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Determinants of Adoption of Improved Crossbred Cattles: A Case Study of Suba and Laikipia Districts, Kenya

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Abstract
Recognizing that more than 10% of the Kenyan GDP and 50% of agricultural GDP are comprised of sales within the livestock subsector; the purpose of this research is to identify the determinants of adoption of improved crossbred cattle in rural Kenya. This research has important implications for increasing the dairy subsectors' productivity, improving nutrient intake within rural Kenya and motivating higher rates of foreign direct investment in a sustainable, beneficial sector. We used a publicly available (www.ifpri.org) dataset called "Land Tenure, Agricultural Productivity and the Environment, 2001." A logistical regression analysis is employed to answer our research questions. The results showed that: family members education, having an extra job in addition to farming, and exposure to external market forces (was the farmer a local, or immigrant) all greatly contributed to the likelihood of adoption. This research aims to gnaw away at the ambiguity and lack of research associated with the Kenyan dairy sub-sector and aims to facilitate greater understanding and investment in the sector.
Keywords: Adoption, Logistic regression, Kenya, Crossbreed cattle

1. Introduction

It is widely recognized that the development of the dairy sector within developing countries has played a vital role in bolstering milk production (De Haan, C. 1995). Adoption of improved agricultural technologies and practices result in multiple benefits to the adopters which include: enhanced food security, improved income, and reduced poverty (Barrett, Carter and Timmer, 2010). Recognizing that increased levels of technology adoption is positively correlated with higher milk yields, poverty alleviation, and ultimately increased production and productivity, it is necessary to bolster production capacity. While this is true globally, what makes it unique, and of particular importance within the Kenyan context is that the livestock sub-sector is estimated to contribute over 30% of the farmgate value of agricultural commodities (KALRO). Moreover, roughly 10% of the national GDP and 50% of the agricultural GDP are comprised by livestock sales, which are largely cattle related (KALRO).
While cattle make up such a large and important aspect of the GDP, prevailing production constraints such as poor breed characterisation and continued reliance on inefficient breeds has hindered Kenyan ability to grow this aspect of the economy (KALRO).

The Kenyan extension service have acknowledged the abovementioned and have made significant efforts to disseminate improved livestock technologies over the last several decades. However, the benefits of the technology will only be realized provided that the intended users adopt the available technologies. A timely assessment to see whether the technologies are embraced and utilized by farmers is important to identify constraints, learn from experience and inform future technology adoption and dissemination. Therefore, the purpose of this study to identify the factors that influence farmer's adoption and use of improved crossbred cattle in Kenya.

2. Literature Review

Recent studies on livestock technology adoption indicate that the adoption of new technology changes significantly over time and space. A farmer as an end user decision maker always ventures for better living standard and seeks any possible way to adopting new advanced technology to fulfil this aim. (Nell et al., 1998). The question to answer here is why some apparently beneficial technologies are not quickly adopted in livestock production. It's equally important for researchers to develop technologies that can be easily transferred and adopted to smallholder farmers especially in developing countries otherwise their researches would be ineffectual.

The majority of the population living in Kenya depends heavily on crop and livestock farming for their livelihood. Livestock plays a crucial socio-economic role; source of income, dairy and food production. There is a need to analyze the determinants that contribute positively to the adoption of new advanced technology in livestock production as well as analyzing the constraints for the diffusion and adoption process. While researchers have made a significant effort in developing technological advanced farming and livestock farming methods for farmers, the adoption of those innovations in poor countries is minimal.

Quite often high yielding technologies that would increase productivity are not adopted. The study done by De Haan (1995) showed that, it's easier to adopt crop technology than livestock technology. Although Besley and Case indicated the yet to be answered questions regarding the technology adoption, Bindlish and Evenson (1993) explained that usually new technology is either introduced to poor farmers through other farmers' experiments or through extension services and social learning pushes diffusion and adoption.

Although earlier studies by Feder and Zilberman (1985) emphasized on the farm size and lack of access to credits to be the main constraints of the technology adoption process, the recent literatures focused on the role of farmers education and capacity of the farmers to make decision in the diffusion process (Foster and Rosenzweig ; Cameron, Conley and Udry). As evidenced in Conley and Udry works, social learning for technology adoption by farmers in Ghana has been of success while learning by doing is important as per studies done by Cameron in rural Indian village.

Rogers (1995) indicated that some individuals adopt technology earlier than others mainly due to socioeconomic factors, and individual attributes such as personality values and communication behaviours.

In the analysis of the determinants of adopting the zero grazing technology in Kenya, the study showed the negative relationship between the adoption and the number of adults in the family, and also the distance to urbanized centers. Alternatively, the adoption was positively influenced by the farm size, experience in farming, availability of veterinary services and of course years of education (Staal et al.2001b)

3. Data and Methods

3.1 Data

To answer the stated research questions we used a publicly available (www.ifpri.org) dataset called "Land Tenure, Agricultural Productivity and the Environment, 2001". The survey was conducted in 2001 in two rural districts (Suba and Laikipia) of Kenya. A total of 310 households were randomly selected and interviewed. The survey collected a wide range of information from sampled households.

3.2 Model specification

In this paper, the decision to adopt a given improved crossbred cattle takes a binary choice situation because farmers have decisions of either to adopt or not the technology under consideration. In economic problems like this where the dependent variable is not continuous, the ordinary least square procedures will not do a good job in estimation. This is because the least squares estimator is biased as well as inconsistent (Hill, Griffiths, & Lim, 2011). So in such cases, an alternative estimation technique must be sought. The most frequently utilized econometric approaches in modelling decision making patterns that involve qualitative dependent variables are probit and logit probability models. Since the probit model is numerically involving and complex, in this paper we use the logit model. In the following, drawing on Hill, Griffiths, & Lim (2011: 595), we briefly present the theoretical and empirical model of logistic regression. Assume L is a logistic random variable, then its probability density function is:

$$\lambda(l) = \frac{e^{-1}}{(1+e^{-1})^2}, -\infty < l < \infty$$

The corresponding cumulative distribution function for a logistic random variable is:

$$\Lambda(l) = P[L \leq l] = \frac{1}{1+e^{-1}}$$

Since this function has a closed form expression it makes the analysis relatively easier.

In the logit model, the probability p that the observed value y takes the value 1 is given by:

$$P = \frac{1}{1+e^{-(\beta 1+\beta 2x)}} = \frac{\exp\,(\beta 1+\beta 2x)}{1+\exp\,(\beta 1+\beta 2x)}$$

It follows that the probability that y=0 is:

$$1\text{-}\,P = \frac{1}{1+\exp\,(\beta 1+\beta 2x)}$$

This model is called a logit model and β_1 and β_2 are unknown parameters to be estimated using the maximum likelihood estimation procedure.

We have a binary dependent variable (ADOPT) which involves whether farmers adopt cross breed cattle or not given their social, economic, as well as institutional attributes.

$$\text{ADOPT}=\begin{cases} 1 & \textit{if at least one crossbreed cattle is adopted} \\ 0 & \textit{if no crossbreed cattle is adopted} \end{cases}$$

Hence, to model farmers crossbreed cattle adoption decision we employed a logit model with maximum likelihood estimation procedure. Hence, our empirical model may be specified as:

$$\text{ADOPT} = \beta_o + \beta_1\text{SEX} + \beta_2\text{HEADEDUC} + \beta_3\text{CHILDEDUC} + \beta 4\text{LOCAL} + \beta_5\text{LAND} + \beta_6\text{NUMCHILD} + \beta_7\text{SECOCCUP} + \beta_8\text{MKTDIST} + \beta_9\text{FBO} + \varepsilon$$

Where: ADOPT is a binary dependent variable, β_{o} is the intercept, $\beta_{1\text{-}9}$ are parameters to be estimated, ε the error term, and the explanatory variables defined in the following section.

3.3 Description of Explanatory Variables and Hypotheses

The objective of the present paper is to empirically identify the determinants of smallholder farmers crossbred cattle adoption decisions. The factors that are hypothesized to influence farmers adoption decision are classified into farmers socio-economic attributes (household head education, gender, whether the head was born in the village and household members education level), household resource endowments (land, household size, if the head has secondary occupation) and institutional factors (membership in farmers based associations and market access). In the following we briefly present the description of the explanatory variables and their hypothesized effect on the probability of adoption of crossbreed cattle (Table 1 depicts definition of the variables with their expected signs).

We expect that the presence of higher level of human capital in a household will increase the likelihood of adoption of crossbreed cattle. We represent household human capital by the head's education level (HEADEDUC) and the number of children in the household who have completed secondary education (CHILDEDUC). We hypothesize that male-headed households (SEX) are relatively more socially connected and have more access to information and expected to take operational decisions that entail risk. The closer a district lies from market locations the higher the probability that they will take up improved technologies such as crossbreed cattle. So we expect that distance to market (MKTDIST) will have negative effect on the likelihood of adoption. Adoption of improved cross breed cattle like other investment activities require greater start up funds and higher level of operational and maintenance costs. Hence, we expect that availability of credit to farmers through their membership in local Farmers Based savings and credit Organizations (FBO) can enhance adoption of the technologies. The influence of whether a farmer has a second occupation (SECOCCUP) on adoption decision is not clear. On one hand, we know that if a farmer engages in additional gainful activity his/her income level increases making the probability of adoption higher. On the other hand, engagement in second occupation might indicate less time available for livestock production operation which is time-intensive and negatively influencing adoption decision.

Table 1: Definition of Variables Used in the Econometric Model and their Expected signs

Variable name	Definition	Expected sign
ADOPT	A dichotomous variable; a value of 1 if the farmer adopted at least one improved crossbreed cattle; 0 otherwise.	
	Socio-economic attributes	
SEX	Gender of the household head 1 if male; 0 if female	+
HEADEDUC	1 if the head completed at least primary education, 0 otherwise	+
CHILDEDUC	Number of children in the household who have completed secondary education	+
LOCAL	1 if the farmer always lived in the district; 0 otherwise (Non-local).	-
	Resource endowments	
LAND	Total size of land operated in hectare (logged)	+/-
NUMCHILD	Total number of children in the household	+/-
	Institutional factors	
SECOCCUP	1 if the farmer maintains second occupation in addition to farming; 0 otherwise.	-
MKTDIST	Distance to the nearest market in kilometres	-
FBO	1 if any member of the household is a member of farmers based credit & savings organization; 0 otherwise	+

The number of male and female members of the household (NUMCHILD) which are an important source of labour for the farming enterprise is hypothesized to be positively influencing adoption. The effect of the size of the land owned (LAND) on adoption decision is indefinite. This is because land is an indicator of wealth and the larger the size of the land owned the wealthier the farmer tend to be and the less financial constraint that the technology adoption entails. Alternatively, farmers who own larger land might mainly focus on crop production and have less time and labour and do not favour adoption of improved cattle. Since farmers who were not born and lived in the local village (LOCAL) relatively lack cultivable land for crop production, their likelihood of improved livestock technology adoption is expected to be higher compared to the local ones.

Our second set of hypothesis states there is significant difference between adopters of crossbreed cattle farmers and non-adopters with regard to their income. To test this we use independent samples t-test procedure.

To test the overall statistical significances of our model, we specified the null hypothesis. H_o: the coefficients are zero: $\beta_0 = \beta_1 = \ldots \beta_k = 0$

We used the likelihood ratio (LR) test (this procedure is more or less similar with the F-test in OLS regression model). Following Hill, Griffiths, & Lim (2011) the LR is given by:

$$LR = 2(lnL_u - lnL_R)$$

L_u and L_R stand for the log-likelihood function values in the unrestricted and restricted models respectively. The null hypothesis is rejected if the value L_R is greater than the Chi-square distribution critical value. In addition, we conducted a number of model evaluation tests and diagnostics.

4. Results

4.1 Descriptive socioeconomic characteristics of sample households

Table 2 (for continuous variables) and 3 (for categorical variables) summarize the most important social, economic and demographic attributes of the sample households in the study areas. It appears that compared to non-adopters, adopters tend to have larger land size, more family members with higher education level, more number of children and live relatively closer to market area (although the result is not statistically different).

Table 2: Characteristics of adopters and non-adopters of improved cross breed cattle (continuous variables)

	Adopters			Non-adopters			
Attribute	**No.**	**Mean**	**Std. Dev.**	**No.**	**Mean**	**Std. Dev.**	**t-statistic**
CHILDEDUC	77	2.415584	2.462084	193	.7564767	1.481754	-6.8176***
LAND	77	8.612338	6.994599	193	5.899223	5.325581	-3.4422***
NUMCHILD	76	6.434211	2.777699	191	5.010471	3.050435	-3.5277***
MKTDIST	76	.9486842	2.137007	186	1.502957	6.202519	0.7601NS

Note: *** indicates significance at 5% level, NS= not significant

Although there is no meaningful statistical difference exist between adopters and non-adopters with regard to the head's gender and education level, the descriptive results show adopting households are mostly headed by men and the heads have relatively higher level of education. However, adopting households tend to maintain a second job in addition to farming, born and lived in the local village, and not members of farmers based local associations.

Table 3: Characteristics of adopters and non-adopters of improved cross breed cattle (categorical variables)

	Adopters		Non-adopters		chi2 statistic
	No.	**%**	**No.**	**%**	
SEX					
Male head	62.0	80.5	145.0	75.1	0.8939 NS
Female head	15.0	19.5	48.0	24.9	
HEADEDUC					
Primary & up	52.0	74.3	139.0	73.2	0.0334 NS
No school	18.0	25.7	51.0	26.8	
LOCAL					
Local	41.0	53.2	139.0	72.0	8.7299***
Non-local	36.0	46.8	54.0	28.0	
SECOCCUP					
Second job	55.0	71.4	85.0	44.0	16.5361***
No second job	22.0	28.6	108.0	56.0	
FBO					
FBO Member	24.0	33.3	32.0	17.3	7.8207***
Not Member	48.0	66.7	153.0	82.7	

Note: *** indicates significance at 5% level, NS= not significant

4.2 Is there any difference in household income between adopters and non-adopters?

To test this hypothesis we run an independent samples t-test and the results presented in Appendix 1 show that adopters had a statistically significantly higher level of income (t(268)=-5.2921, p=0.0000) compared to non-adopters (18,549.22). We cannot make any causal inference between adoption and income based on this result. In the future this relationship should be investigated applying appropriate econometric procedures and suitable data.

4.3 Determinants of adoption of improved cross breed cattle: Empirical logit model results

The logistic regression results of the determinants of the likelihood of farmers to adopt at least one improved cross breed cattle are reported in Table 4 (results with odds ratio are presented in Appendix 3). Summary statistics are provided in Appendix 2. From the table we can see that the direction (sign) of the influence of all of the variables included in the model are in line with our expectations. To test the overall significance of the model, we used a likelihood ratio (LR) chi-square test. The null hypothesis is that all of the coefficients in the model are zero. The LR chi2(9) value is 52.77 with the associated probability of Prob > chi2=0.0000. Based on this result we reject the null hypothesis and conclude that at least one of the covariates have a significant effect. In OLS regression, we used R^2 to evaluate the amount of variance explained by the model. But in logistic regression, there is no comparable value. However, McFadden R^2 can be used as a rough alternative but with caution. In our case its value is 0.2011 indicating approximate amount of variability explained by the fitted model (low R^2 value is a norm in logistic regression (Hosmer & Lemeshow (2000)). In general, the higher the McFadden R^2, the better the fit is.

Table 4: Logistic regression results

```
------------------------------------------------------------------------------
Logistic regression                               Number of obs   =        236
                                                  LR chi2(9)      =      52.77
                                                  Prob > chi2     =     0.0000
Log likelihood =  -109.5225                       Pseudo R2       =     0.1941
------------------------------------------------------------------------------
 ADOPTXBREED |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
  Maleheaded |   .3012356   .4552658     0.66   0.508     -.591069     1.19354
    EducHead |   .0045504   .4277717     0.01   0.992    -.8338667    .8429675
     childed |   .3582309   .1054484     3.40   0.001      .151556    .5649059
      immigr |  -.8046813   .4044672    -1.99   0.047    -1.597422   -.0119401
 LogLandsize |   .3825421    .245988     1.56   0.120    -.0995856    .8646698
    numchild |   .0498702   .0639139     0.78   0.435    -.0753987    .1751391
SECOCCUPAT~N |   .9258552   .3679967     2.52   0.012      .204595    1.647115
     mktdnce |  -.0957119   .0984736    -0.97   0.331    -.2887167    .0972928
         fbo |   .1794327   .4171639     0.43   0.667    -.6381936    .9970589
       _cons |  -2.630584   .7107972    -3.70   0.000    -4.023721   -1.237447
------------------------------------------------------------------------------
```

Having secondary occupation and having more number of children who are attending secondary school and above were found to positively and significantly influence the probability of adoption of cross breed cattle. The variable indicating whether the household head lives in his/her existing village continuously is found to be negatively and significantly associated with adoption decision. This implies that the likelihood of farmers who were born and lived in their village to adopt improved cross breed cattle is lower compared to those newcomers. For ease of interpretation of the model output & to make the results more comprehensible (Acook, 2010), we use the results presented in Table 5.

Table 5: Percentage Change in Odds

```
------------------------------------------------------------------
ADOPT    |       b         z     P>|z|      %      %StdX     SDofX
---------+--------------------------------------------------------
Malehead |   0.30124    0.662   0.508     35.2      13.7    0.4263
EducHead |   0.00455    0.011   0.992      0.5       0.2    0.4433
 childed |   0.35823    3.397   0.001     43.1      96.3    1.8822
  immigr |  -0.80468   -1.989   0.047    -55.3     -31.3    0.4666
lnLandsze|   0.38254    1.555   0.120     46.6      34.7    0.7794
numchild |   0.04987    0.780   0.435      5.1      16.5    3.0615
SECOCCUP |   0.92586    2.516   0.012    152.4      59.0    0.5010
 mktdnce |  -0.09571   -0.972   0.331     -9.1     -41.5    5.5941
     fbo |   0.17943    0.430   0.667     19.7       7.4    0.4002
------------------------------------------------------------------
       b = raw coefficient
       z = z-score for test of b=0
   P>|z| = p-value for z-test
       % = percent change in odds for unit increase in X
   %StdX = percent change in odds for SD increase in X
   SDofX = standard deviation of X
```

The probability of adoption is 55.3% lower for those households who always lived in their village than for newcomers. On the other hand, having another job in addition to farming increases the likelihood of adoption by 152.4% more than those without. Having a one-standard-deviation-higher number of household members who are attending secondary school or higher increases the probability of adoption by 96.3%. All of these three influences are statistically significant at 5% level and consistent with our a priori expectations and previous literature.

Model evaluation and diagnostics

To assess the adequacy of our model, its predictive capacity and goodness of fit, we run several diagnostic tests. In the following we briefly present the results.

- *Multicollinearity*

The results of the collinearity diagnostics (Table 6) (VIF=1.24<10) doesn't show any evidence of the problem of multicollinearity in our model.

Table 6: Collinearity Diagnostics

Variable	VIF	SQRT VIF	Tolerance	R-Squared
ADOPT	1.28	1.13	0.7819	0.2181
Maleheaded	1.18	1.09	0.8469	0.1531
EducHead	1.24	1.11	0.8085	0.1915
childed	1.57	1.25	0.6384	0.3616
immigr	1.13	1.06	0.8851	0.1149
lnLandsize	1.28	1.13	0.7808	0.2192
numchild	1.37	1.17	0.7308	0.2692
SECOCCUP	1.17	1.08	0.8515	0.1485
mktdnce	1.06	1.03	0.9409	0.0591
fbo	1.15	1.07	0.8709	0.1291
Mean VIF	1.24			

- *Model specification*

Model specification is tested using linktest. The result shows that _hatsq (p=0.150) is insignificant implying our model doesn't suffer from specification error.

```
Logistic regression                               Number of obs   =        236
                                                  LR chi2(2)      =      54.67
                                                  Prob > chi2     =     0.0000
Log likelihood = -108.56977                       Pseudo R2       =     0.2011
------------------------------------------------------------------------------
 ADOPTXBREED |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
        _hat |   .8549669   .1739479     4.92   0.000     .5140353    1.195898
      _hatsq |  -.1360611   .0944917    -1.44   0.150    -.3212614    .0491391
       _cons |   .1219329   .2351287     0.52   0.604    -.3389108    .5827767
------------------------------------------------------------------------------
Note: 1 failure and 0 successes completely determined.
```

- **Goodness of fit: Are the data fit the model well?**
    - *Hosmer-Lemeshow (H-L) and Pearson Chi-square test*

We employed the H-L and the Pearson Chi-square tests to assess the fit of our logistic model against the data (Hosmer & Lemeshow, 2000). Both of the results confirm our model fits the data adequately well. The result of H-L shows that the p value (Prob>chi2 =0.2880) is not statistically significant indicating that our model fits the data reasonably well. The results of Pearson chi-square test also led us to the same conclusion (see details of the results in Appendix 4).

```
Logistic model for ADOPT, goodness-of-fit test

       number of observations =       236
             number of groups =       10
      Hosmer-Lemeshow chi2(8) =       9.68
                  Prob > chi2 =       0.2880
```

- *Percent correctly predicted*

As the results presented in the Appendix 5 shows our model correctly predicts 77.54%. This is relatively higher percentage indicating the reliability of our model in classifying observations into one of the two categorical outcomes. Receiver Operating Characteristic (ROC) curve can also graphically show the extent of our model's predictive power (Hosmer & Lemeshow, 2000) (see the graph in Appendix 6). The larger the area under ROC, the better the prediction power. In our case, the area under the curve is 0.7951 indicating adequate predictive capacity of our model.

6. Limitations of the study

Our analysis managed to effectively address our research questions and identified the factors that influence smallholders probability of adopting cross breed cattle in rural Kenya. First, although the results seem interesting, they are limited in a number different areas. The paper utilized a survey dataset which was collected in 2001 and hence results might not correspond to the present day condition unless they are verified using fresh and newly collected data. Second, the data focused only in two rural villages of Kenya and the lessons learned from the results can be extended to other villages with similar biophysical and socioeconomic characteristics. However, generalization cannot be possible. Third, several theoretically important covariates are not included in our model due to data unavailability (since the data was collected for other purposes) . This obviously limits the adequacy and efficiency of the model. Fourth, although our logistic regression model passed different specification and goodness of fit tests, we recognize that still there is a room for improvement to make it more powerful and stronger. Other specification forms such as multinomial logit and instrumental variable procedures should be considered in the future. In general, the results of this paper should be seen in light of these limitations.

7. Conclusion

Acknowledging the positive impacts of adopting crossbred varieties within the dairy sub-sector, such as increased milk production, higher milk protein, and overall greater food security through increased productivity, our paper aimed to investigate the factors that contributed to rural farmer adoption of crossbred cattle varieties within two Kenyan districts: Suba and Laikipia. The results of our logistic regression model show that family members education level and having additional occupation other than farming positively impact their likelihood of adoption, and farmer's time spent in the particular location inversely influence the probability of adoption. Moreover, although they did not statistically significant, the other variables in the model consistently depicted the expected signs. The results of this research offer practical, potentially far reaching implications.

In today's rapidly evolving world of development, the above data offers practical advice as to how the government and development practitioners should best emphasize their effort to guarantee crossbred adoption and increase productivity by investing in making education accessible in rural areas and making financial capital available through micro-finacing schemes to make the start up investment easier.

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Appendices

Appendix 1

Two-sample t test with equal variances

Group	Obs	Mean	Std. Err.	Std. Dev.	[95% Conf.	Interval]
no	193	18549.22	1264.849	17571.84	16054.44	21044.01
if at le	77	32792.21	2850.953	25017.01	27114.04	38470.37
combined	270	22611.11	1274.703	20945.51	20101.45	25120.77
diff		-14242.98	2691.377		-19541.92	-8944.053

diff = mean(**no**) - mean(**if at le**) t = -5.2921

Ho: diff = 0 degrees of freedom = 268

Ha: diff < 0 Pr(T < t) = **0.0000**

Ha: diff != 0 Pr(|T| > |t|) = **0.0000**

Ha: diff > 0 Pr(T > t) = **1.0000**

Appendix 2

Descriptive summary of the explanatory variables

Variable	Obs	Mean	Std. Dev.	Min	Max
Maleheaded	270	.7666667	.423738	0	1
EducHead	260	.7307692	.4444156	0	1
childed	270	1.22963	1.960353	0	9
immigr	270	.6666667	.4722799	0	1
landsize	270	6.672963	5.96423	0	35
numchild	267	5.41573	3.039127	0	17
SECOCCUPATIN	270	.5185185	.5005848	0	1
mktdnce	262	1.342176	5.352074	0	82
fbo	257	.2178988	.4136238	0	1

Appendix 3

```
Logistic regression                               Number of obs   =        236
                                                  LR chi2(9)      =      52.77
                                                  Prob > chi2     =     0.0000
Log likelihood =  -109.5225                       Pseudo R2       =     0.1941
```

ADOPTXBREED	Odds Ratio	Std. Err.	z	P>|z|	[95% Conf.	Interval]
Maleheaded	1.351528	.6153044	0.66	0.508	.553735	3.298739
EducHead	1.004561	.4297226	0.01	0.992	.4343665	2.323251
childed	1.430796	.1508751	3.40	0.001	1.163643	1.759282
immigr	.4472305	.1808901	-1.99	0.047	.2024176	.9881309
LogLandsize	1.466007	.3606201	1.56	0.120	.9052125	2.374222
numchild	1.051135	.0671821	0.78	0.435	.9273737	1.191412
SECOCCUPAT~N	2.524026	.9288332	2.52	0.012	1.227028	5.191982
mktdnce	.9087257	.0894855	-0.97	0.331	.7492244	1.102183
fbo	1.196538	.4991526	0.43	0.667	.5282458	2.710299

Appendix 4: Pearson chi-square test of goodness of fit

```
Logistic model for ADOPT, goodness-of-fit test

       number of observations =       236
 number of covariate patterns =       231
            Pearson chi2(221) =       212.84
                  Prob > chi2 =       0.6409
```

Appendix 5: Classification

```
Logistic model for ADOPT

              -------- True --------
Classified |         D            ~D  |      Total
-----------+--------------------------+-----------
     +     |        22            13  |         35
     -     |        40           161  |        201
-----------+--------------------------+-----------
   Total   |        62           174  |        236

Classified + if predicted Pr(D) >= .5
True D defined as ADOPTXBREED != 0
--------------------------------------------------
Sensitivity                     Pr( +| D)   35.48%
Specificity                     Pr( -|~D)   92.53%
Positive predictive value       Pr( D| +)   62.86%
Negative predictive value       Pr(~D| -)   80.10%
--------------------------------------------------
False + rate for true ~D        Pr( +|~D)    7.47%
False - rate for true D         Pr( -| D)   64.52%
False + rate for classified +   Pr(~D| +)   37.14%
False - rate for classified -   Pr( D| -)   19.90%
--------------------------------------------------
Correctly classified                        77.54%
--------------------------------------------------
```

Appendix 6 ROC curve