Modelling technology adoption decisions by smallholder cassava producers in East Africa

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Overview of presentation

• Introduction
• Methodology
• Results and Discussion
• Conclusions and policy implications
• Further work
Leading cassava producers (FAO, 2014)

Million tonnes

Nigeria
Thailand
Indonesia
Brazil
Ghana
DR Congo
Cambodia
India
Angola
Mozambique
Malawi
Tanzania
Cameroon
Côte d'Ivoire
Madagascar
Uganda
Research questions

• What is the current status of cassava production and productivity in Uganda, Tanzania and Malawi?

• What is the current adoption rate of improved cassava production technologies?

• What is the economic impact of *B. tabaci* on smallholder farmers?
Methods

• Literature review
• Questionnaire development
  • Pre-survey workshops
  • Pilot surveys
• Farmer surveys using multi-stage random sampling procedure
• A total of 1200 farmers interviewed
• Econometric modelling
Methods (cont.)

Sample

- Uganda
  - Districts (6)
  - Farmers (n=450)

- Tanzania
  - Districts (4)

- Malawi
  - Districts (4)
  - Farmers (n=400)
Multivariate probit model

\[ Y_{ijm}^* = X_{ijm}' \beta_m + \varepsilon_{ijm} \]  \hspace{1cm} (1)

\[ Y_{ijm} = \begin{cases} 
1 & \text{if } Y_{ijm}^* > 0 \\
0 & \text{otherwise} 
\end{cases} \]  \hspace{1cm} (2)

where: m denotes technology choices for household i and plot j. \( Y_{ijm}^* \) is a latent variable which captures the unobserved preferences for technology m. This latent variable is assumed to be a linear combination of observed plot and household characteristics \( X_{ijm} \), and unobserved characteristics captured by the stochastic error term, \( \varepsilon_{ijm} \). \( \beta_m \) is the vector of parameters to be estimated is \( \beta_m \).

Multivariate probit model (cont.)

\[ \Omega = \begin{bmatrix}
1 & \rho_{12} & \rho_{13} & \ldots & \rho_{1m} \\
\rho_{12} & 1 & \rho_{23} & \ldots & \rho_{2m} \\
\rho_{13} & \rho_{23} & 1 & \ldots & \rho_{3m} \\
\ldots & \ldots & \ldots & 1 & \ldots \\
\rho_{1m} & \rho_{2m} & \rho_{3m} & \ldots & 1 \\
\end{bmatrix} \]

where the off-diagonal elements in the covariance matrix, \( \rho_{jm} \), represents the unobserved correlation between the stochastic components of the \( j \)th and \( m \)th technology options. This specification with non-zero diagonal elements allows for correlation across the error terms of several latent equations, which represent unobserved characteristics that affect the choice of technology.
Results: Descriptive statistics of the sample

<table>
<thead>
<tr>
<th></th>
<th>Uganda</th>
<th>Tanzania</th>
<th>Malawi</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age (years)</td>
<td>46.03 (14.65)</td>
<td>51.07 (13.49)</td>
<td>47.42 (15.16)</td>
</tr>
<tr>
<td>Male (%)</td>
<td>65</td>
<td>80</td>
<td>76</td>
</tr>
<tr>
<td>Education (years)</td>
<td>8.13 (4.13)</td>
<td>8.72 (5.94)</td>
<td>5.88 (3.39)</td>
</tr>
<tr>
<td>Household size</td>
<td>8.52 (3.95)</td>
<td>7.52 (3.75)</td>
<td>6.31 (2.65)</td>
</tr>
<tr>
<td>No. of Children</td>
<td>4.26 (2.37)</td>
<td>4.40 (2.47)</td>
<td>2.91 (1.69)</td>
</tr>
</tbody>
</table>

*Source: Field surveys. Figures in brackets are standard deviations*
Results: Descriptive statistics (cont.)

<table>
<thead>
<tr>
<th></th>
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<th>Tanzania</th>
<th>Malawi</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total land/farm size (acres)</td>
<td>1.90 (1.51)</td>
<td>4.25 (3.54)</td>
<td>1.69 (1.97)</td>
</tr>
<tr>
<td>Land under cassava (acres)</td>
<td>1.21 (1.31)</td>
<td>2.46 (1.83)</td>
<td>1.44 (2.19)</td>
</tr>
<tr>
<td>Access to credit (%)</td>
<td>16</td>
<td>22</td>
<td>33</td>
</tr>
<tr>
<td>Member of organisation (%)</td>
<td>47</td>
<td>43</td>
<td>34</td>
</tr>
<tr>
<td>Extension (%)</td>
<td>30</td>
<td>31</td>
<td>45</td>
</tr>
</tbody>
</table>

Source: Field surveys. Figures in brackets are standard deviations
## Results: Adoption of improved cassava production technologies

<table>
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<th>Tanzania</th>
<th>Malawi</th>
</tr>
</thead>
<tbody>
<tr>
<td>Inorganic fertiliser (%)</td>
<td>0.0</td>
<td>0.0</td>
<td>3.0</td>
</tr>
<tr>
<td>Pesticide use (%)</td>
<td>1.0</td>
<td>2.0</td>
<td>2.0</td>
</tr>
<tr>
<td>Improved cassava variety (%)</td>
<td>70</td>
<td>11</td>
<td>51</td>
</tr>
<tr>
<td>Intercropping (%)</td>
<td>31</td>
<td>72</td>
<td>36</td>
</tr>
<tr>
<td>Plant spacing (%)</td>
<td>70</td>
<td>69</td>
<td>50</td>
</tr>
<tr>
<td>No. of Obs.</td>
<td>400</td>
<td>428</td>
<td>400</td>
</tr>
</tbody>
</table>

*Source: Field surveys*
## Results: Multivariate probit model (Tanzania)

<table>
<thead>
<tr>
<th>Variable</th>
<th>Improved cassava varieties</th>
<th>Legume intercropping</th>
<th>Plant spacing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Farm size</td>
<td>0.662 (1.96) **</td>
<td>-0.321 (-2.45)**</td>
<td>0.176 (2.03)**</td>
</tr>
<tr>
<td>Distance to market</td>
<td>-0.112 (2.46) **</td>
<td>-0.403 (-1.81)*</td>
<td>-0.403 (-2.26)**</td>
</tr>
<tr>
<td>Extension</td>
<td>0.737 (3.05) **</td>
<td>0.155 (2.72) **</td>
<td>0.395 (2.49)**</td>
</tr>
<tr>
<td>Livestock</td>
<td>0.982 (2.80) ***</td>
<td>0.694 (1.76) *</td>
<td>0.206 (1.02)</td>
</tr>
<tr>
<td>Credit</td>
<td>0.173 (2.56) **</td>
<td>0.3516 (1.81)*</td>
<td>0.237 (1.02)</td>
</tr>
<tr>
<td>Household size</td>
<td>0.348 (1.61) **</td>
<td>0.118 (2.65)**</td>
<td>0.155 (2.34)**</td>
</tr>
</tbody>
</table>

Note: t statistics in parentheses; * p<0.05, ** p<0.01, *** p<0.001
### Results: Multivariate probit model (Tanzania)

<table>
<thead>
<tr>
<th></th>
<th>Improved cassava varieties</th>
<th>Legume intercropping</th>
<th>Plant spacing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Male</td>
<td>0.142 (0.49)</td>
<td>0.696 (3.15)**</td>
<td>0.484 (2.08)**</td>
</tr>
<tr>
<td>Age</td>
<td>-0.606 (-1.79) **</td>
<td>0.564 (1.83)*</td>
<td>-0.293 (-0.96)</td>
</tr>
<tr>
<td>Education</td>
<td>0.034 (0.15)</td>
<td>0.0441 (0.25)</td>
<td>0.122 (1.65)</td>
</tr>
<tr>
<td>Constant</td>
<td>-1.629 (-1.11)</td>
<td>0.997 (0.86)</td>
<td>2.026 (1.67)</td>
</tr>
<tr>
<td>Wald Chi2 (d.f.=40)</td>
<td>941.29</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log pseudo likelihood</td>
<td>-370.69</td>
<td></td>
<td></td>
</tr>
</tbody>
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Note: *t* statistics in parentheses; * p<0.05, ** p<0.01, *** p<0.001
Correlation coefficients for MVP equations

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<th>Plant spacing</th>
</tr>
</thead>
<tbody>
<tr>
<td>Improved varieties</td>
<td></td>
<td>-0.29 (-2.06)**</td>
<td>0.25 (1.59)*</td>
</tr>
<tr>
<td>Legume intercropping</td>
<td>-0.29 (-2.06)**</td>
<td></td>
<td>-0.29 (-2.58)**</td>
</tr>
</tbody>
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Note: t statistics in parentheses; * p<0.05, ** p<0.01, *** p<0.001

Likelihood ratio test of \( \rho_{21} = \rho_{31} = \rho_{32} = 0 \):

\[
\chi^2(3) = 19.21 \quad \text{Prob} > \chi^2 = 0.0167
\]
Conclusions

• Both socio-economic and farm characteristics are significant in conditioning farmer’s decisions to adopt improved technologies.

• Results suggest that adoption covariates differ across technologies. Farm size positively influences adoption of improved cassava varieties but negatively influences legume intercropping.

• Access to markets significantly influences farmers’ adoption decisions. Households located closer to markets are more likely to adopt improved cassava production technologies.

• The size of the household has a positive effect on the adoption of improved cassava production technologies, probably because of increased labor availability.
Conclusions (cont.)

• Older farmers are significantly less likely to adopt improved cassava varieties and plant spacing, perhaps because young farmers are stronger and better able to provide the labor needed

• The decision to adopt improved cassava varieties is positively and significantly influenced by livestock ownership

• Credit constrained households are less likely to adopt improved cassava production technologies, because adoption of such technologies requires purchased inputs (hence cash outlay)

• Institutional factors such as access to extension services increase adoption of all improved cassava production technologies
Further work

- Field trials to validate surveys
- Publications in the pipeline…..
  - Mwebaze P, et al. Socio-economic and baseline survey data for future impact assessments of cassava production in East Africa (in prep for *Agricultural Economics*)
  - Mwebaze P, et al. Modelling technology adoption by cassava farmers in East Africa (in prep for *Food Policy*)
Thank you!

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- Any questions or comment? Please email: paul.mwebaze@csiro.au