The Dynamics of Smallholder Marketing Behavior
Explorations Using Ugandan and Mozambican Panel Data

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ABSTRACT

Market participation by smallholders farmers has the potential to pull farmers out of poverty while at the same time increasing food security at the more aggregate level. This paper looks at the dynamics of smallholder maize and beans marketing in Uganda and Mozambique. Using panel data from both countries, we categorize households according to their gross sales position over multiple periods of time and differentiate the occasional seller from the persistent seller. We describe patterns in the dynamics of smallholder commodity marketing and explore correlations with factors identified in previous theoretical and empirical work that are assumed to affect market participation. We also estimate multinomial random-effects models and compare the results of such an analysis of the dynamics of smallholder marketing with a static analysis.

Keywords: market participation, commercialization, subsistence, panel data
This publication has been prepared as an output of the Mozambique Strategy Support Program (MozSSP), which is facilitated through funding from the United States Agency for International Development (USAID) mission office in Mozambique. This work was also undertaken as part of the CGIAR Research Program on Policies, Institutions, and Markets (PIM) led by the International Food Policy Research Institute (IFPRI). The author would like to thank Benedito Cunguara for facilitation of access to data used in this paper. This paper has not gone through IFPRI’s standard peer-review procedure. The opinions expressed here belong to the author, and do not necessarily reflect those of PIM, IFPRI, CGIAR, MozSSP, or USAID.
1. INTRODUCTION

Developing countries remain overwhelmingly agrarian societies. For Africa south of the Sahara, the employment share of agriculture is almost 60 percent and many counties derive a quarter or more of their gross domestic product (GDP) from the agricultural sector (Gollin and Rogerson 2014). In Uganda, according to the latest information available, 72 percent of the working population was engaged in agriculture (UBOS 2014). In Mozambique, the agricultural sector contributes almost 30 percent to GDP (Worldbank 2015). Moreover, a large share of the sector takes the form of subsistence or semisubsistence agriculture, where households produce mainly staple foods on a small scale using rudimentary technology, mainly for auto-consumption. In Uganda, it is estimated that about 43 percent of the working population is engaged in subsistence agriculture, whereby amounts to roughly 6 million people (UBOS 2014). Subsistence agriculture is even more pervasive in Mozambique, employing between 80 and 90 percent of the population.

Studies have found that increasing market participation is correlated with higher economic well-being in terms of both consumption expenditure and asset holdings (for example Barrett and Dorosh 1996). While access to productive assets, especially land, is an important determinant of market participation, there is also some evidence that breaking out of subsistence reduces poverty, suggesting that at least part of the causality runs from market participation to well-being (Krishna 2004; Krishna et al. 2006). Market access has also been found to be important for technology adoption (Zeller, Diagne, and Mataya 1998) and its subsequent sustainability (Barrett 2008). Markets are considered key coordinating institutions allowing for specialization and trade, enabling societies to reap important welfare gains. This prospect of increased reliance on the market for both inputs and outputs, including labor, also opens the way for structural transformation, whereby the agricultural sector becomes much more productive but less important in terms of employment generation (Peter Timmer 1988).

These insights resulted in a global push to get prices right through market liberalization within the developing world during the 1980s and the 1990s. However, the results were often disappointing, and today market participation rates remain stubbornly low in many parts of the world. Theoretically, the disappointing supply response, both in terms of new producers entering the market and increased sales as a result of higher prices has been explained by pointing out the dual nature of farm households as both producers and consumers. In the absence of a full set of functioning markets, decisions in the production sphere become dependent on decisions in the consumption sphere, leading to a breakdown of separability and complicating supply response (Singh et al. 1986). A study by de Janvry, Fafchamps, and Sadoulet (1991) showed how transaction costs result in failing markets for particular households and commodities, leading to high levels of subsistence agriculture typical in many developing countries. This theoretical work has sparked a series of empirical studies that investigate the importance of transaction costs as a barrier to market participation (Key, Sadoulet, and De Janvry 2000; Renkow, Hallstrom, and Karanja 2004). More recently, attention has shifted to factors that influence the probability that a household will end up with a marketable surplus, focusing more on the determinants of household supply and demand (Alene et al. 2008; Mather, Boughton, and Jayne 2013).

Most of this theoretical work is based on agricultural household models, where income as well as own- and cross-price effects often interact in ways that make the overall effect ambiguous and thus essentially an empirical question. The empirical evidence comes in the form of case studies, in which market participation is calculated for a particular crop using household survey data for a country. Market participation decisions are also often correlated to household characteristics, assets, infrastructure, and prices. Barrett (2008) reviewed about 12 studies that investigated market participation using cross-section household survey data, mostly in grain markets in eastern and southern Africa. More recently, the emergence of detailed agricultural panel data has resulted in studies that try to deal with unobserved heterogeneity as a confounding factor affecting market participation. Olwande et al. (2015) used correlated random effects models on a balanced four-wave panel of 1,243 households that covered the first decade of
this century. But aside from the ability to control for unobserved heterogeneity, panel data also allow one to investigate the dynamics of market participation, an area we feel has not been explored sufficiently to date.

In this paper, we will contrast the dynamics of household marketing behavior for two crops (maize and beans) and two countries (Uganda and Mozambique). Maize is the most important staple throughout eastern and southern Africa. In Uganda, while maize is surpassed by matooke and cassava in terms of caloric consumption, it is the most widely grown crop (Haggblade and Dewina 2010). Relative to other staples, maize also has a high value-to-weight ratio and is therefore also widely traded. Maize is produced all over Uganda by small-scale farmers, but especially the Eastern Region is known for its maize production. The World Food Programme procures large quantities of maize in this region to counter food deficits in the North Eastern Region of Uganda and food crises in the wider Horn of Africa. Maize yields remain low, fluctuating around 1.5 tons per hectare. The fact that maize production has increased from around 0.7 million tons in around 2000 to about 2.4 million tons in 2008/2009 should therefore be attributed to an increase in the cultivated area (UBOS 2010). In Mozambique, maize is also the most widely produced staple. Especially in the northern provinces, where rainfall is more reliable, and to a lesser extent in the central provinces, smallholder farmers are predominantly involved in maize production. Maize is also the most widely sold staple in the country. Maize in the north is exported to Malawi and Tanzania, and central provinces provide maize to Maputo and other urbanized areas. It also takes the most important role in household consumption budgets. Mozambique produced 2.2 million tons in 2013 (Benson, Mogues, and Woldeyohannes 2014). Productivity is below 1 ton per hectare.

The second crop we will consider is beans. Beans are the most important legume in the world, and considered essential as a source of complex carbohydrates, essential micronutrients, dietary fiber, vitamin B, and antioxidants in the diets of the poor. Beans are also grown throughout Uganda and are often intercropped with maize. They are the second most widely grown crop in Uganda. In fact, within Uganda, and throughout the region, beans and maize have an intimate relationship, as they are grown together, traded together, and consumed together (Haggblade and Dewina 2010). Bean production is more important in the Western and Northern regions, and average productivity is also about 1.5 tons per hectare. Total production of beans in Uganda in 2008/2009 was just under 1 million tons (UBOS 2010). As with maize, the increase in bean production over time mainly comes from increased area under cultivation. Beans are relatively less important in Mozambique. In 2008, production stood at around 200,000 metric tons (Benson, Mogues, and Woldeyohannes 2014). Yields are very low, in general between 200 and 500 kg per hectare. The rest of the paper is organized as follows: We start with a brief literature review. We then present a simple conceptual framework that guides the selection of variables we investigate in subsequent sections. We then present the data and some descriptives. We then explore correlations between patterns of smallholder commercialization and household characteristics, and bring all explanatory variables together in a multivariate model. A final section concludes.

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1Throughout the text, tons refer to metric tons.
2. RELATED STUDIES

There is a vast literature on market participation for cash crops (for example, Fafchamps and Hill (2005) for coffee in Uganda, Boughton et al. (2007) for cotton and tobacco in Mozambique). Some of these studies focus on market participation in the context of innovations in the food supply chain, such as contracts between smallholders and agro-processors or supermarkets (Barrett et al. 2012), Maertens, Minten, and Swinnen 2012, Reardon et al. 2003), or voluntary standards (for example, Giovannucci and Ponte 2005). However, as noted by Mather, Boughton, and Jayne (2013), in the context of the new international food price environment and rapid urbanization, broadening the base of smallholder staple market participation represents an important means to improve food security. We therefore focus on marketing of agricultural commodities that are also widely consumed within the region, such as grains and beans.

Therefore, a good starting point for a literature review is Barrett (2008), who provided a good summary of studies on market participation for staple foods in eastern and southern Africa during the 1990s and the first half of the first decade of 2000. He noted that the evidence is consistent with low levels of sales in the market. In addition to the low levels, there is also very high concentration, with just a few farmers accounting for the bulk of sales and many farmers selling just a few kilograms. All reviewed studies also found strong associations between the probability of being a (net) seller on the one hand, and productive assets (such as land) and favorable geography on the other hand. While private asset holdings have a direct influence on market participation, there are also indirect effects. For instance, asset ownership facilitates access to credit, which in turn facilitates productive investments. Wealth is also likely to have an impact on market participation through its influence on technology adoption (Heltberg and Tarp 2002). Finally, the empirical evidence underscores the importance of transaction costs and their determinants, such as market information availability, the ability of farmers to organize themselves, and the level of competition among traders, to name just a few. Since the overview by Barrett (2008), plenty of new studies have emerged and it is beyond the scope of this paper to give a complete overview. In this literature review, we will highlight only the more relevant studies, in that they deal with commercialization in Uganda or Mozambique, or use panel data.

Muto and Yamano (2009) used panel data to investigate whether the introduction of cell phone coverage in Uganda increased market participation though its effect on transaction costs. In particular, they used data on 856 Ugandan households in 94 communities, where the number of communities covered by mobile phone networks more than doubled between 2003 and 2005. They estimated fixed-effects models explaining market participation and quantities marketed for matooke and beans, and they controlled for endogeneity of mobile phone ownership at the household level using instrumental variables. They found that after the expansion of coverage, sales of matooke in remote communities increased, but sales of maize did not. From this, they concluded that mobile phone coverage expansion seems to induce market participation of farmers in remote areas who produce perishable crops.

Mather, Boughton, and Jayne (2013) looked at the roles of market access, technology, and resource endowments in explaining smallholder maize market participation in southern and eastern Africa. One of their case study countries was Mozambique, for which they used the 2002 and 2005 waves of the Trabalho de Inqurito Agrcola (TIA). They estimate Tobit and double-hurdle models using correlated random effects. They found that in Mozambique, only 16 percent of households are net sellers, and the median smallholder sells only 8 percent of the value of the production of maize. They found no effect of distance to markets on market participation, but did find large effects of market information provision. Among other findings, rainfall and drought stress also influence marketing. The response to price changes is heterogeneous, with positive effects on amounts marketed in high-potential areas and negative effects in low-potential areas. Marginal changes in land result in large effects on the quantities sold. Finally, female-headed households sell less maize in spite of an equal chance of participating in the market.
Olwande et al. (2015) also use correlated random effects with a balanced four-wave panel of 1,243 households that covers this first decade of the century. They concentrated on three crops with different properties (maize, kale, and dairy) in Kenya. They explored some dynamics in the descriptive part, noting that apart from maize, there is little growth in market participation over time. They pointed out that only a minority of households consistently sell from year to year and market concentration remains high. They found access to land, productive assets, technology use, expected prices and rainfall amounts, and reliability to be important determinants of market participation.

Adong, Tony, and Swaibu (2014) used panel data to investigate food crop commercialization in Uganda, also exploring issues related to seasonality of market participation. They estimated two different models. One model uses random-effects probit to explain the probability of selling at least one of five main crops in one season. The second model used pooled ordinary least squares to explain volumes sold, using the same explanatory variables. They found that market participation is generally lower in the second season, which has shorter rains and therefore results in lower yields. This observation, together with some interesting differences in the regressions depending on whether market participation was measured in the first or second season, leads the authors to conclude that “in the second season households are more worried about their food security/sufficiency needs than in the first season probably due to less output” (Adong, Tony, and Swaibu 2014, 16).
3. CONCEPTUAL FRAMEWORK

At the microeconomic level, almost all work on market participation and smallholder commercialization builds on the theory of agricultural household models, which explicitly accounts for the fact that agricultural households are both production and consumption units. In a developing-country context, the absence of a full set of functioning markets makes decisions in the production sphere dependent on decisions in the consumption sphere, leading to a breakdown of separability (Singh et al. 1986). In particular, de Janvry, Fafchamps, and Sadoulet (1991) show how transaction costs result in failing markets for particular households and commodities, leading to high levels of subsistence agriculture as observed in many developing countries.

Figure 3.1 illustrates the main message of the theoretical work on market participation. It depicts household-level demand and supply curves for a crop that the households both consume and produce. There are three different households (households A, B and C). To keep things simple, we assume all three households have the same demand curve (\( D^A = D^B = D^C \)). There is a market price for the commodity, determined by aggregate demand and supply (\( p^m \)), but there are transaction costs involved in sales or purchases of the crop. We assume that transaction costs are symmetrical (\( \tau > 0 \)), such that the commodity can be bought at (\( p^m + \tau \)) and sold at (\( p^m - \tau \)). While de Janvry, Fafchamps, and Sadoulet (1991) stressed that these transaction costs are household specific, we will assume here they are the same for all three households.

**Figure 3.1 Market participation and transaction costs**

![Diagram of market participation and transaction costs](image)

Source: Author’s drawing based on Barrett (2008).

Note: S are supply curves and D is demand curves, p and q are prices and quantities, \( p^m \) is the market price, and \( \tau \) is a transaction cost.

The figure neatly summarizes all factors that affect market participation by the households for the specific commodity. The most obvious factor is the market price \( (p^m) \). Focusing on the production side of the farm household, and disregarding transaction costs for now, an increase in the price would encourage farmers to produce more, moving up along the individual supply curve. This was the main thinking behind the wave of market liberalizations that swept across much of the developing world in the 1980s and 1990s.
During that time, many countries actively engaged in staple food markets, keeping prices artificially low. “Getting prices right” was therefore regarded as the fastest way to increase food production and marketing. However, such an analysis does not take into account the fact that farm households are also consumers. For households that are net buyers, such as household A and, to a lesser extent household B, an increase in the market price will not result in an increase in the quantity sold in the market by these households. In addition, even for those who are net sellers, such as household C, an increase in the price will have positive income effects, which may also affect demand for the commodity. The shift of the demand curve to the right may result in a situation in which the household now markets less of the commodity than before the increase in price. Theoretically, the demand effect may be so large that the household becomes a net buyer.

The above theoretical model predicts that households will be either net buyers or net sellers. Only in the exceptional case when the shadow price of the household is exactly equal to the market price would we not observe any sales or purchases of the commodity. This is clearly at odds with what we observe in reality, where a large proportion of the households are neither seller nor buyer. This is where transaction costs come in. As can be seen in the figure, transaction costs create a band around the price. When the shadow price of the household falls within this band created by the transaction costs, the household will self-select out of the market (household B). Therefore, the lower the transaction costs, the narrower the band and the larger the chance that any given household will be participating in the market, either as seller (household C) or as buyer (household A).

This simple conceptual framework shows that prices are clearly important, as are transaction costs. However, the response to price changes depends critically on the location of the household-level demand and supply curves, which determine the shadow price for the commodity. Thus, factors that are likely to shift the supply curve at the household level are also important factors in market participation. For instance, household A’s supply curve would be typical of a household with few productive assets, rudimentary technology, or both. If this household could increase productivity, in that it could supply more at a given price (shifting $S_A$ to the right), it may eventually become a net seller. Similarly, the household-level demand for the commodity may also shift. We will follow this conceptual framework and categorize our explanatory variables into four categories: prices, factors that affect transaction costs, factors that affect household-level supply, and factors that affect household-level demand.
4. DATA AND DESCRIPTIVE STATISTICS

We will use panel data from Uganda and Mozambique. For Uganda, we will be using the Uganda National Panel Survey (UNPS), which set out to track about 3,100 Ugandan households between the 2009/2010 and 2011/2012 agricultural seasons at a yearly interval, making for three waves. The UNPS is collected by the Uganda Bureau of Statistics, with technical assistance from the World Bank. The survey is designed as a Living Standard Measurement Survey, which is also used as the basis for the three yearly Uganda National Household Surveys (UNHS). In fact, the UNPS is a subset of the UNHS that was done in 2005/2006. The UNPS (as well as the UNHS 2005/2006) is an LSMS Integrated Survey on Agriculture (LSMS-ISA) specifically designed to capture and improve the quality of agriculture-related data. The agricultural module of the LSMS-ISA collects data at the plot level on production, input use and disposal, making it an excellent survey to study smallholder marketing behavior.

For Mozambique, we will be using the so-called Partial Panel Survey, which revisited in 2011 a subset of about 1,200 households that were interviewed as part of the 2008 TIA. It thus consists of two waves that are three years apart. The data were collected by Michigan State University in close collaboration with the Mozambican Ministry of Agriculture’s Directorate of Economics. Since the TIA focuses on agriculture, this dataset too has detailed information on the marketing of all commodities produced by smallholder agricultural households.

As mentioned in the introduction, we will restrict attention to two crops: maize and beans. Table 4.1 shows the percentage of households that report growing the crop listed in the rows for Uganda and Mozambique. By and large, beans and maize are in both countries the most widely grown crops. In Uganda, matooke is also an important crop. In Mozambique, cassava is almost as important as beans. Maize and beans, however, provide the obvious common denominator for our study.

Table 4.1 Percentage of households growing

<table>
<thead>
<tr>
<th>Crop</th>
<th>Uganda</th>
<th>Mozambique</th>
</tr>
</thead>
<tbody>
<tr>
<td>Beans</td>
<td>37.46</td>
<td>57.32</td>
</tr>
<tr>
<td>Maize</td>
<td>37.01</td>
<td>84.26</td>
</tr>
<tr>
<td>Matooke</td>
<td>27.27</td>
<td>-</td>
</tr>
<tr>
<td>Sweet potatoes</td>
<td>24.14</td>
<td>16.52</td>
</tr>
<tr>
<td>Cassava</td>
<td>23.34</td>
<td>53.68</td>
</tr>
</tbody>
</table>


We restrict our sample to households that report production of the crop in any two consecutive waves of the panel. For Mozambique, this means that we consider only households that reported positive harvests for maize/beans in both the 2008 and 2011 waves. There are 553 households in the Mozambique data that report positive production of beans in both 2008 and 2011, and 1,014 that report positive maize production in both waves. In total, we thus have 3,134 crop-year observations for Mozambique. For Uganda, this means that observations are included from households that report positive production of the respective crop in both 2009/2010 and 2010/2011 or that report positive production of the crop in both 2010/2011 and 2011/2012. For maize in Uganda, there are about 1,000 households producing maize in both 2009/2010 and 2010/2011 and about 950 households producing maize in both 2010/2011 and 2011/2012. For beans in Uganda, the numbers are 1,106 households that report positive production in both 2009/2010 and 2010/2011, and 937 households that report positive production of the crop in both 2010/2011 and 2011/2012. This amounts to a total of about 6,115 crop-year observations for Uganda. Overall, we have 9,250 crop-year-country observations, representing just under 5,576 changes between two waves.

\(^2\)In Uganda, the agricultural calendar year comprises two agricultural seasons. The first growing season runs from January to June and the second growing season runs from July to December. We used maize production reported in the form of both grains and cobs. Cobs were converted into grain equivalents using a 1 kg cob = .38 kg grain conversion.
In this article, we will mainly concentrate on household gross sales of agricultural produce. We are aware that many other studies we reviewed employ a wider definition that also includes purchases of commodities. For instance, many studies use the concept of net sales, where purchases of the crop are deducted from sales and a net position is obtained. Such a definition would allow for a substantial part of households that do not cultivate the crop under investigation but report (small) amounts purchased. We want to focus on commercialization, defined as smallholder producers’ selling a surplus in the market. To this end, we will exclude form our analysis farmers that do not report growing the crop. In addition, factors influencing sales and purchases are likely to be very different, and purchase decisions and sales decisions may be made by different people within the household. At a more practical level, one of the household level datasets we will be using is focused on agriculture and has no household consumption data.

Since the concept of sales is of such importance within this study, it needs to be defined properly. We try as much as possible to capture genuine commodity sales, where the raw, unprocessed product is handed over to another party (consumer, trader, processor) and a price is paid in cash. Still, we are constrained by the way sales are defined in the respective questionnaires. In the TIA, there is a question that asks specifically if the crop has been sold and at what price. This ranges from selling small amounts to neighbors, local shops, and itinerant traders, over associations and cooperatives, to wholesalers and companies. For the UNPS, we use Section 5 on crop disposal, where a similar question is asked on how much of the total production was sold, and at what price. Alternatives to sales are gifts, quantities used for own consumption, quantities processed (for example, into animal feed), and quantities saved (for example, for seeds) or stored. As such, this definition in both datasets excludes barter trade, swapping, or giving away for free.

Starting from the 9,250 observation pooled dataset, we find that about 43 percent of crop-wave-country observations also involve positive sales. This proportion is higher for beans (44 percent) than for maize (41 percent) and the difference is statistically significant (two-sided P-value = .011). There is also a significant difference between countries, with Uganda’s reported share of crop-wave observations involving positive sales standing nearly 10 percentage points higher than Mozambique’s (two-sided P-value = .001). There is also significant variation over time (two-sided P-value = .001), with 47 percent of crop-country observations involving positive sales in 2009 and only 33 percent in 2008. But this variation may be because our 2008 data include only Mozambique which has on average significantly fewer sellers of maize/beans. However, when we restrict our sample to Uganda, the differences between 2009, 2010, and 2011 remain significant (two-sided P-value = .001). These figures are very close to what others have found in cross-sections. For example, using data from the TIA 2002 Boughton et al. (2007) found that a little more than 30 percent of Mozambican maize producers also sell maize. Mather, Boughton, and Jayne (2013) find households reporting net sales of maize to range from 43 percent in Kenya between 1997 and 2007 to 16 percent in Mozambique between 2002 and 2005. Using a slightly more recent subset of the same Kenyan panel used in Mather, Boughton, and Jayne (2013), Olwande et al. (2015) found that on average about 42 percent of Kenyan households reported maize sales.

Apart from the somewhat low levels of market participation of smallholder producers, another characteristic of subsistence farming is high concentration in the amounts sold. To get a sense of the inequality in amounts sold in our data, we calculated percentiles at selected probabilities for the distribution of total quantity sold across producing households. The results are again differentiated across the three dimensions of our data (country, crop, and time) and are presented in Table 4.2. Consistent with market participation rates above, we find that the majority of farmers are not selling. At the other end of the distribution we find that 1 percent of the farmers account for between 26 and 32 percent of total quantities sold. Inequality in total quantities sold seems to have being gone down over the years. Inequality is also markedly higher in Uganda then in Mozambique.

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3 In other words, this study is less about market participation but rather about smallholder commodity marketing behavior.
Table 4.2 Inequality in amounts sold

<table>
<thead>
<tr>
<th></th>
<th>50.0%</th>
<th>75.0%</th>
<th>90.0%</th>
<th>95.0%</th>
<th>97.5%</th>
<th>99.0%</th>
<th>100.0%</th>
</tr>
</thead>
<tbody>
<tr>
<td>All</td>
<td>0%</td>
<td>4.87%</td>
<td>23.30%</td>
<td>39.03%</td>
<td>54.17%</td>
<td>70.55%</td>
<td>100%</td>
</tr>
<tr>
<td>2008</td>
<td>0%</td>
<td>2.27%</td>
<td>19.66%</td>
<td>36.06%</td>
<td>51.38%</td>
<td>68.54%</td>
<td>100%</td>
</tr>
<tr>
<td>2009</td>
<td>0%</td>
<td>5.26%</td>
<td>23.13%</td>
<td>39.62%</td>
<td>54.70%</td>
<td>70.17%</td>
<td>100%</td>
</tr>
<tr>
<td>2010</td>
<td>0%</td>
<td>5.01%</td>
<td>23.87%</td>
<td>39.13%</td>
<td>53.27%</td>
<td>71.22%</td>
<td>100%</td>
</tr>
<tr>
<td>2011</td>
<td>0%</td>
<td>6.02%</td>
<td>25.67%</td>
<td>41.66%</td>
<td>56.51%</td>
<td>71.75%</td>
<td>100%</td>
</tr>
<tr>
<td>Beans</td>
<td>0%</td>
<td>6.28%</td>
<td>26.73%</td>
<td>44.12%</td>
<td>58.81%</td>
<td>73.61%</td>
<td>100%</td>
</tr>
<tr>
<td>Maize</td>
<td>0%</td>
<td>4.88%</td>
<td>23.97%</td>
<td>40.38%</td>
<td>55.90%</td>
<td>73.18%</td>
<td>100%</td>
</tr>
<tr>
<td>Mozambique</td>
<td>0%</td>
<td>3.04%</td>
<td>19.72%</td>
<td>34.70%</td>
<td>49.74%</td>
<td>67.09%</td>
<td>100%</td>
</tr>
<tr>
<td>Uganda</td>
<td>0%</td>
<td>5.84%</td>
<td>25.17%</td>
<td>41.31%</td>
<td>56.54%</td>
<td>72.48%</td>
<td>100%</td>
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</tbody>
</table>


The descriptive statistics above look at market participation at one point in time, allowing us to identify gross sellers for a crop in a particular year and country. While it is interesting to look at what determines the probability of selling at one point in time, we are more interested in what influences the transition between states over time. The panel nature of our data allows us to investigate the dynamics of market participation. That is, we can use the repeated observations to differentiate the occasional seller from the farm household that consistently sells at every point in time. This last farmer may be a different type, say the commercially oriented farmer, which may be quite different in characteristics from the farmer that occasionally sells. Alternatively, we can focus on farmers that transition from subsistence to commercial and try to identify preconditions in terms of asset ownership, market access, and the price environment for moving out of subsistence.

Since we have only two waves of data for one of the countries, we decided to create a classification on the basis of two consecutive waves only. In particular, we categorize a household-country-crop observation as commercialized if it is associated with positive sales in each of two consecutive waves. Similarly, we define a case to be subsistent if no sales are recorded in any two consecutive waves. We can also define two different transitions. Cases in which no sales are recorded in the first wave but positive sales are recorded in the second wave may be commercializing, while cases involving positive sales in the first period but no sales in the second wave may be becoming subsistent.

The drawbacks from classifying households or observations as above are well known from the poverty dynamics literature, where this method is sometimes called the spells approach. First of all, the classification is heavily dependent on the number of waves used. For instance, if we define the commercialized farmers as those farmers that have been selling in three consecutive waves of the panel, the percentages will be smaller. For instance, for maize producers in Uganda, if we define commercialized farmers to be those that sell in two consecutive years of the three years for which we have data, we find about 18 percent of households are commercialized. However, if we make the definition of a commercialized farmer stricter by requiring the farmer to sell in all three waves, this percentage drops to about 8 percent. A second drawback is that measurement error is likely to overstate transitions (meaning the commercializing and becoming subsistent categories in our analysis). Finally, there are also the drawbacks of relying on a binary indicator that does not take into account how much is actually sold. In other words, should someone that sells a few kilograms of maize every period be considered a commercialized farmer, playing in the same league as the farmer who sells about 2 tons every year?

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This issue is likely to be less of a problem in our application than in the poverty dynamics literature. There, transitions are defined relative to a poverty line, and small measurement errors in the welfare indicator may change whether a household is classified as poor or not. This is likely to be less of an issue when the classifying variable is zero versus nonzero.
Table 4.3 summarizes the transitions between any subsequent rounds for the pooled crop-country observations. The first column looks at transitions within the pooled dataset. It shows that about 41 percent of transitions in the 5,576 crop-country combinations involve zero sales in both subsequent waves. On the other hand, one-quarter of all pairs of successive observations involve positive sales in both the current and the previous round and are thus labeled commercialized according to the categorization above. Next, about 18.5 percent of the observations involve transitions from a state in which no sales were recorded to a state involving positive sales. The next two columns, columns 3 and 4, show the same figures but by country. We see that subsistence is more pervasive in Mozambique than in Uganda, and commercialization is higher in Uganda. It is also interesting to note that a relatively high proportion of observations involve sliding into subsistence in Uganda as compared with Mozambique. However, one must bear in mind that the Mozambique transitions are computed over a longer period (between 2008 and 2011) than the transitions in Uganda, which are yearly. If we disaggregate by crop (columns 4 and 5) we find that for maize there is a slightly higher proportion in the subsistence category (43 percent) then for beans (39 percent).

Table 4.3 Commercialization transitions

<table>
<thead>
<tr>
<th>Category</th>
<th>All</th>
<th>Mozambique</th>
<th>Uganda</th>
<th>Maize</th>
<th>Beans</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>41.12%</td>
<td>47.67%</td>
<td>38.56%</td>
<td>42.92%</td>
<td>39.06%</td>
</tr>
<tr>
<td>Commercialized</td>
<td>25.29%</td>
<td>20.68%</td>
<td>27.10%</td>
<td>25.20%</td>
<td>25.38%</td>
</tr>
<tr>
<td>Commercializing</td>
<td>18.41%</td>
<td>19.08%</td>
<td>18.16%</td>
<td>17.21%</td>
<td>19.80%</td>
</tr>
<tr>
<td>Becoming subsistent</td>
<td>15.17%</td>
<td>12.57%</td>
<td>16.19%</td>
<td>14.66%</td>
<td>15.75%</td>
</tr>
</tbody>
</table>


Figure 4.1 plots the (the natural logarithm of) quantities sold in two successive periods in the graphical equivalent of a transition table. The x-axis shows the amount reportedly sold in a period (referred to as t-1) for each household. The y-axis shows (the natural logarithm of) quantities sold for the same households in the subsequent period (referred to as period t). Note that since we have three waves in our Uganda panel, some households will actually appear twice in the plot. The scatter plot is characterized by substantial overplotting, especially around the origin. This is because, as we know from Table 4.3, more than 41 percent of transitions involve zero sales in both successive rounds. But there is also a concentration of points on the axes. For instance, the strictly positive section of the x-axis collects all instances that involve a switch from positive sales into zero sales, about 15 percent of the observations according to Table 4.3. Similarly, the strictly positive section of the y-axis represents transitions from zero sales in t-1 to positive sales in t. The diagonal line in the figure represents points where sales in the previous wave are equal to sales in the current wave, that is, the no-change steady state.

In cases of over-plotting, non-parametric methods can be used to aid interpretation (Deaton 1989). We use 2 dimensional kernel estimation to estimate the densities, and visualize this using contour plots. The contour plots are overlaid in Figure 4.1. The contours clearly show highest probability mass around the origin, and higher probability of being on the y axis than being on the x-axis. This means instances where farmers enter into trading are more likely than instances where farmers transition into subsistence, which is consistent with Table 4.3. More interestingly, it seems a relatively larger part of the probability mass is located above the 45 degree line. This means that over time, farmers that sold a positive amount of maize or beans have been selling more of it.
Figure 4.1 Market participation dynamics for pooled dataset

5. BIVARIATE ANALYSIS

In this section we will correlate some key explanatory variables to dynamic measures of market participation, and contrast them with correlations to static measures of market participation. The selection of variables is based on what variables are used in four recent influential publications (Bellemare and Barrett 2006; Alene et al. 2008; Mather, Boughton, and Jayne 2013; Olwande et al. 2015).

Supply Curve Shifters

As we have seen in the conceptual framework, the individual supply (and demand) curves are important in determining the household-specific shadow price of the commodity, the location of which determines whether a household will sell, buy, or be autarkic. Supply shifters are factors that are likely to change the productivity of the household. They include productive assets such as land and labor, but also productivity-enhancing technology. We will look at the most important one here.

In agriculture, land is obviously a key input. Households that have large swaths of land available for farming are more likely to produce a surplus than land-scarce households. Previous research has found consistent correlations between land holdings and market participation patterns. Maize market participation in Uganda is no exception, as is illustrated in 5.1. This figure, inspired by Barrett and Dorosh (1996), shows three nonparametric regressions. Each regression, represented by a solid line, traces out the probabilities (indicated on the y-axis) of households being in a certain state at different levels of the continuous variable on the x-axis. For example, the upward-sloping solid black line corresponds to the probability of being commercialized, which is plotted against the log of land holdings (in hectares) at the time of the first wave. It shows that at low levels of total land holdings (at around log(-1) or about 0.36 hectares), only about 15 percent of households report to have been selling maize or beans in two subsequent waves. The proportion of commercialized households seems to increase gradually with landholdings. At the other end of the spectrum, at around log(3), or 20 hectares of total landholdings, about 35 percent of the households report having sold maize or beans in two subsequent waves. The other solid black line slopes down. This line represents households that report not having sold maize or beans in either of two subsequent waves (that is, what we labeled subsistent). Starting from a probability of around 60 percent for households with little land, the probability drops sharply with land size up to about log(1) or 2.72 hectares, after which it levels off.

Both patterns are in contrast to observations that fall in the commercializing and becoming subsistent categories. These nonparametric regressions, which are not shown on the graph to avoid clutter, remain flat at around 10–20 percent throughout the range of landholdings. We also plotted a third nonparametric regression that is based on the pooled cross-sectional data. Here, we simply plotted the probability that a household sells maize or beans at a point in time against landholdings at that point in time, similar to the graph in Barrett and Dorosh (1996). We see how the concept of being a seller is also positively related to landholdings, but in a slightly different way than the concept of commercialization. In particular, we see a sharp increase with land size in the probability of being a seller. The slope of the nonparametric curves is much steeper than if we use the concept of commercialization. In addition, when using cross-section data, there is a marked kink in the curve at around log(1), or 2.72 hectares, after which additional landholdings do not seem to affect the probability of being a seller any more.

The parametric regressions were produced using the R package locfit, the dashed lines are corresponding simultaneous confidence bands using the tube formula method and extensions, based on Sun and Loader (1994).
In addition to land, labor is also an important input in agricultural production. While the quantity of labor, proxied by household size, is discussed in the next section as a potential demand curve shifter, we include the quality of labor under the header of a supply curve shifter. In particular, we will include the education level of the household head as an indicator of labor quality in the regression below. We construct a variable that creates categories for no education, between one and six years of education, and more than six years of education. We find that in our pooled dataset, about 24 percent of household heads have no formal education and about 55 percent have at least some primary education. However, there are marked differences between the countries, and education levels are much lower in Mozambique. We also find that of those who have no formal education, only about 37 percent of observations involve positive sales, while this proportion increases to 45 percent if household heads report at least some primary education.

A third important supply curve shifter is technology. We therefore look at use of fertilizer and improved seeds. For improved seeds, we were able to construct an indicator at the crop level. Around 15 percent of household-year-crop-country observations involve improved seeds. Overall, we find that those who report using improved seeds are slightly more likely (53 percent) to be selling than those who do not use improved seeds (51 percent; two-sample chi-squared test of equality of proportions, two-sided P-value = .051). Also, improved seeds are rarely used for beans. The use of improved seeds is much more common in Mozambique than in Uganda. For fertilizer, we construct a dummy at the household level that is equal to 1 if the household uses chemical fertilizer on any of its plots. Fertilizer use is even lower than use of improved seeds, at around 8 percent. Uganda, famous for its low levels of fertilizer use, registers less than 6 percent.
Demand Curve Shifters

The four studies mentioned above all included measures of household composition in the regressions. Bellemare and Barrett (2006) included household size, gender of the household head, and the dependency ratio in their regression. Alene et al. (2008) did not include total household size, but only the number of adults and the gender of the head. Mather, Boughton, and Jayne (2013) also use number of adults, but also included the dependency ratio. They also differentiated between single female heads and female heads with spouse. Olwande et al. (2015) included numbers of prime-age women and men separately and also included the number of dependents. In our multivariate analysis below, we will include an indicator variable for female headedness, total household size, and the dependency ratio.

We find that in our sample, around 25 percent of households are headed by a female. Female-headed households are more common in Uganda than in Mozambique. Of those households that are commercialized in that they sell maize or beans in two subsequent rounds, just under 20 percent are headed by a female. Households that are not commercialized, on the other hand, are on average headed by a female in 27 percent of the cases (two-sample chi-squared test of equality of proportions, two-sided P-value = .001). We find equally significant differences if we look at observations involving no sales in two subsequent rounds, where almost 30 percent are female headed, and a slightly lower female headedness for the commercializing subgroup (2 sample chi-squared test of equality of proportions, two-sided P-value = .069). There is no difference for those that are becoming subsistent. Looking at cross-sectional data, we find that just under 20 percent of those that report sales are female headed (2 sample chi-squared test of equality of proportions, two-sided P-value = .001).

Average household size is about six in the pooled sample. Because Uganda has one of the highest fertility rates in the world, household size in Uganda is higher by almost one individual. We find not significant difference in the household size of commercialized households (two-sided P-value = 0.833). Similarly, average household size does not differ between those that sell and those that do not sell in cross-sectional data.

For defining the dependency ratio, we follow Bellemare and Barrett (2006) and calculate the ratio as the number of individuals under 15 years of age plus the number of individuals over 64 years of age divided by the total number of individuals in the household. In our pooled sample, this leads to an average dependency ratio of around 52 percent. As a consequence of the high fertility rate, Uganda also has one of the youngest populations. Therefore, the dependency ratio is slightly higher in Uganda than in Mozambique. Dependency ratios are also slightly lower in the commercialized subgroup (two-sided P-value = 0.059), but we find no significant difference between the dependency ratio in the subsistence subgroup and the other groups (two-sided P-value = .918). Restricting ourselves to cross-sectional data, we find no difference in the dependency ratios of households that report sales and those that don’t (two-sided P-value = .549).

We also include age of the household head. We find overall average age of the head is around 46 years, with household heads in Uganda on average almost 10 years older than in Mozambique. Figure 5.2 shows a slightly lower age for household heads that engage in genuine commercialization (category com, com+ means becoming commercial, sub means no sales in any two rounds and sub+ means transitioning form seller to nonseller), but it also shows that a lot of these young entrepreneurs slide back into subsistence.
FIGURE 5.2 Age of household head


Patterns by Transaction Costs

An important subset of the literature on market participation has concentrated on the role of transaction costs (Goetz 1992; Key, Sadoulet, and De Janvry 2000; Renkow, Hallstrom, and Karanja 2004; Muto and Yamano 2009; Alene et al. 2008). A major component of transaction costs consists of expenses related to transportation. Smallholder farmers usually transport their produce to the market using bicycles or motorbikes. About 41 percent of households in our sample own a bicycle, and there is no difference between Mozambique and Uganda in this regard. Bicycle ownership has been going up steadily over the years, from about 39 percent in 2008 to almost 46 percent in 2011. Of all the households that report owning a bicycle, about 27 percent are commercialized in the sense of having two consecutive periods of positive sales. In the subset of households who do not report having a bicycle, only 23 percent report being commercialized, and the difference is significant (two-sample chi-squared test of equality of proportions, two-sided P-value < .001).

When we define commercialized households based on cross-section data only, the proportions double and the difference remains. While motorcycles are a common sight in Uganda, surprisingly few households in our sample report owning one. Only 7 percent reports having a motorbike in Uganda, and this proportion reduces to a little more than 2 percent in Mozambique. However, just as for bicycles, we find that relatively more motorbike owners report sales in two successive survey rounds (32 percent versus 25 percent, two-sample chi-squared test of equality of proportions, two-sided P-value = .003).
Transaction costs are much broader than just transportation costs. They also include costs related to price discovery. Assets that facilitate the flow of information are therefore also expected to affect transaction costs and thus market participation decisions. For instance, access to a radio may provide farmers with information on weather, expected production in neighboring districts, and prices in consumer centers. In our data, overall 63 percent of households have a radio. Radio ownership is about 10 percent lower in Mozambique than in Uganda. As expected, we find that among those that own a radio, commercialization is more common than among those that do not report having a radio (27 versus 20 percent, two-sample chi-squared test of equality of proportions, two-sided P-value \( \leq .001 \)).

**Patterns by Price**

A final major determinant of market participation as outlined in the conceptual framework above is prices. Obviously, we observe farmgate prices only for households that have have sold. We follow Mather, Boughton, and Jayne (2013) and predict farmgate prices for farmers that do not sell using a regression model on the subset of farmers that do sell. We include a series of household characteristics and location-specific variables to generate a complete set of farmgate prices to be included in the analysis.

Figure 5.3 depicts nonparametric regressions of the probability of being commercialized at different price levels. The black curve exploits the time dimension in the panel and defines commercialized as selling in two subsequent periods. The gray curve plots the probability of selling in a single cross-section conditional on the price. As the cross-sections indicate, farmers do not seem to be very responsive to prices. If we define commercialization as involving more than one period, it seems that at relatively low price levels in the initial period, the probability of commercialization decreases with price. In all, similar to other studies, we find very low price elasticities with respect to market participation.

**Figure 5.3 Price response to market participation**

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Studies on market participation usually look at both the participation decision and the actual quantities traded. Since Bellemare and Barrett (2006) found that these decisions are made sequentially rather than simultaneously, Cragg’s (1971) double-hurdle model has become the workhorse method in the empirical literature. The double-hurdle model allows the determination of quantities traded when they are not zero to depend on different parameters or variables from those determining the probability of its being zero (Cragg 1971). Recent studies that have used the double-hurdle model are Olwande et al. (2015) and Mather, Boughton, and Jayne (2013). An alternative approach is to treat the zeros as cases of unobserved data and use a Heckman sample selection model. This method is used in Alene et al. (2008).

As mentioned in the literature review, most studies on market participation employ cross-sectional data, and only recently, studies have started to appear that use panel data. The main problem with models estimated using cross-sectional data is that unobserved time-invariant household-level characteristics, often related to ability and preferences, may bias coefficient estimates of observable determinants if they are correlated. One of the main advantages of panel data is that one can control for household-level time-invariant effects. Hence, recent studies on market participation such as Olwande et al. (2015) and Mather, Boughton, and Jayne (2013) use correlated random effects models to account for unobserved heterogeneity.

Apart from controlling for unobserved heterogeneity to come to better coefficient estimates, panel data can also be used to study dynamics at the household level. In the words of Verbeek: “panel data are not only suitable to model or explain why individual units behave differently but also to model why a given unit behaves differently at different time periods (for example, because of a different past)” Verbeek (2008, 342). In this study, we will exploit the panel nature of the data to investigate whether households that are selling in each round differ in terms of characteristics from households that are never selling. In particular, we categorize every two successive observations in time into the four categories described above; (commercialized; subsistent; commercializing; and becoming subsistent) and regress this on a series of explanatory variables in the initial year. Since there are four categories, we estimate a multinomial model. We also add a random effect at the household level to account for the correlation in the error term that is caused by repeated observations, and we add fixed effects for country and crop. Standard errors are generated using a multilevel bootstrap procedure. Table 6.1 provides descriptive statistics for the variables we will include in the regressions.

Table 6.1 Descriptive statistics

<table>
<thead>
<tr>
<th>Variable</th>
<th>Min</th>
<th>1stq</th>
<th>Median</th>
<th>Mean</th>
<th>3rd</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Totland</td>
<td>0.05</td>
<td>1.50</td>
<td>3.00</td>
<td>4.82</td>
<td>5.75</td>
<td>83.50</td>
</tr>
<tr>
<td>Log totland</td>
<td>-3.00</td>
<td>0.41</td>
<td>1.10</td>
<td>1.09</td>
<td>1.75</td>
<td>4.43</td>
</tr>
<tr>
<td>Hhsiz</td>
<td>1.00</td>
<td>3.00</td>
<td>5.00</td>
<td>5.11</td>
<td>7.00</td>
<td>17.00</td>
</tr>
<tr>
<td>Femhead</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.24</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Dep</td>
<td>0.00</td>
<td>0.33</td>
<td>0.50</td>
<td>0.44</td>
<td>0.60</td>
<td>1.00</td>
</tr>
<tr>
<td>Primary</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td>0.58</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Secondary</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.24</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Price</td>
<td>-160</td>
<td>523</td>
<td>791</td>
<td>700</td>
<td>865</td>
<td>1214</td>
</tr>
<tr>
<td>Hasradio</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td>0.70</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Hasbicycle</td>
<td>0.00</td>
<td>0.00</td>
<td>1.00</td>
<td>0.53</td>
<td>1.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Hasmotorcycle</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.08</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Impseed</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.11</td>
<td>0.00</td>
<td>1.00</td>
</tr>
<tr>
<td>Fert</td>
<td>0.00</td>
<td>0.00</td>
<td>0.00</td>
<td>0.06</td>
<td>0.00</td>
<td>1.00</td>
</tr>
</tbody>
</table>


6For instance, we use household size in 2009 to explain the probability of being commercialized, meaning that the household sold in both 2009 and 2010.
The results for the regressions are presented in Table 6.2. The first model, (1), presents the estimates for the commercialized category. The second model, (2), presents the estimates for the subsistence category. The two following models, (3) and (4), present results of the commercializing and becoming subsistent categories. Finally, model (5) is a static model estimating the probability of selling at one point in time by the explanatory variables at the same point in time. This last model is for reference, because this is what other studies generally estimate. Comparing model (5) with model (1) gives us an idea whether different conclusions would arise from a static or a dynamic point of view. When discussing the tables more in detail, we will often compare them with the four studies we highlighted in the literature review (Bellemare and Barrett 2006; Alene et al. 2008; Mather, Boughton, and Jayne 2013; Olwande et al. 2015).

Table 6.2 Commercialization transitions

<table>
<thead>
<tr>
<th>Variable</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>2.577</td>
<td>-14.810</td>
<td>-15.500</td>
<td>-0.145</td>
<td>1.826</td>
</tr>
<tr>
<td>Land</td>
<td>0.501 ***</td>
<td>-0.581 ***</td>
<td>-0.033</td>
<td>0.184 ***</td>
<td>0.530 ***</td>
</tr>
<tr>
<td>Hhsize</td>
<td>-0.024</td>
<td>0.076 *</td>
<td>0.004</td>
<td>-0.031</td>
<td>-0.035 **</td>
</tr>
<tr>
<td>Femhead</td>
<td>-0.601 **</td>
<td>0.384</td>
<td>-0.223</td>
<td>0.122</td>
<td>-0.381 **</td>
</tr>
<tr>
<td>Depratio</td>
<td>-0.709</td>
<td>-0.199</td>
<td>0.522 *</td>
<td>0.115</td>
<td>-0.311</td>
</tr>
<tr>
<td>Agehead</td>
<td>-0.021 ***</td>
<td>0.019 **</td>
<td>0.002</td>
<td>-0.005</td>
<td>-0.015 ***</td>
</tr>
<tr>
<td>Primary</td>
<td>0.227</td>
<td>-0.301</td>
<td>0.063</td>
<td>-0.107</td>
<td>0.024</td>
</tr>
<tr>
<td>Secondary</td>
<td>-0.106</td>
<td>-0.074</td>
<td>0.161</td>
<td>-0.171</td>
<td>-0.318 *</td>
</tr>
<tr>
<td>Price</td>
<td>-0.007 ***</td>
<td>0.001</td>
<td>0.002 **</td>
<td>0.001</td>
<td>-0.003 ***</td>
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<td>0.131</td>
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<td>-0.091</td>
<td>-0.101</td>
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<td>Hasbicycle</td>
<td>-0.176</td>
<td>-0.042</td>
<td>0.073</td>
<td>0.065</td>
<td>-0.008</td>
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<td>Hasmotorbike</td>
<td>0.086</td>
<td>-0.122</td>
<td>-0.040</td>
<td>-0.006</td>
<td>-0.003</td>
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<tr>
<td>Improvedseed</td>
<td>-0.162</td>
<td>0.017</td>
<td>-0.085</td>
<td>0.251</td>
<td>0.167</td>
</tr>
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<td>Fertilizer</td>
<td>0.134</td>
<td>-0.113</td>
<td>0.022</td>
<td>0.305</td>
<td>0.380 *</td>
</tr>
<tr>
<td>Nobs</td>
<td>3,385</td>
<td>3,385</td>
<td>3,385</td>
<td>3,385</td>
<td>5,619</td>
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</table>


We find that land is significantly associated with a higher chance of being in the category of commercialized and reduces even more the odds that one is subsistent. Land, being a critical factor of production that enables households to produce a surplus, has a positive influence on (net) sales in each of the four reference studies. Land does not seem to be related to the probability of moving out of subsistence. What is surprising is that it also seems to increase the odds of becoming subsistent, although the coefficient is much lower than in models (1) and (2). Finally, turning to model (5), we do not find that a dynamic analysis yields very different results from a static analysis.

Household size is a shifter of both demand and supply, working in opposite directions. When it acts as a demand shifter, we expect that larger households to consume more, reducing marketable surplus. When it acts as a supply shifter, households provide cheap labor, which is another essential input in agriculture.7 We find that household size increases the chance of being subsistent. We find no effects on any of the other categories. This is consistent with Bellemare and Barrett (2006), the only study that includes household size, which finds no significant effect. Other studies include variations of household size, such as prime-age adults or gender-disaggregated indicators. Results vary, with Alene et al. (2008)

7 But larger households may also mean women, a key source of agricultural labor, need to spend more time on reproductive activities (Van Campenhout 2014).
7. CONCLUSION

Nudging farmers to break out of subsistence and embrace a more commercial mind-set is important for both regional food security and poverty reduction. Farmers that produce for the market using inputs bought on the market provide key ingredients for structural transformation. In this study, we use panel data from Uganda and Mozambique to explore the dynamics of smallholder maize and beans marketing. We rely on the theory of agricultural household models, which identifies determinants of household-level demand and supply, transaction costs, and prices to be the most important factors driving smallholder marketing decisions.

The panel data consist of almost 10,000 household-country-crop-year observations. We find that levels of commodity sales in the market are around 40 percent, underscoring the subsistence nature of maize and beans growing in Mozambique and Uganda, and in line with what other researchers have found. We also find that concentration is extremely high, with the largest 1 percent transactions accounting for about 30 percent of all sales. If we define smallholder marketing as observations involving sales in two subsequent rounds, we find that only about 25 percent of cases fall in the category of commercialized. The descriptive analysis of the dynamics of maize and beans marketing also reveals that over time, farmers that sold a positive amount have been selling more.

When relating market participation patterns to supply curve shifters, nonparametric regressions suggest that landholdings are positively related to commercialization, especially below 3 hectares. However, the slope is less steep than what would be found if commercialization is defined on the basis of a single period. Labor is a second supply curve shifter, and we proxy quality of labor by the education level of the head of the household. We find that the percentage of observations that involve positive sales indeed increases with education. Technology adoption is also likely to shift the supply curve outward. We find that those who use improved seeds are slightly more likely to be selling.

For demand curve shifters, we mainly look at household characteristics. We find no relation between household size and the likelihood of being commercialized. However, households that are commercialized have a slightly lower chance of being headed by a female, and this holds irrespective of whether we define commercialization based on a single point in time or based on two successive rounds of the panel. The dependency ratio is slightly lower in commercialized households when this is based on two successive rounds. We also look at assets that should reduce transaction costs and find that bicycle, motorbike, and radio ownership all increase the probability of being commercialized. We also run a nonparametric regression of prices against the probability of selling and find that the relationship is negative at the lower end of the price distribution.

The multivariate analysis presents a random-effects multinomial logit that investigates the determinants of four different categories of households: those that are always selling, those that are never selling, those that are selling in the first but not in the second period, and those that are selling in the second but not in the first period. We also compare the results with a regression that uses a static concept of commercialization. We find that landholdings are positively related to consistently selling, and negatively related to consistently not selling. Households that are headed by females are less likely to be commercialized, and higher dependency ratios reduce the probability of being commercialized. Increased age of the head increases levels of subsistence, and the education level of the head does not seem to be related to the dynamics of commercialization. We find no effects of assets such as radios and bicycles on the likelihood of being commercialized, casting doubt on the importance of transaction costs as the main driver of observed high levels of subsistence. We also find no effect of technology adoption, but conjecture this is caused by a lack of data on adopters.
In all, our study confirms most of the results that follow from other studies that employ a static concept of commercialization. However, our study suggests that household demographics such as the sex of the household head and the dependency ratio are particularly important for the dynamics of smallholder maize and beans marketing. We find that for genuine commercialization, having a female household head is a higher barrier than previously established using cross-sectional studies. But there are also marked differences in the effect of the dependency ratio on market participation depending on whether a static or a dynamic definition is used.
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