_t$ held at its mean value.

The results from the second hurdle equation are largely what one would expect a priori. The conventional marginal response to higher expected profitability relative to alternative crops ($G^L_C$-$G_A$) is present. The greater the discrepancy between the estimated long run returns with full knowledge as compared to current returns, the less area is planted, which is consistent with farmers gaining knowledge through trials. Increased available area ($A_T$) reduces the proportion of the available area in chick peas, which is logical given these farmers are in the trial phase. Increased family labour ($l_f$) to facilitate such trials, and increased seeding capacity both increases the area grown, while evidence of longer lags in the adoption of wheat crops reduces the probability of adoption and intensity.

The 'risk' variables are also in line with what one would expect from a risk averse producer. Increased risk aversion and a belief that chick peas are more risky than their alternative crop reduces both the probability of adoption and intensity of adoption, while the greater the perceived covariance the greater both are. The interaction terms imply that the more risk averse one is the greater is the impact of relative riskiness and covariance. A combination of the relevant elasticity's[3] reveals that, ceteris paribus, increased risk aversion reduces the area under trial, an increase in the covariance between wheat and chick peas increases the area, while an increase in the variance of chick peas relative to the alternative enterprise reduces it. Although not strictly significant, RP and $Cov_{WC}$ are retained in the specification because of their inclusion in the interaction terms. The relatively high aggregate estimate of the elasticity for RP is a feature of all specifications estimated.

In the participation equation, having grown the crop previously ($A_{cs}$(Dum)) increases the probability of clearing the first hurdle, as does the estimate of the value of trialing the crop relative to a new wheat variety ($V_t$).

In-order to interpret the implications of the double hurdle aspect of the model further, it is useful to identify the distribution of predicted adopters with the actual values. Table 3 presents these results, with the correct predictions (based on an adopter having a predicted probability >0.5 in the first hurdle, and a positive expected area in the second) highlighted in bold. Thus, 25 of the 35 adopters are correctly predicted as such, clearing both hurdles. The remaining 10 who did adopt are all predicted as having a non-corner solution to the intensity equation, but fail at the first hurdle. Of the 64 correctly identified non-adopters, 20 'fail' at both hurdles, 35 fail at the first hurdle only, while 9 are predicted as potential adopters but are at a corner solution of the intensity equation.

Table 3. Predicted v. actual adopters.

| | | | Actual values | |
|---|---|---|---|---|
| | | | 0 | 1 |
| | 1st Hurdle | 2nd Hurdle | | |
| Predicted values | 0 | 0 | **20** | |
| | | 1 | **35** | 10 |
| | 1 | 0 | **9** | |
| | 1 | 1 | 15 | **25** |

Although illustrative of how the model works, such a table, or estimates of the proportion of correct predictions, should not be used as a measure of the goodness of fit of the model (Veall and Zimmermann, 1996). Instead we report one of the "$R^2$" type measures, given by

$$\sigma_n = \frac{p_{11} + p_{22} + p_{\sim 1}^2 + p_{\sim 2}^2}{1 - p_{\sim 1}^2 - p_{\sim 2}^2} \qquad (10)$$

where $p_{ij}$ is the fraction of times the realization was outcome i when the model predicted outcome j, and $p_{\sim j}$ is the fraction of times alternative j is predicted. However, this measure is for the zeros only, and takes no account of the contribution of the continuous part of the data.

[3] "Adding up" the elasticities to identify the full impact of a change in (e.g.) RP implies one is abstracting from any covariance between variables used in the composites.

The $R^2$ measure reported in Table 2 is given by

$$R^2 = \frac{2(l_m - l_0)}{2(l_m - l_0) + N} \tag{11}$$

where $l_m$ and $l_0$ are the log likelihoods for the full model and a model with just constants in both hurdles, respectively and N the number of observations. There is no consensus on the appropriate goodness-of-fit measure for these type of models, and a wide variety are available. Although the one proposed above is not the preferred choice of Veall and Zimmermann (1994) in terms of a Tobit model, the advantage of its use here is that it can be applied uniformly across double hurdle, Heckman and Tobit specifications.

***Heckman***

Both first hurdle dominance and complete dominance versions of the Heckman model have been estimated, but the complete dominance restriction ($\rho=0$) is accepted using a LL ratio test, with a test statistic of 0.3 compared to a critical value of $\chi^2_{0.05,1}$ of 3.84. Table 4 reports the results for the complete dominance model.

Note that in the intensity equation, there are no elasticities reported for the probability of adoption: conditional upon clearing the first hurdle, a positive level of area is ensured. The marginal impact underlying the intensity elasticity is given by:

$$\frac{\partial E[y_i \mid y_i > 0]}{\partial x_i} = \beta \; (1 - \lambda_i^2 + \alpha_i \lambda_i) \tag{12}$$

where

$$\alpha_i = -\beta x_i / \sigma \quad \text{and } \lambda_\mathrm{i} = \frac{\phi(\alpha_i)}{\Phi(\alpha_i)}$$

Table 4. Heckman Complete Dominance Model *(equations 4-5, $\rho$=0 )*

| Variable | Coef. | Std. Err. | Z | P>\|z | Elasticities | |
|---|---|---|---|---|---|---|
| Intensity equation | | | | | Intensity | Adoption |
| $G_C^L$-$G_A$ | 0.133 | 0.057 | 2.330 | 0.02 | 0.268 | |
| $G_C^L$-$G_C^C$ | -0.187 | 0.066 | -2.829 | 0.005 | -1.242 | |
| $A_T$ | -0.227 | 0.042 | -5.443 | 0 | -0.279 | |
| $S_c$ | 0.204 | 0.053 | 3.859 | 0 | 0.470 | |
| $L_f$ | 0.116 | 0.037 | 3.093 | 0.002 | 0.651 | |
| $R_r$ | 0.151 | 0.051 | 2.976 | 0.003 | 0.603 | |
| RP | 0.280 | 0.273 | 1.024 | 0.306 | 1.913 | |
| $Cov_{WC}$ | 0.115 | 0.051 | 2.274 | 0.023 | 0.397 | |
| $\sigma_C^2$-$\sigma_A^2$ | -0.183 | 0.064 | -2.862 | 0.004 | -0.405 | |
| ($\sigma_C^2$-$\sigma_A^2$) *RP | -1.208 | 0.492 | -2.454 | 0.014 | -1.486 | |
| Intercept | 0.014 | 0.155 | 0.092 | 0.927 | | |
| $\sigma$ | 0.036 | 0.004 | | | | |
| Adoption equation | | | | | | |
| $G_C^L$-$G_A$ | 3.412 | 1.237 | 2.758 | 0.006 | | 1.846 |
| $G_C^L$-$G_C^C$ | 1.607 | 0.690 | 2.329 | 0.020 | | 0.286 |
| $T_W$ | -2.434 | 1.359 | -1.791 | 0.073 | | -0.370 |
| $A_{CS}$ | -3.613 | 1.558 | -2.319 | 0.020 | | -0.415 |
| $V_t$ | 3.492 | 1.570 | 2.224 | 0.026 | | 1.237 |
| RP | -53.809 | 26.714 | -2.014 | 0.044 | | -27.200 |
| $Cov_{WC}$ | -2.738 | 1.413 | -1.938 | 0.053 | | -0.698 |
| ($\sigma_C^2$-$\sigma_A^2$) | -2.925 | 1.712 | -1.709 | 0.088 | | -1.438 |
| $Cov_{WC}$*RP | 26.345 | 12.531 | 2.102 | 0.036 | | 11.813 |
| ($\sigma_C^2$-$\sigma_A^2$) *RP | -22.500 | 10.941 | -2.056 | 0.040 | | -2.048 |
| Intercept | 20.487 | 10.969 | 1.868 | 0.062 | | |

Log Likelihood = 21.827

$R^2$=0.477

$\sigma_n$ =0.556

There are a number of changes in the inferences that can be made if one compares Table 4 and Table 2. The 'risk' variables in the Heckman model tend to have smaller impacts on the intensity of adoption, and the impact of RP is much less. The estimated responsiveness of planted area to relative profitability ($G_C^L$-$G_A$) is also lower, with the elasticity reduced by some 80%, and the impact of long run v short run profitability has reversed sign.

The set of variables significant in the Heckman adoption equation is somewhat reduced compared to the combined list of the adoption and participation variables in the double hurdle. In the Heckman model the implied responsiveness of adoption to the 'risk' variables is increased across the board; for risk aversion the equation implies an elasticity of -17 if one combines values across all terms; +11 for the covariance of returns; -3.5 for the relative variance. The area suitable for chick peas ($A_t$) is not significant. Both previous planting of the crop and the estimated value of trialing increase the probability of adoption, whereas increased time to adopt wheat varieties reduces the probability.

The Heckman and double hurdle models are not nested: they represent fundamentally different representations of the process, and so one cannot provide a formal test of relative performance. However, comparison of the $R^2$ values indicate a slight preference for the Heckman model, as does the estimate of $\sigma_n$, based on the predicted and actual adopters reported in Table 7.

Table 7. Predicted v. actual adopters: Heckman model

| | Actual values | |
|---|---|---|
| | 0 | 1 |
| Predicted values | | |
| 0 | **73** | 15 |
| 1 | 6 | **20** |

*Tobit*

Table 6 reports the results for a standard Tobit model. This specification is nested within the double hurdle, and it is interesting to note the implications of using this more restricted form of model. The first item of note is the fact that, relatively, the elasticities for adoption are greater than those for intensity, which is the reverse of the results in Table 2. Secondly, the elasticities for adoption tend to be larger. Thus, observed variation in the exogenous variables will have a greater impact on expected adoption probabilities in the tobit model, than they do in the 'tobit' element of the double hurdle model. This is possibly due to the fact that the tobit is now having to discriminate across all non-adopters, whereas in the double hurdle model some 60% of farmers are predicted to be non-adopters from the first hurdle alone. The elasticity of the risk aversion variable for intensity is also much higher while those of the relative profitability variables is halved. Of perhaps most importance is the emergence of $A_{cs}$ and $V_t$ as significant determinants of the area grown. The double hurdle models suggest that these variables are affecting participation, but not intensity. In the tobit model they either have to affect both adoption and intensity, or have no effect on either. Their role as determinants of the adoption decision is dominating the estimation, leading to the significant estimates, but one has to then also make the inference that these variables are important in determining area, when they clearly are not (otherwise they would have appeared as significant variables in the double hurdle intensity equation). Similarly, the rate of return variable ($R_r$) has dropped out of the estimation of the tobit model, whereas it is significant in the double hurdle.

It is noticeable that while the ability of the Tobit to discriminate between adopters and non-adopters is high (the estimate of $\sigma_n$ is not that much different than the other models), the estimate of the overall fit is considerably reduced, suggesting that the ability of the model to explain the intensity of adoption is being compromised by the 'single indicator' approach. The formal relationship between the Tobit specification reported in Table 6 and an independent double hurdle model was also tested. The first hurdle equation contained those variables found significant in the earlier model ($A_{CS}$(Dum) and $V_t$) and the model was re-estimated. The restrictions imposed by the Tobit model were rejected when compared against this new model, with a LL ratio value of 11.76 against a critical value of 7.82 ( $\chi^2_{0.05,3}$). These results suggest that the use of the tobit model is inappropriate for this data set, and would lead to erroneous inferences of the significant determinants of adoption of chick peas.

Table 6. Tobit model (*equation 2)*

| Variable | Coef. | Std. Err. | T | P>\|t | Elasticities Intensity | Elasticities Adoption |
|---|---|---|---|---|---|---|
| $G_C^L$-$G_A$ | 0.354 | 0.099 | 3.587 | 0.001 | 0.723 | 2.817 |
| $G_C^L$-$G_C^C$ | -0.438 | 0.130 | -3.37 | 0.001 | -0.383 | -1.493 |
| $T_w$ | -0.210 | 0.105 | -1.999 | 0.048 | -0.157 | -0.612 |
| $A_T$ | -0.228 | 0.102 | -2.23 | 0.028 | -0.167 | -0.650 |
| $S_{pd}$ | 0.177 | 0.062 | 2.836 | 0.006 | 0.262 | 1.021 |
| $S_c$ | 0.322 | 0.107 | 3.004 | 0.003 | 0.270 | 1.051 |
| $L_h$ | -0.121 | 0.067 | -1.803 | 0.074 | -0.113 | -0.439 |
| $A_{CS}$ | 0.124 | 0.053 | 2.331 | 0.022 | 0.070 | 0.273 |
| $V_t$ | 0.269 | 0.103 | 2.623 | 0.010 | 0.469 | 1.825 |
| RP | -3.860 | 2.002 | -1.928 | 0.057 | -9.600 | -37.380 |
| $Cov_{wc}$ | -0.213 | 0.115 | -1.857 | 0.066 | -0.268 | -1.042 |
| $\sigma_C^2$-$\sigma_A^2$ | -0.377 | 0.134 | -2.821 | 0.006 | -0.912 | -3.549 |
| $Cov_{WC}$*RP | 1.742 | 0.702 | 2.481 | 0.015 | 3.843 | 14.964 |
| ($\sigma_C^2$-$\sigma_A^2$) *RP | -2.201 | 0.990 | -2.222 | 0.029 | -0.986 | -3.837 |
| Intercept | 1.617 | 0.855 | 1.891 | 0.062 | | |
| $\sigma$ | 0.094 | 0.013 | | | | |

Log Likelihood =7.623

$R^{2=}$ 0.118

$\sigma_n$ =0.446

Table 7. Predicted v. actual adopters: Tobit model

| | Actual values | |
|---|---|---|
| | 0 | 1 |
| Predicted values | | |
| 0 | **69** | 11 |
| 1 | 10 | **24** |

*Probit*

The outcome of estimating a probit model has already been reported: because we accept independence across the residuals in the Heckman model, the adoption equation reported in Table 4 is simply a probit.

## 5. Conclusions

This paper has presented a number of alternative models that may be used to explain the adoption and intensity decision, and applied them to a particular innovation: the growing of chick peas in Western Australia. The results of all models give support to the general underlying model of adoption proposed in Abadi Ghadim and Pannell (1997): attitudes towards risk, and perceptions of relative riskiness of chick peas are important factors determining adoption, as is the perceived gains in knowledge from trialing the crop, as well as their relative profitability. However, their relative importance, and vectors of influence vary across specifications. For example, both the Double Hurdle and Heckman models suggest that an increased value of trialing will increase adoption levels, but have no impact on the area actually grown. The application of the Tobit model, however, would draw one to the conclusion that it also has a significant impact on area. A similar result holds for prior experience in growing the crop. The restrictive nature of the Tobit, in using a single latent variable to explain both adoption and intensity, also appears to distort the impact of variables which are significant in determining intensity, as identified by the more liberal specifications. The Heckman and Double Hurdle provide competing explanations of the underlying process determining non-adoption, and generate some important differences in the interpretation of the risk variables in particular. The structural differences in the models are not that great: a censored as compared to truncated second hurdle equation. Further development of both the theoretical framework for the use of double hurdle models in adoption studies, and in techniques of and model evaluation would appear to be fruitful avenues for research.

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