Optimistic Entrepreneurs: Agro-dealer Turnover and Consumer Impacts in Tanzania

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Abstract

We analyze firm turnover (i.e., entry and exit) among agro-dealers in rural Tanzania and study its implications for small-holder farmers. We calculate annual agro-dealer entry and exit rates of 34 and 18 percent, respectively – more than double the rates typically observed for micro-, small-, and medium-enterprises (MSMEs) operating in other sectors in low-income countries. While few observable agro-dealer characteristics predict exit, exit is more common when local competition is stronger. We develop a theoretical model of firm entry and exit under information asymmetries to better understand how turnover impacts market quality beliefs, and use the model to interpret our empirical findings. We show farmers' beliefs about agricultural input quality improve when agro-dealers exit; our model suggests that this is because farmers believe agro-dealers selling low-quality agricultural inputs exit. Farmers who regularly purchase inputs from the same agro-dealer have lower quality expectations for a new market entrant. These findings suggest agro-dealer turnover may play an important role in understanding farmer perceptions of agricultural input quality and related agricultural technology adoption decisions.

1 Introduction

Markets in low-income countries are are often characterized by significant information asymmetries, where buyers struggle to assess product quality before purchase. For example, most agricultural inputs—seeds, fertilizer, and pesticides—are either experience or credence goods, meaning that farmers cannot easily evaluate their agronomic quality until after use. Agricultural input suppliers (i.e., agro-dealers)—often operating as micro-, small-, and medium-enterprises (MSMEs)—play a critical role in these markets. They sell agricultural inputs to farmers but they also serve as key sources of agricultural information and advice, particularly important in contexts where formal public extension is usually underfunded or absent (Rutsaert & Donovan, 2020; Sones et al., 2015). Similarly, farmers cannot readily establish the quality of the agricultural information and advice supplied by agro-dealers.

Prior research suggests that these information asymmetries partially explain the low adoption of modern agricultural inputs in Sub-Saharan Africa (and the consequent low agricultural production and yields), as farmers reduce investment when they are uncertain about the quality of agricultural inputs sold in their markets (Ashour et al., 2019; Bulte et al., 2023; Gilligan & Karachiwalla, 2021; Michelson et al., 2021). Given the information challenges due to weak government regulation and limited enforcement (Kansiime, 2021; Michelson et al., 2025), farmers often rely on repeated interactions with agro-dealers to gain insights into quality (Hoel et al., 2024). However, frequent turnover in the agro-dealer sector may disrupt this process. The entry and exit decisions of new and existing agro-dealers may confound farmer learning, further exacerbating information asymmetries.

In this paper, we analyze firm turnover (i.e., entry and exit) among agro-dealers and explore the implications for small-holder farmers. We find comparatively high turnover rates among agro-dealers relative to the rates in the MSME literature. High firm turnover rates theoretically signal three key conditions commonly associated with competitive markets: high contestability, market fragmentation, and hyper-localized demand. Competitive pressure drives each of these conditions, and these conditions simultaneously help maintain competitive markets. Theory therefore suggests that high firm turnover likely benefits consumers, even in markets that are not perfectly competitive (NEED CITATIONS). Firm entry, for example, can stimulate job creation and local economic growth, indirectly benefiting consumers through improved economic conditions. However, firm exit can disrupt a consumer's choice set and introduce switching costs as consumers search for another supplier. Firm exit can also lead to job losses, prompting lower consumer spending and weakening local economies. Understanding the net welfare impacts of high firm turnover on consumers is therefore complex, even in a context of relatively limited information asymmetries. When information asymmetries are present (as is the case for the agro-dealer sector that we study), the consumer welfare effects of high firm turnover are even more unclear.

We develop a theoretical model of firm turnover under information asymmetries in Section 2. Our model considers how consumers form beliefs about firm product quality based on past transactions, information-sharing, and previous expectations. The model predicts that when a firm perceived to sell low-quality products exits the market, consumer expectations of market-level product quality improves. Conversely, when a firm perceived to sell high-quality products exits the market, consumer expectations worsen. Finally, our model predicts that a new market entrant's impact on consumer expectations depends on whether a consumer's existing market is perceived to be comprised of mostly firms that sell higher- or lower-quality products.

We test the model empirically using data from Tanzania's Morogoro Region—an important hub for agriculture and food production. Our data includes a three-round census of all agro-dealers in this region collected between 2015 and 2020. Each agro-dealer operates within one of 97 markets that were identified in the region. We merge the agro-dealer census with a survey of 1,241 smallholder collected in 2019. These farmers all reside within 3 to 7 kilometers of one of the 97 markets in the census. To further test the implications of our theoretical model, we also collect and analyze a smaller cross-sectional dataset of 150 farmers in the same region in 2022.

We establish three primary empirical findings. First, we find that agro-dealer turnover rates are substantially higher than those observed for MSMEs operating in non-agricultural sectors in low-income countries (Kremer et al., 2014; Liedholm, 2002; McCaig & Pavcnik, 2021; McKenzie & Paffhausen, 2019). Using the three-round census of agro-dealers over five years, we calculate an annual agro-dealer exit rate of 18 percent and an annual agro-dealer entry rate of 34 percent. Our agro-dealer exit rate is as much as 4.5 times higher than MSME exit rates previously documented in similar low-income settings (Kremer et al., 2014; McCaig & Pavcnik, 2021; McKenzie & Paffhausen, 2019) and our agro-dealer entry rate is nearly double (Liedholm, 2002; McCaig & Pavcnik, 2021). The turnover rates we observe are consistent with agro-dealer sectors in other countries: data from the International Maize and Wheat Improvement Center show Kenyan agro-dealers exit at an annual rate of 27 percent and data collected by (Gilligan & Karachiwalla, 2021) show agro-dealers in Uganda exit at an annual rate of 17 percent and enter at an annual rate of 33 percent. Together, these results on agro-dealer turnover suggest that agro-dealers operate in a more dynamic environment relative to MSMEs operating in other sectors in low-income countries.

Second, we show agro-dealer exit is not related to the majority of observable firm characteristics. One exception is the licensing status of the agro-dealer: agro-dealers without a government-issued license to sell fertilizer are more likely to exit. Operating without such a license could be a signal of informality or of limited operational investment. Instead, provide evidence that market factors are important in agro-dealer turnover: agro-dealer exit is strongly correlated with increased market competition and with fewer competitor exits. Contrary to our results, previous studies have found that firm age and size are linked to lower exit rates among MSMEs (Aga & Francis, 2017; Kremer et al., 2014; McKenzie & Paffhausen, 2019; Mead & Liedholm, 1998). Our findings suggest that, unlike in other sectors, agro-dealer survival is less influenced by firm-level characteristics and more significantly shaped by market dynamics.

Finally, our results show that high rates of firm exit have important implications for markets characterized by information asymmetries. Our results indicate that farmer assessment of market-level agricultural input quality improves when agro-dealers exit a market. Our theoretical model suggests that consumers believe that market-level product quality improves because they assume that the exiting firms were those that offered low-quality products. We show however that, on average, farmers do not adjust their market-level beliefs about agricultural input quality in response to new market entrants. This is consistent with our theoretical model which predicts a new market entrant will moderate consumer beliefs. However, we also show that farmers who have a stable relationship with an agro-dealer become more concerned about the quality of agricultural inputs and information provided by a new market entrant. This last finding is consistent with our model's prediction that when positive information signals for incumbents dominate a market, consumer beliefs about aggregate product quality within a market worsen with a firm entry.

Our findings make three contributions to the literature. First, a considerable literature analyzes agricultural technology adoption decisions of small-holder farmers. Suri and Udry (2022) provides a recent review. Much of this literature has focused on farmer-specific constraints, including those related to knowledge, credit, liquidity, savings, and insurance. Such studies mostly ignore intermediaries – particularly actors along the agri-input supply chain.[1] Agro-dealers are critical to the adoption of productivity-enhancing agricultural inputs, but several sectoral features make agro-dealers difficult to study (as highlighted by A. Dillon et al. (2025)). These features include sampling challenges, informality, and the enduring persistence of models and empirical strategies in development economics that focus on farm households rather than the market actors they engage with. Our study joins a very small number of recent studies with a focus on the agro-dealer sector. Kariuki et al. (2025) conduct a randomized controlled trial with Kenyan agro-dealers to understand how subsidizing their margins for new seed varieties impacts stocking and sales behavior. Dar et al. (2024) study the role of agro-dealers in supplying information and technology adoption among farmers in India. We expect our study analyzing agro-dealer turnover to provide an important building block for understanding this unique market and its implications for agricultural productivity in developing countries.

We also contribute to research focused on MSME operations and dynamics in low-income countries (Aga & Francis, 2017; Klapper & Richmond, 2011; Kremer et al., 2014; Liedholm, 2002; McCaig & Pavcnik, 2021; McKenzie & Paffhausen, 2019; Mead & Liedholm, 1998). TALK ABOUT MAIN FINDINGS OF THESE STUDIES.... To our knowledge, we are the first to empirically analyze the implications of MSME firm turnover for consumers.

Finally, we analyze the consequences of high turnover in a market characterized by asymmetric information. Our theoretical model can be applied to a wide variety of markets characterized by asymmetric information, including restaurants, healthcare, product repair, and educational services.

The paper proceeds as follows: Section 2 presents our theoretical model. Sections 3 and 4 describe the institutional setting and data, respectively. Section 5 characterizes the high agro-dealer turnover we observe as well as agro-dealer entry and exit decisions. Section 6 analyzes the consumer welfare impacts associated with high agro-dealer turnover. Finally, Section 7 concludes.

[1] See Bergquist and Dinerstein (2020) and B. Dillon and Dambro (2017) for an associated literature on output market intermediaries.

2 Model of Firm Turnover Under Information Asymmetries

Consider a region with N heterogeneous firms that sell heterogeneous experience or credence goods over T periods. There are M markets in the region with n_{mt} firms in each m market for each period t. Entry and exit decisions are taken simultaneously by firms in each period. Specifically, incumbents decide whether to stay in business or exit, while potential new market entrants decide whether to enter the market or stay out. After a new entrant enters a market in period t, it is an incumbent in period $t+1$.

Each firm i_m's true product quality in period t is either high (i.e., $q_{imt} = q_H$) or low (i.e., $q_{imt} = q_L$) where $q_H > q_L$. While true product quality is unobserved, each consumer j from market m has beliefs about the product quality of firms in their own market. Let parameter π_{jimt} describe consumer j_m's expected probability that firm i_m sells high-quality products in period t. Parameter π_{jimt} depends on three components: α_{jimt}, α_{-jimt}, and p_{jmt}. The first and second components reflect information signals specific to firm i_m: information based on consumer j_m's own experience or interaction with firm i_m is denoted by α_{jimt}, whereas information based on the experience or interaction with firm i_m by others' (i.e., consumers in market m that are not j) is denoted by α_{-jimt}. The signal α_{-jimt} can be determined by reviews, third-party certifications, or simple word-of-mouth. Information accrues over time, so that both α_{jimt} and α_{-jimt} reflect all past learning. Thus repeated transactions with or the accumulation of additional external signals related to firm i_m can prompt changes in α_{jimt} and α_{-jimt}, respectively. Even though consumer beliefs about firm i_m update each period, some uncertainty about the true product quality of firm i_m always persists due to the presence of information asymmetries. When consumers lack reliable firm-specific information, their beliefs are anchored to their market-level beliefs p_{jmt}. Such anchoring always applies to a new market entrant.

In Equation 1 below, we assume consumer j_m's expectation of the probability that firm i_m sells high-quality products (π_{jimt}) can be modeled using a logistic function, ensuring the expected probability remains between 0 and 1:

$$\pi_{jimt} = \frac{1}{1 + e^{-(\alpha_{jimt} + \alpha_{-jimt}) - p_{jmt}}} \quad \text{where } \alpha_{jimt}, \alpha_{-jimt}, \text{and } p_{jmt} \in (-1, 1) \tag{1}$$

We define each information signal so that as $\alpha_{jimt} \to 1$ or $\alpha_{-jimt} \to 1$, consumer j_m's own or others' experience suggest that firm i_m is likely to sell high-quality products. If $\alpha_{jimt} \to -1$ or $\alpha_{-jimt} \to -1$, consumer j_m's own or others' experience suggest that firm i_m is likely to sell low-quality products. In the absence of firm-specific information, $\alpha_{jimt} = 0$ and $\alpha_{-jimt} = 0$ and Equation 1 only depends on market-level beliefs p_{jmt}.

Parameter p_{jmt} reflects period t market-level beliefs, which are formed based on firms operating in the same market m in the previous period $t-1$. Specifically, p_{jmt} is a function of the average π_{jimt} of incumbents. Incumbents are firms that operated in market m in period $t-1$ and continued to operate in period t. Non-incumbents are those that choose to exit the market between the end of period $t-1$ and prior to start of period t. Let $\mathrm{I}_{it} \in \{0,1\}$ such that $\mathrm{I}_{it} = 1$ for incumbents and $\mathrm{I}_{it} = 0$ for firms in market m that exited. The total number of incumbents in market m in period t is less than or equal to the total number of firms operating in that market in the prior period (i.e., $n^{inc}_{mt} \leq n_{m(t-1)}$). Consumer j_m's market-level beliefs can now be defined as follows:

$$p_{jmt} = 2\left[\frac{1}{n^{inc}_{mt}}\left(\sum_{i=1}^{n_{m(t-1)}} \pi_{jim(t-1)} I_{it}\right)\right] - 1 \quad \text{where } \pi_{jim(t-1)} \in (0,1) \text{ and } p_{jmt} \in (-1,1) \qquad (2)$$

As $p_{jmt} \to 1$ all firms in market m are expected to sell high-quality products. As $p_{jmt} \to -1$ all firms in market m are expected to sell low-quality products. If $p_{jmt} = 0$, either market-level product quality is expected to be a balanced mix of firms selling high- and low-quality products, or consumer j_m has a neutral prior about market-level product quality. The latter means that consumer j_m does not believe incumbents offer high- or low-quality products.

Lemma 1. *π_{jimt} increases with α_{jimt}, α_{-jimt}, and p_{jmt}.*

Proof. Mathematically, $\frac{\partial \pi}{\partial \alpha_{jimt}} > 0$, $\frac{\partial \pi}{\partial \alpha_{-jimt}} > 0$, and $\frac{\partial \pi}{\partial p_{jmt}} > 0$.[2]

Figure 1 demonstrates how π_{jimt} adjusts to different beliefs about market-level product quality and firm-specific information signals. For ease of notation, let $\tilde{\alpha}_{jimt} = \alpha_{jimt} + \alpha_{-jimt}$, the combined firm-specific information signals such that $\tilde{\alpha}_{jimt} \in (-2,2)$. We plot $\pi_{jimt}(\tilde{\alpha}_{jimt})$ for p_{jmt} equal to -1, 0, and 1. These describe the scenarios where incumbents are believed to be selling low-quality products, a balanced mixed, or high-quality products, respectively. Notably, -1 and 1 capture the boundary values of p_{jmt}.

[2]Detailed derivations are in the Appendix.

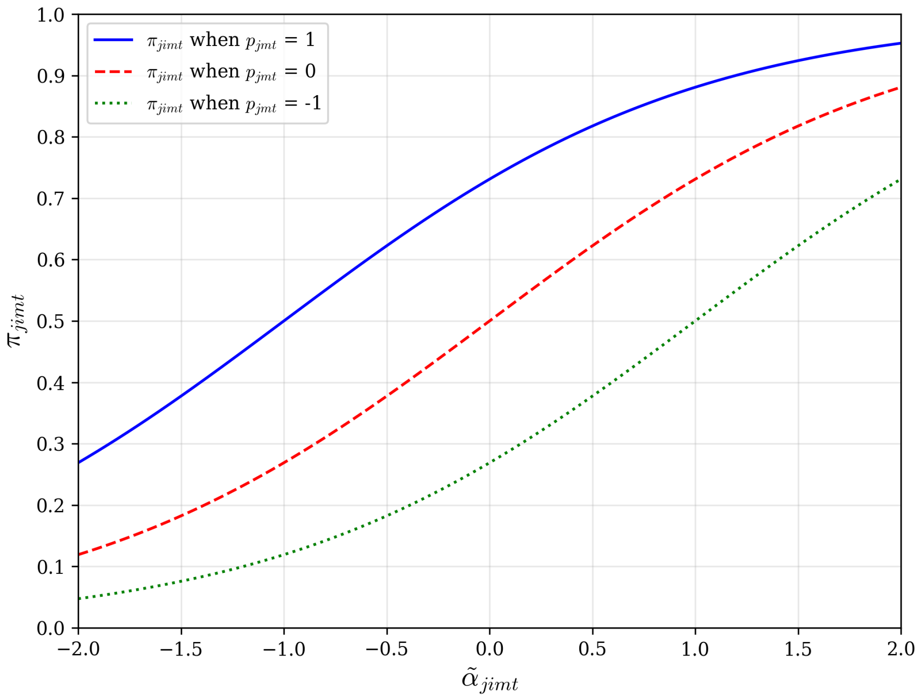

Figure 1: Equation 1 with Varying Parameters

Inserting beliefs into a simple expected value formula we find:

$$
\begin{aligned}
E[q_{jimt}] &= \pi_{jimt} q_H + (1 - \pi_{jimt}) q_L \\
&= \frac{1}{1 + e^{-(\alpha_{jimt} + \alpha_{-jimt}) - \left[2\left(\frac{1}{n_{mt}^{inc}}\left[\sum_{i=1}^{n_{m(t-1)}} \pi_{jim(t-1)} I_{it}\right]\right) - 1\right]}} q_H \\
&+ \left(1 - \frac{1}{1 + e^{-(\alpha_{jimt} + \alpha_{-jimt}) - \left[2\left(\frac{1}{n_{mt}^{inc}}\left[\sum_{i=1}^{n_{m(t-1)}} \pi_{jim(t-1)} I_{it}\right]\right) - 1\right]}}\right) q_L
\end{aligned}
\tag{3}
$$

Finally, consumer j's expectation of product quality for all n_m firms in period t is the average of $E[q_{jimt}]$. This average ($E[Q_{jmt}]$) is defined in Equation 4 below and reflects consumer j's beliefs about market m's overall product quality in period t.

$$
E[Q_{jmt}] = \frac{1}{n_{mt}} \sum_{i=1}^{n_{mt}} E[q_{jimt}] \tag{4}
$$

Our theoretical model offers three key insights.

Theorem 1. *If an exiting firm is believed by a consumer to have sold below-average product quality* *for its market, then consumer beliefs about the market's overall product quality improve.*

Proof. Assume that firm $k \in n_{mt}$ exits market m, and that $E[q_{jkmt}] < E[Q_{jmt}]$. Namely, consumer j_m believes firm k sold below-average quality products in market m. When a firm that sells below-average product quality is removed from the summation in Equation 4, $E[Q_{jmt}]$ increases. Thus consumer j_m's beliefs about the market's overall product quality improve.

Theorem 2. *If an exiting firm is believed by a consumer to have sold above-average product quality for its market, then consumer beliefs about the market's overall product quality worsen.*

Proof. Assume that firm $k \in n_{mt}$ exits market m, and that $E[q_{jkmt}] > E[Q_{jmt}]$. Namely, consumer j_m believes firm k sold above-average quality products in market m. When a firm that sells above-average product quality is removed from the summation in Equation 4, $E[Q_{jmt}]$ decreases. Thus consumer j_m's beliefs about the market's overall product quality worsen.

Theorem 3. *A new market entrant moderates consumer beliefs about the market's overall product quality.*

Proof. A new market entrant changes market m's overall product quality as follows, where subscript E denotes the new market entrant:

$$E[Q_{jmt}] = \frac{1}{n_{mt}^{inc} + 1} \left(\sum_{i=1}^{n_{mt}^{inc}} E[q_{jimt}] + E[q_{jEmt}] \right) \tag{5}$$

For a new market entrant, $\tilde{\alpha}_{jEmt} = 0$ which means that π_{jEmt} only depends on market-level beliefs p_{jmt}. Since p_{jmt} is fixed for all firms (i.e., incumbents and new market entrants) in a given market m, the following is true:

$$E[q_{jimt}] \begin{cases} > E[q_{jEmt}], \forall i_m \in n_{mt}^{inc} \text{ where } \tilde{\alpha}_{jimt} > 0 \text{ (i.e., positive information signal dominates)} \\ = E[q_{jEmt}], \forall i_m \in n_{mt}^{inc} \text{ where } \tilde{\alpha}_{jimt} = 0 \text{ (i.e., no information signal)} \\ < E[q_{jEmt}], \forall i_m \in n_{mt}^{inc} \text{ where } \tilde{\alpha}_{jimt} < 0 \text{ (i.e., negative information signal dominates)} \end{cases} \tag{6}$$

The difference between $E[q_{jimt}]$ and $E[q_{jEmt}]$ depends on $\frac{\partial\pi}{\partial\tilde{\alpha}}\big|_{\tilde{\alpha}_{jimt}}$. Therefore, the effect of new market entry on consumer j_m's market-level product quality beliefs depends on the strength of aggregated information signals for incumbents in that market: $\sum_{i=1}^{n_{mt}^{inc}}\left(\frac{\partial\pi}{\partial\tilde{\alpha}}\big|_{\tilde{\alpha}_{jimt}}\right)$.

Theorem 3.1. *If positive information signals for incumbents dominate a market, then consumer beliefs about overall product quality for that market worsen when a new entrant enters the market.*

Proof. Let $\frac{1}{n_{mt}^{inc}}\sum_{i=1}^{n_{mt}^{inc}} E[q_{jimt}] > E[q_{jEmt}]$ define the scenario in which positive information signals for incumbents dominate market m (i.e. $\sum_{i=1}^{n_{mt}^{inc}} \frac{\partial\pi}{\partial\tilde{\alpha}}\big|_{\tilde{\alpha}_{jimt}} > 0$). Under this scenario, the following inequality holds: $\frac{1}{n_{mt}^{inc}+1}\left(\sum_{i=1}^{n_{mt}^{inc}} E[q_{jimt}] + E[q_{jEmt}]\right) < \frac{1}{n_{mt}^{inc}}\sum_{i=1}^{n_{mt}^{inc}} E[q_{jimt}]$. Thus consumer j_m's beliefs about market m's overall product quality worsen when a new entrant enters market m.

Theorem 3.2. *If negative information signals for incumbents dominate a market, then consumer beliefs about overall product quality for that market improve when a new entrant enters market m.*

Proof. Let $\frac{1}{n_{mt}^{inc}}\sum_{i=1}^{n_{mt}^{inc}} E[q_{jimt}] < E[q_{jEmt}]$ define the scenario in which negative information signals for incumbents dominate market m (i.e. $\sum_{i=1}^{n_{mt}^{inc}} \frac{\partial\pi}{\partial\tilde{\alpha}}\big|_{\tilde{\alpha}_{jimt}} < 0$). Under this scenario, the following inequality holds: $\frac{1}{n_{mt}^{inc}+1}\left(\sum_{i=1}^{n_{mt}^{inc}} E[q_{jimt}] + E[q_{jEmt}]\right) > \frac{1}{n_{mt}^{inc}}\sum_{i=1}^{n_{mt}^{inc}} E[q_{jimt}]$. Thus consumer j_m's beliefs about market m's overall product quality improve when a new entrant enters market m.

Theorem 3.3. *If no information signals are present in a market, then a new market entrant has no effect on a market's overall product quality.*

Proof. Let $\frac{1}{n_{mt}^{inc}}\sum_{i=1}^{n_{mt}^{inc}} E[q_{jimt}] = E[q_{jEmt}]$ define the scenario in which no information signals for incumbents are present (i.e. $\sum_{i=1}^{n_{mt}^{inc}} \frac{\partial\pi}{\partial\tilde{\alpha}}\big|_{\tilde{\alpha}_{jimt}} = 0$). This may arise if there are no incumbents, there are no information signals for any incumbent, or if aggregated information signals equal zero. Under this scenario, the following equality holds: $\frac{1}{n_{mt}^{inc}+1}\left(\sum_{i=1}^{n_{mt}^{inc}} E[q_{jimt}] + E[q_{jEmt}]\right) = \frac{1}{n_{mt}^{inc}}\sum_{i=1}^{n_{mt}^{inc}} E[q_{jimt}]$. Thus consumer j_m's beliefs about market m's overall product quality do not adjust when a new entrant enters market m.

While firm entry and exit in any market m occurs simultaneously, our model parses them out to analyze their distinct effects on consumer beliefs regarding market m's overall product quality. Results suggest that firm exits lead to a directional change in consumer beliefs depending on the perceived product quality of the exiting firms, whereas firm entry introduces a moderating effect, shifting consumer beliefs toward market-level priors unless strong incumbent signals dominate. This differentiation allows us to examine how the interplay of firm entry and exit shapes consumer perceptions and expectations over time in markets characterized by information asymmetries.

3 Setting

Our research site is the Morogoro Region of Tanzania, an agricultural hub dominated by small-scale agricultural production (of cash and food crops), livestock keeping, and sugarcane and sisal plantations (United Republic of Tanzania, 2020). In this section, we describe the regulatory environment in which Tanzanian agro-dealers operate and asymmetric information in the products sold and information provided by agro-dealers.

3.1 Regulatory Environment

Agro-dealers sell a variety of agricultural inputs including fertilizer, seeds, and pesticides. However, a majority of sales are from fertilizer (Benson et al., 2012; Michelson et al., 2025). Similar to other sub-Saharan African countries, the Tanzanian government regulates domestic fertilizer markets in several ways. Since 2017, the government has used bulk procurement for all fertilizer imports, almost all of which is imported (United Republic of Tanzania, 2017). The government also sets the quantity annually of fertilizer that enters the country. Note that analysis by Tanzania's National Audit Office indicated systemic fertilizer shortages during this period. Though our data show a net increase in agro-dealer numbers during this period (see Section 5), the quantity of fertilizer imported into Tanzania did not consistently increase (United Republic of Tanzania, 2019).[3] The Tanzanian government also regulates the transport of fertilizer. There were no significant farmer- or agro-dealer-level government fertilizer subsidy programs operating at the time of the study (Michelson et al., 2025). Two policies related to the agro-dealer sector are especially pertinent to the firms studied in this analysis. These policies, expanded on below, affect agro-dealers' licensing and pricing decisions.

First, the Tanzanian government requires agro-dealers to have a license to sell different types of agricultural inputs including fertilizer, seed, and pesticides. Specifically, a Tanzania Fertilizer

[3]The audit notes (p.33): "...for financial years 2020/21 and 2021/22, fertilizers available for domestic utilization were below the demanded fertilizers."

Regulatory Agency (TFRA) license is required to sell fertilizer; it is free and valid for 3 years, but receipt requires two documents: either (1) a Taxpayer Identification Number (TIN) and a TFRA Certificate of Participation—which is received upon completion of a training conducted by TFRA—or (2) a TIN and a college or university certificate or diploma in agriculture, horticulture, or agronomy. Though required, government enforcement of the TFRA license—and other agricultural input licenses—is weak due to a lack of institutional and human resource capacity (Kansiime, 2021; Michelson et al., 2021). As a result, many agro-dealers operate without a TFRA license. A 2019 Tanzanian government audit of government agencies and regulations managing the country's agricultural inputs system commented on this:

> "Review of inspections report from TFRA for the year 2018 revealed that, there were [agri]-dealers who were not registered but still sell and distribute fertilizers to farmers in their [local government authorities]. It was stated that most of the fertilizer sellers were unaware of the procedures to be followed including the need to be registered" (United Republic of Tanzania, 2019, p. 70).

Based on their own visits, the National Audit Office found that over 50 percent of fertilizer-selling agro-dealers in the country were not registered by TFRA (United Republic of Tanzania, 2019, p. 78). The audit argues that reasons for low TFRA registration include a lack of understanding among agro-dealers of the registration procedures and process, and also a lack of enforcement (i.e., insufficient and infrequent inspections of agro-dealers). The audit noted that TFRA only inspected around 30 percent of Tanzania's regions annually (United Republic of Tanzania, 2019, p. 79).

Second, the Tanzanian government has set "indicative prices" for fertilizer sales based on the mode of transport (i.e., rail or road) used and the distance from the importation port in Dar es Salaam. The guide prices are set before the agricultural season and are intended to function as caps on the prices that agro-dealers can sell fertilizer by region; these prices are broadcasted in the media and made available through local governments. While agro-dealers are free to set the price of the fertilizer they sell, it must be at or below the indicative price set by the government. The 2019 government audit also reviewed the indicative pricing system and noted that there were problems with both informing agro-dealers of the prices and enforcing that the prices were adhered to:

> "... indicative prices did not reach all intended users. The information ends at regional and [local government authority] levels without flowing down to the village level. It was also noted that, some of the agro-dealers did not display the agricultural input prices as per the requirements. Therefore, some farmers were unaware of the indicative prices established. The reason for inaccessibility to indicative price observed include inadequate conduct of inspections to assess compliance of indicative prices" (United Republic of Tanzania, 2019, p. xiii).

Many agro-dealers have complained that the Tanzanian government sets the price caps too low to cover their costs (The Citizen, 2021a, 2021b), which may also contribute to compliance issues.

3.2 Asymmetric Information in the Agro-dealer Sector

Fertilizer sales—like that for other agricultural inputs—are characterized by asymmetric information. Agricultural inputs like seeds, fertilizer, and pesticides are experience or credence goods, meaning that their essential characteristic (i.e., their agronomic performance) cannot be evaluated *ex ante*. Moreover, quality signals are often obscured by production stochasticity caused by weather and "fit risk," the risk of potential mismatch between the technology used and the local agronomic conditions (including weather and soil quality) where the farmer will use it (Heiman et al., 2020). Agro-dealers provide information and advice to farmers on agricultural input selection and usage, but the quality of this guidance can also be difficult to evaluate before implementation.

Previous studies (Hoel et al., 2024; Michelson et al., 2021; Michelson et al., 2025) have focused on fertilizer markets and usage in Tanzania's Morogoro Region, gathering data on fertilizer quality, farmers' beliefs about fertilizer, and farmers' fertilizer use. Given the information asymmetries present in agricultural input markets and the weak regulatory environment in the agro-dealer sector, it is perhaps not surprising that farmers have expressed concerns about the quality of agricultural inputs sold by agro-dealers. In particular, Michelson et al. (2021) and Michelson et al. (2025) provide evidence that farmers on average believe that agro-dealers in the Morogoro Region sell low-quality and agronomically compromised urea fertilizer.

Similar farmer concerns about urea fertilizer quality have been documented in neighboring Uganda (Bold et al., 2017; Hoel et al., 2024) and in West Africa (Austin et al., 2013). Farmer concern is not bourne out by the testing of fertilizer samples conducted by either academic researchers (summarized in Michelson et al., 2023) or by the International Fertilizer Development Corporation, which conducts tests and advises on the testing of fertilizer quality throughout the world. Despite fertilizer being of reliably good quality—consistent with industry standards—farmers *still* believe that bad quality fertilizer is sold in their markets.

Why do farmers have incorrect beliefs about fertilizer quality, and why do they fail to learn the truth? Hoel et al. (2024) show that in Tanzania's Morogoro Region, these misconceptions arise from misattribution—a cognitive bias where farmers wrongly attribute low yields to fertilizer quality instead of factors like weather, incorrect application quantity, fertilizer type, or timing. As a result, farmers mistake bad luck or poor management for fertilizer quality issues, hindering their ability to accurately assess the product's true quality over time. A randomized controlled trial in Michelson et al. (2025) shows that farmers in this same region improved their beliefs about fertilizer quality following an information campaign. Yet belief updating was incomplete and heterogeneous; while overall concerns about fertilizer quality declined, a significant share of farmers remained skeptical, suggesting that learning was slow and beliefs were somewhat resistant to change.

Incorrect beliefs have real consequence for farmer investment. An evolving literature provides empirical evidence that suggests that suspicion or uncertainty about agricultural input quality reduces willingness-to-pay as well as depresses farmer demand and use (Bulte et al., 2023; Gharib et al., 2021; Hoel et al., 2024; Hsu and Wambugu, 2022; Michelson et al., 2025; Miehe et al., 2023).

The persistence of farmer beliefs that fertilizer is bad quality in a region in which reliably good quality is established is important to our context, theoretical model, and analysis. Our sample excludes "low-quality" agro-dealers in terms of the agronomic quality of their fertilizer,[4] yet farmers *believe* there is low-quality fertilizer being sold. Thus farmers perceive a range of high- and low-quality agro-dealers (in this fertilizer quality dimension) in their markets, leading them to believe that they offer differentiated and heterogeneous fertilizer when they do not. Asymmetric information contributes to the existence and persistence of these beliefs (Hoel et al., 2024).

[4]Agro-dealers could of course be considered low-quality in other dimensions (e.g., agricultural information quality, customer service, product or service variety and availability, etc.)

4 Data

We use four primary datasets. Our agro-dealer turnover analysis in Section 5 relies on the agro-dealer data from Uganda and Tanzania described in Subsections 4.1 and 4.2, respectively. Our consumer impact analysis in Section 6 merges the Tanzania agro-dealer data with farmer data and additionally leverages other cross-sectional farmer data. Both are described in Subsection 4.3.

4.1 Uganda Agro-dealer Data

We use a three-round census of all agro-dealers operating within specific hubs located in Western, Central, and Eastern Uganda.[5] Data collection was completed in the third quarter of 2014, the first quarter of 2016, and the first quarter of 2017. To complete the census, first 118 major markets within these hubs were identified. Then all agro-dealers in each market were identified and surveyed during each round.

4.2 Tanzania Agro-dealer Data

We also use a three-round census of all agro-dealers in Tanzania's Morogoro Region. Data collection was completed in the first quarters of 2016, 2019, and 2020,[6] just before the long rains planting season and related agricultural input sales.[7] To complete the census, we first identified 97 major markets within the study region. We then identified and surveyed all agro-dealers in each market for every round.

In each round we collected information about agro-dealer characteristics related to business practices, asset ownership, number of non-owner employees, licensing, operational scale, years of operation, and shop infrastructure. The first three columns of Table 1 present descriptive statistics for the agro-dealer census by round. Across rounds, some agro-dealers appear once, while others appear two or three times. In total, our census includes 384 *unique* agro-dealers. Column 4 of Table 1 presents descriptive statistics for each unique agro-dealer using data from the first round in which they appear in our sample. We supplement the agro-dealer census with a final follow-up

[5] Gilligan and Karachiwalla (2021) used this data and the ten market hubs are distributed as follows: Western Uganda (Kasese, Hoima, and Masindi), Central Uganda (Kiboga, Luwero, Mubende, Mityana, and Masaka), and Eastern Uganda (Mbale and Iganga).

[6] Data collection for the first and second rounds commenced in the last quarter of the previous calendar year.

[7] Michelson et al. (2021) used the 2016 data while Michelson et al. (2025) used both the 2019 and 2020 data.

(non-census) survey with 202 of the 515 agro-dealers in the third quarter of 2022. These follow-up agro-dealer data were collected to better understand firm entry and exit decisions (see Sections 5.3 and 5.4, respectively).[8]

As shown in Table 1, across all three rounds, nearly all agro-dealers had a cellphone, less than a third owned transportation assets, and around forty percent had a government-issued TFRA license. Moreover, across time, agro-dealers did not have other business locations that sold fertilizer, had about one employee besides the owner present at the time of interview, and had been operating at the same location for just over four years. In the last row of Table 1, we define the share of other agro-dealer exits as the number of *other* agro-dealers that exit a market between two rounds divided by the number of agro-dealers in that market at the start of the previous round.[9] On average, the share of *other* agro-dealer exits for a specific agro-dealer is between 20 and 33 percent across rounds. This estimate suggests that a fifth to a third of an agro-dealer's competitors within the same market exit from one round to the next.

The average distance between markets and their nearest neighboring market is 6.6 kilometers (km).[10] Table 2 provides additional characteristics for the 97 markets across and between rounds. Over time, the share of markets with at least one agro-dealer decreases. To better understand competitive dynamics within markets, Table 2 also aggregates information across all agro-dealers within a market. The number of agro-dealers in each market varies widely: from 0 to 29 depending on the round. On average, the number of agro-dealers in each market increases from about two to four over time. Overall, the agro-dealer sector is growing, with agro-dealers increasingly concentrating in fewer markets—intensifying competition.

The last two rows of Table 2 capture agro-dealer turnover within a market in between rounds.

[8]These follow-up agro-dealer data are not a census for two reasons: First, we did not attempt to survey any new market entrants. Second, a phone survey was conducted, resulting in high attrition rates. Many former agro-dealers were unreachable due to either obsolete contact information or busy schedules. As a result, there is potential selection bias in the agro-dealer follow-up survey since feedback was captured only from those who had working phone numbers and who were willing to participate.

[9]The share of other agro-dealer exits is a measure specific to agro-dealers, not markets. Suppose agro-dealer A is in a market which has four agro-dealers in total in round one (e.g., A, B, C, and D). Agro-dealers B and C exit between rounds one and two, leaving agro-dealers A and D. This share for agro-dealers B and C is 33 percent (i.e., one of their three competitors in their market exited in between rounds) while that for agro-dealers A and D is 67 percent (i.e., two of their three competitors in their market exited in between rounds). For each agro-dealer in a market, the survival outcomes of others in that same market are considered.

[10]Distances are broadly distributed, with 47.4 percent of markets 1 to 5 km from their nearest neighboring market, 10.3 percent under 1 km, 24.7 percent between 5 and 10 km, and 17.6 percent over 10 km. Also, distances between markets are calculated as great-circle distances in kilometers using the haversine formula.

Table 1: Descriptive Statistics for Tanzania Agro-dealer Census by Round

	Round 1	Round 2	Round 3	Unique
Agro-dealer Characteristics	Mean (Std. Dev.)	Mean (Std. Dev.)	Mean (Std. Dev.)	Mean (Std. Dev.)
Owns a car or truck	0.22	0.31	0.25	0.24
	(0.41)	(0.46)	(0.44)	(0.43)
Owns a smartphone or mobile phone	0.99	0.99	0.99	0.99
	(0.12)	(0.10)	(0.10)	(0.11)
Has organizational certifications displayed	0.23	0.24	0.19	0.20
	(0.42)	(0.43)	(0.39)	(0.40)
Uses outdoor signage for advertising purposes	0.77	0.59	0.89	0.68
	(0.42)	(0.49)	(0.32)	(0.47)
Number of other locations that sell fertilizer	0.40	0.27	0.27	0.35
	(0.79)	(0.59)	(0.58)	(0.74)
Has a license to sell fertilizer	0.40	0.46	0.40	0.39
	(0.49)	(0.50)	(0.49)	(0.49)
Number of additional employees present	0.84	0.80	1.04	0.85
	(0.76)	(0.74)	(0.74)	(0.75)
At least one additional employee present	0.71	0.67	0.84	0.71
	(0.46)	(0.47)	(0.36)	(0.46)
Number of years operating at current location	4.18	4.71	4.39	3.31
	(4.33)	(4.68)	(4.99)	(3.76)
Declared as permanent as compared to seasonal	0.98	0.96	0.97	0.97
	(0.13)	(0.20)	(0.16)	(0.18)
Share of *other* agro-dealer exits relative to previous round		0.32	0.20	0.28
		(0.35)	(0.26)	(0.32)
Observations	224	298	360	384

Notes: all agro-dealers identified in the census sold fertilizer at the time of survey administration. They should all have a license issued by the Tanzania Fertilizer Regulatory Authority to sell fertilizer as mandated by the 2009 Fertilizers Act. Broadly, the "has a license to sell fertilizer" variable captures whether agro-dealers have the appropriate government authorization to sell a specific agricultural input at their business location. It is most likely true that if agro-dealers reported having other locations that sell fertilizer, those same locations would also sell other agricultural inputs. Yet the "number of other locations that sell fertilizer" variable might be an under-estimate given that agro-dealers could have other locations that sell agricultural inputs other than fertilizer. Agro-dealer owner traits—such as education level and age—were only available for agro-dealers in round one so they are excluded. We impute values for seven, two, and three variables with low rates of missingness across rounds one, two, and three, respectively, using the median value for each round. Imputations were made for between two to eight observations per variable. The imputed variables include "has organizational certifications displayed," "uses outdoor signage for advertising purposes," "number of other locations that sell fertilizer," "has a license to sell fertilizer," "number of additional employees present," "has at least one additional employee present," "number of years operating at current location," and "declared as permanent as compared to seasonal." The last column presents descriptive statistics for the unique agro-dealers in our stacked sample. Characteristics for these 384 agro-dealers are associated with the first round that they appear in the census.

We define the share of agro-dealer exits as the number of agro-dealers that *exit* a market in between two rounds divided by the number of agro-dealers at the start of the previous round.[11] On average, this share is 37 percent between rounds one and two and 22 percent between rounds two and three.

[11]The share of agro-dealer exits is a measure specific to markets, not agro-dealers. Suppose, again, agro-dealer A is in a market which has four agro-dealers in total in round one (e.g., A, B, C, and D). Agro-dealers B and C exit between rounds one and two, leaving agro-dealers A and D. The share of agro-dealer exits for the market is 50 percent (i.e., two of the four agro-dealers in the market exited in between rounds).

The share of new market entrants is similarly defined: the number of agro-dealers that *enter* a market in between two rounds divided by the number of agro-dealers at the start of the previous round.[12] Between rounds, this share ranges from about 45 to 70 percent on average. These results suggest that markets experience considerable agro-dealer turnover.

Table 2: Descriptive Statistics for Markets by Round

	Round 1	Round 2	Round 3
	Mean (Std. Dev.)	Mean (Std. Dev.)	Mean (Std. Dev.)
Share with active agro-dealers	0.95	0.92	0.89
	(0.22)	(0.28)	(0.32)
Number of agro-dealers	2.31	3.07	3.71
	(2.26)	(3.90)	(4.55)
Share of agro-dealer exits relative to previous round		0.37	0.22
		(0.39)	(0.31)
Share of new market entrants relative to previous round		0.68	0.46
		(0.87)	(0.65)
Observations	97	97	97

4.3 Tanzania Farmer Data

We merge the Tanzania agro-dealer census with a dataset of 1,241 small-holder farmers in Tanzania's Morogoro Region. The farmer data were collected in the first quarter of 2019, at the same time as the 2019 agro-dealer data were collected. Farmers and agro-dealers are merged using markets; all farmers in our sample reside within 3 to 7 km of one of the markets in which agro-dealers operate. Importantly, this allows us to later explore the relationship between recent firm turnover within a market and farmer beliefs within the same market.

Table 3 presents relevant descriptive statistics for this farmer sample. The majority of surveyed farmers were male and the head of their household. On average, farmers were 45 years old, with a household size of just over five members, owned approximately six acres of land, and had been farming at the same location for about 16 years. Seventy-seven percent completed at most primary school and 39 percent believed they are risk averse relative to other farmers.

The data also capture farmers' beliefs about the quality of fertilizer offered by agro-dealers in

[12] The share of new market entrants is also a measure specific to markets, not agro-dealers. Suppose, again, agro-dealer A is in a market which has four agro-dealers in total in round one (e.g., A, B, C, and D). Regardless of the survival outcomes of agro-dealers A, B, C, and D, agro-dealer E enters the market between rounds one and two. The share of new market entrants for the market is 25 percent (i.e., one new agro-dealer entered a market where four agro-dealers already existed). The definition we use is from Liedholm (2002).

farmers' proximate market. Farmers were asked: "if ten other farmers, like you, purchase a one-kilogram bag of fertilizer in your proximate market this week, how many would be bad quality?" Table 3 shows farmers believed on average three out of ten farmers in this scenario would receive bad quality fertilizer.[13] A binary version of this metric captures whether farmers had *any* level of concern regarding fertilizer quality in their proximate market: 70 percent of farmers believed at least one out of ten farmers would have received bad quality fertilizer.

Table 3: Descriptive Statistics for Farmer Dataset

Farmer Characteristics	Mean	Std. Dev.	Min	Max
Is female	0.42	0.49	0.00	1.00
Age	44.76	12.44	18.00	88.00
Household size	5.43	2.49	1.00	35.00
Number of children under the age of five years	0.74	0.89	0.00	8.00
Household head	0.75	0.43	0.00	1.00
Highest level of education				
No schooling	0.10	0.30	0.00	1.00
Primary school	0.77	0.42	0.00	1.00
Secondary school	0.11	0.31	0.00	1.00
Vocational training	0.01	0.09	0.00	1.00
University (e.g., diploma, BSc, MSc, PhD)	0.01	0.11	0.00	1.00
Number of acres of land owned	5.69	4.94	0.00	20.00
Number of years of farming experience	15.69	11.43	0.00	70.00
Is risk adverse	0.39	0.49	0.00	1.00
Fertilizer Quality Perceptions				
Farmers out of ten receiving bad quality	3.18	2.83	0.00	10.00
Concerned about quality	0.70	0.46	0.00	1.00
Observations				1,241

Notes: we winsorize the variable "number of acres of land owned" only for data above the 95th percentile given its long-tailed distribution. We impute two variables with low rates of missingness using the median value for the sample. Imputations were made for 14 observations for the"number of acres of land owned" variable and 21 observations for the "number of years of farming experience" variable.

One limitation of the farmer data just described is that it lacks information about the relationship between farmers and specific incumbent firms. To better understand farmer-firm relationships, we implemented an additional short survey with 150 Tanzania farmers in 15 villages (representing 9 market clusters) in Tanzania's Morogoro Region in 2022. These data represent two of the seven administrative districts in the region, with ten farmers from each village surveyed in the third quarter of 2022. Table 4 presents descriptive statistics for this sample. About three-fourths of the farmers were male and two-thirds completed up to a primary education. On average, farmers were

[13]This question was used for quality belief elicitation in Michelson et al. (2021), Ashour et al. (2019), Hoel et al. (2024) and others.

45 years old, had over 19 years of farming experience, and owned roughly five acres of land. These farmers share a similar demographic distribution with those represented in Table 3.

Similar to the large sample survey, farmers were asked to estimate the quality of agricultural inputs. For comparison purposes, we note that the large sample survey framed the question around bad quality, while in this survey the question was framed around good quality. Unlike the large sample survey, we collected beliefs distinguishing between incumbent firms and a hypothetical new market entrant. For both kinds of firms we also asked about beliefs regarding both input quality and information quality.[14] Summary information regarding farmers responses are provided in Table XX. As a preview of later findings, we see the perceived quality of inputs and information provided by a current firm are on average higher than the perceived quality of inputs and information provided by a hypothetical new market entrant.

Importantly, these farmers were also asked whether they *usually* purchased agricultural inputs from the same agro-dealer over the past five years. Answers to this question are expected to capture both the stability of a farmer's relationship and their affinity toward a particular agro-dealer. As shown in Table XXX, approximately two thirds (63 percent) of farmers usually purchased from the same agro-dealer.

Table 4: Descriptive Statistics for Farmer Cross-sectional Dataset

Farmer Characteristics	Mean	Std. Dev.	Min	Max
Is female	0.27	0.45	0.00	1.00
Age	45.08	13.25	21.00	71.00
Highest level of education				
No schooling	0.02	0.14	0.00	1.00
Primary school	0.66	0.48	0.00	1.00
Secondary school	0.27	0.44	0.00	1.00
Vocational training	0.02	0.14	0.00	1.00
University (e.g., diploma, BSc, MSc, PhD)	0.03	0.18	0.00	1.00
Number of acres of land owned	4.69	4.86	0.00	40.00
Number of acres of land cultivated in the last 12 months	4.14	2.75	0.25	16.00
Number of years of farming experience	19.40	13.22	2.00	51.00
Observations				150

[14]Specifically, farmers were asked farmers to estimate, out of ten, how many farmers like themselves would receive good quality agricultural inputs/information from a current/new agro-dealer if all ten farmers purchased the same agricultural input on the same day.

5 Characterizing Agro-dealer Turnover

In this section, we estimate agro-dealer turnover rates in two regions of two East African countries—Tanzania and Uganda—and compare them to the existing MSME literature. We then use the Tanzania data to dive deeper into the factors and context influencing agro-dealer entry and exit decisions.

5.1 Estimating Agro-dealer Turnover Rates

To calculate turnover, we first define the agro-dealer entry rate for a pair of rounds in the census as the number of agro-dealers that enter a market between two rounds ($E_{(r,r+1)}$) divided by the number of agro-dealers at the start of the initial round for that pair (N_r). We define the agro-dealer exit rate similarly: the number of agro-dealers that exit a market between two rounds ($X_{(r,r+1)}$) divided by the number of agro-dealers at the start of the initial round for that pair (N_r). These definitions are consistent with those used to calculate MSME entry and exit rates in similar low-income settings (see Liedholm (2002) and Kremer et al. (2014)).

To annualize these entry and exit rates, we first divide each rate for a pair of rounds by the number of years between those rounds ($T_{(r,r+1)}$). This temporal adjustment ensures comparability across the pairs of rounds: rounds one to two, and rounds two to three. Then to calculate an annual turnover rate that spans all rounds, we compute a weighted average of the annual rates. The weights ($W_{(r,r+1)}$) reflect the proportion of time between two rounds within a pair relative to the total time between both pairs of rounds.[15] Equations 7 and 8 calculate the annual agro-dealer entry and exit rate, respectively, for each geography. In Equation 7, $E_{(1,2)}$ and $E_{(2,3)}$ represent the number of new market entrants between rounds one and two, and rounds two and three, respectively. In Equation 8, $X_{(1,2)}$ and $X_{(2,3)}$ represent the number of agro-dealers exits during these same intervals. N_1 (N_2)

[15] For the Tanzania agro-dealer data, there are 2.53 years (i.e., 30.4 months) between rounds one and two and 0.86 years (i.e., 10.4 months) between rounds two and three. To calculate the time in between rounds for a given pair of rounds, we count the number of days from the day *after* the last survey date of the first round to the day *before* the first survey date of the next round. For round one, the last survey date was 5/30/2016 and the first survey date of round two was 12/12/2018. The difference between these dates is 925 days which is 2.53 years. For round two, the last survey date was 3/1/2019 and the first survey date of round three was 1/11/2020. The difference between these dates is 315 days which is 0.86 years. The weight in Equations 7 and 8 associated with agro-dealer turnover between rounds one and two ($W_{(1,2)}$) is 0.75 because $\frac{925}{925+315} = 0.75$. The weight of 0.25 associated with agro-dealer turnover between rounds two and three ($W_{(2,3)}$) is calculated similarly. For the Uganda agro-dealer data, there are 1.39 years (i.e., 16.7 months) between rounds one and two and 1.08 years (i.e., 13 months) between rounds two and three. Given these intervals and survey dates, the associated weights $W_{(1,2)}$ and $W_{(2,3)}$ are 0.56 and 0.44, respectively.

is the number of agro-dealers at the start of round one (two). $T_{(1,2)}$ and $T_{(2,3)}$ indicate the time in years between rounds one and two, and two and three, respectively. Lastly, $W_{(1,2)}$ and $W_{(2,3)}$ are the corresponding weights and are both functions of $T_{(1,2)}$ and $T_{(2,3)}$.

$$\text{Annual Agro-dealer Entry Rate} = W_{(1,2)}\left(\frac{\left(\frac{E_{(1,2)}}{N_1}\right)}{T_{(1,2)}}\right) + W_{(2,3)}\left(\frac{\left(\frac{E_{(2,3)}}{N_2}\right)}{T_{(2,3)}}\right) \tag{7}$$

$$\text{Annual Agro-dealer Exit Rate} = W_{(1,2)}\left(\frac{\left(\frac{X_{(1,2)}}{N_1}\right)}{T_{(1,2)}}\right) + W_{(2,3)}\left(\frac{\left(\frac{X_{(2,3)}}{N_2}\right)}{T_{(2,3)}}\right) \tag{8}$$

Using Equation 8, we calculate an annual agro-dealer exit rate of 18.1 percent in Tanzania and 16.9 percent in Uganda. Using Equation 7, we calculate an annual agro-dealer entry rate of 34.0 percent in Tanzania and 32.9 percent in Uganda.

Our observed annual agro-dealer exit rates are similar in both Tanzania and Uganda, but more than double the annual exit rates documented for MSMEs that operate in non-agricultural sectors in similar low-income settings. In a seminal study on "firm death" leveraging data from 12 different low-income countries, McKenzie and Paffhausen (2019) report 8 percent of MSMEs fail annually. Kremer et al. (2014) suggest an even lower average annual exit rate of 4 to 6 percent for Kenyan retail shops. The annual exit rates we observe for the agro-dealer sector is most similar to those among informal MSMEs in Vietnam (i.e., 14-18 percent) (McCaig & Pavcnik, 2021) and in the Dominican Republic (i.e., 22-29 percent) (Cabal, 1995).

Similarly, our estimated annual agro-dealer entry rates (i.e., 34 percent for Tanzania and 33 percent for Uganda) is at least one third higher than—and up to twice as high as—that observed for non-agricultural MSMEs in previous studies. Liedholm (2002) reports an average annual entry rate of 22 percent across MSMEs in Latin America and Africa, ranging from 19 to 25 percent depending on the country. McCaig and Pavcnik (2021) report an annual entry rate of 16 to 18 percent for informal MSMEs in Vietnam, while Cabal (1995) finds a 21 to 24 percent annual entry rate for informal MSMEs in the Dominican Republic.

Spurious counts of entries and exits could artificially inflate the agro-dealer turnover rates we observe for both geographies. This may arise from design or sampling issues, or from defining "active" agro-dealers inaccurately. For example, seasonal or temporarily inactive agro-dealers may be misclassified as "exits." Similar misclassification could inflate agro-dealer entry counts. However, there are several reasons why we are confident that data issues are not driving our results. In the Tanzanian study region, our data are based on repeated censuses—conducted before the long rains season, when farmers purchase agricultural inputs and agro-dealers open for business—and were collected by a consistent set of enumerators across rounds. Enumerators were instructed to interview all agro-dealers in markets selling or planning to sell fertilizer in the coming long rains season. Our census across rounds focused on agro-dealers with permanent locations, hence seasonal or temporary operations were predominantly excluded (see Table 1). [16] For the Uganda data, Gilligan and Karachiwalla (2021) indicate that in each round, enumerators were directed to survey *all* agro-dealers within each market. Additionally, an average of only 0.004 percent of agro-dealers within a market sold agricultural inputs *seasonally* at baseline (Gilligan & Karachiwalla, 2021). If anything, these details suggest that our agro-dealer entry and exit rates may be lower bounds on the level of firm turnover in the agro-dealer sector more broadly.

Our estimated agro-dealer entry and exit rates are also consistent with agro-dealer turnover rates observed in Kenya. Data provided to us by the International Maize and Wheat Improvement Center (CIMMYT) show Kenyan agro-dealers exit at an annual rate of 27 percent.[17] Collectively, these results on agro-dealer turnover rates suggest that agro-dealers operate in a more dynamic environment relative to MSMEs operating in non-agricultural sectors in low-income countries.

5.2 Heterogeneity of Agro-dealer Turnover

In what follows, we will leverage the richness of the Tanzania data to further explore agro-dealer turnover in Tanzania's Morogoro Region. We first consider whether high turnover in the Morogoro Region is heterogeneous across markets. The gray bars in Figure 2 show the annual net agro-dealer turnover rate for a given market over the four-year study period.[18] The annual net agro-dealer

[16] One potential issue is the possibility of agro-dealers closing in one market but opening in another during the study period. However, our agro-dealer census data reveal that no agro-dealers who exited were observed to re-enter the **same** market. Also, since we track agro-dealer *shops* rather than the individuals operating them, any re-entry into a *different* market after exit is not pertinent for our analysis. Lastly, our follow-up survey with agro-dealers who closed their businesses during the study period ($N = 54$) indicates that this behavior is uncommon. Their self-reported entry and exit data were consistent with census observations, showing no discrepancies.

[17] We do not have access to the full dataset and therefore cannot reproduce the statistics we compute using the Uganda and Tanzania data.

[18] While the agro-dealer census represents 97 markets, data for two of them are not shown in Figure 2. These two markets had agro-dealers operating in round three only. Their respective annual agro-dealer turnover rates could not be estimated.

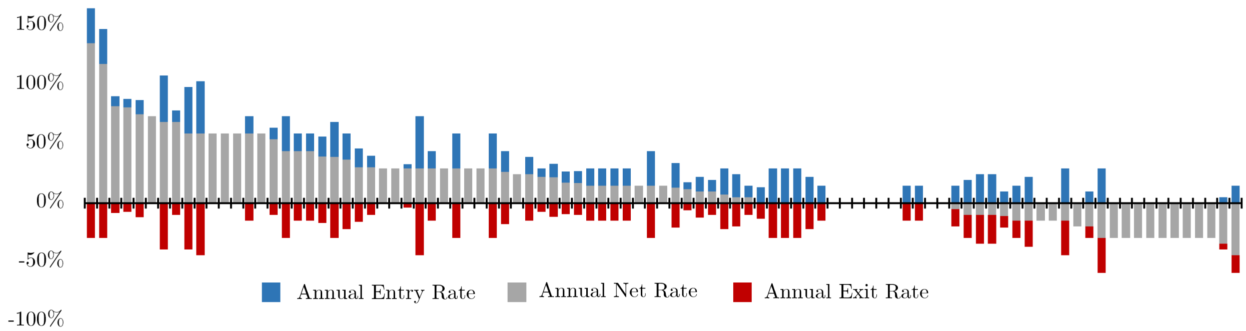

Figure 2: Annual Agro-dealer Turnover by Market: Entry, Net, & Exit Rates

turnover rate is defined as a market's annual agro-dealer entry rate minus its annual agro-dealer exit rate. The figure provides evidence of heterogeneity in agro-dealer turnover across markets: while more than half of markets in the region are growing (i.e. there are more agro-dealers entering than exiting over time), a quarter of markets have fewer agro-dealers at the end of the study period than were operating five years earlier.

Figure 2 not only suggests heterogeneity in agro-dealer turnover *across* markets, but turnover also varies *within* markets. The blue and red bars capture the annual entry and exit rates, respectively, *relative to* the annual net turnover rate. Heterogeneity within markets is most evident for the 15 markets that experience no net change in annual agro-dealer turnover. Of those, eight show no agro-dealer turnover and the remaining seven experience complete replacement (i.e., all existing agro-dealers exited and were replaced by new market entrants).

Finally, we find no statistical evidence of geographic clustering or dispersion among these same markets. Figure 3 shows a map of Tanzania's Morogoro Region, with each circle indicating a market location analyzed in our study. Darker red circles indicate markets with net annual agro-dealer *exit*, while darker blue circles represent those with net annual agro-dealer *entry*. Lighter shades of red and blue depict lower magnitudes of these net changes in annual agro-dealer turnover. While markets in the region experience net growth, net decline, or no change over time, there is no discernible spatial pattern in annual net agro-dealer turnover. It does not appear to be systematically concentrated in either rural or urban areas. A Moran's I test for global spatial autocorrelation yields a null result ($p = 0.215$), indicating that annual net agro-dealer turnover does not exhibit significant spatial dependence. We conclude that the high observed agro-dealer turnover in this region is not spatially correlated.

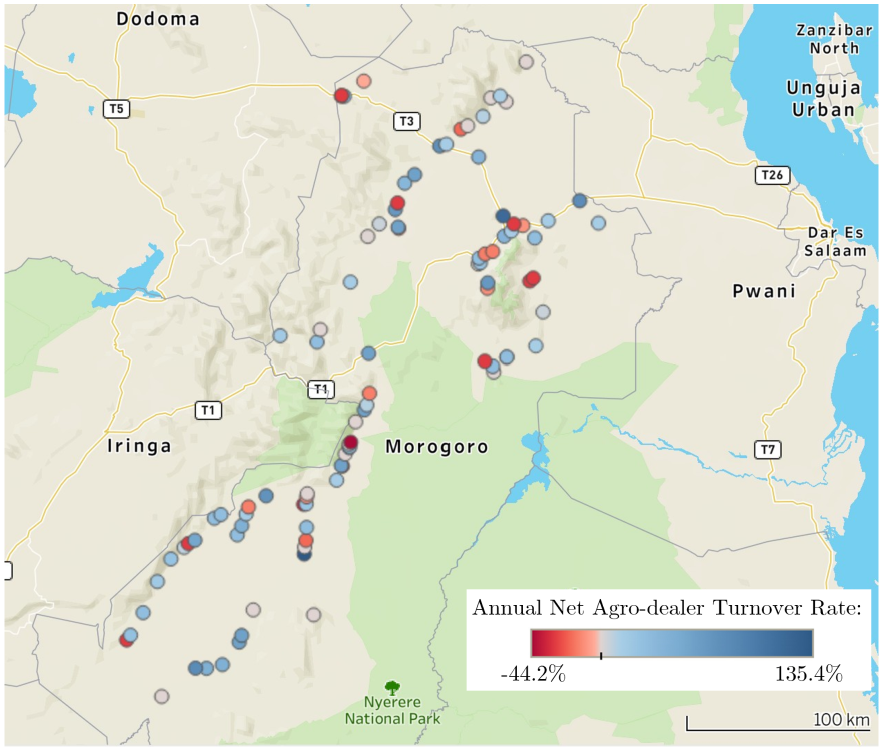

Figure 3: Annual Net Agro-dealer Turnover in Tanzania

5.3 Agro-dealer Entry Decisions

Banerjee and Duflo (2011) characterize the small business ventures commonly pursued by low income individuals as the income-generating activities of "reluctant entrepreneurs". More broadly, MSME entry by low-income entrepreneurs has often been characterized as "buying a job" which signifies a willingness to take any work—even if it is not the best fit—to pay for expenses when current income is insufficient or alternative employment opportunities are not available (Banerjee & Duflo, 2011; Burchell & Coutts, 2019; Jayachandran, 2021; Sohns & Diez, 2019). In other words, entrepreneurs are *pushed* into the market by necessity. Di Falco and De Giorgi (2019) and Rudder (2022) find evidence of this necessity-oriented entry in Sub-Saharan Africa. Their findings show MSME start-up among farming households increases in response to adverse weather shocks. They explain that the increase in entry stems from households being forced into entrepreneurship to help smooth consumption. In this way, MSME entry serves as a coping strategy.

We test whether this characterization holds for Tanzanian agro-dealers using a detailed follow-up survey with agro-dealers collected in 2022. We present strong descriptive evidence that the agro-dealers in our study are *not* "reluctant entrepreneurs" who engage in MSME development because there are no other options. Table **??** presents descriptive statistics from this survey. Eighty-six percent of agro-dealers we surveyed viewed entry into the sector as a "step-up" from their previous primary economic activity. These agro-dealers overwhelmingly agreed that the agro-dealer business was a more lucrative option than alternative income-generating activities, provided greater financial security, or was better aligned with their personal interest and skills. Less than 2 percent reported entering the sector to temporarily smooth consumption or supplement income.

These agro-dealers overwhelmingly entered the sector with the expectation of staying for the long-term. At the time of entry, nearly all firms (i.e., 96 percent) expected to be in business for more than six years. Among those still operating at the time of the survey, 86 percent expected to grow over the next five years.[19] Optimism is sustained even when presented with a hypothetical employment opportunity that is *more* profitable: 84 percent of agro-dealers reported that they would *still* not exit the sector in this scenario. Although based in a hypothetical, this latter question implies agro-dealers were committed to their chosen profession. These results suggest that agro-dealers are 'optimistic entrepreneurs' who initially—and over time—see market entry as a long-term investment and a sustainable income source. Benson et al. (2012) similarly observe in their study of fertilizer supply chains in Tanzania:

> "Agro-dealers are generally optimistic... all but one in the survey sample expect that their fertilizer business will grow during the next three years. When asked why they were optimistic about the prospects for their own businesses, the most common reason offered... was that they are seeing increased efforts to sensitize farmers to the benefits of using fertilizers, and they expect increased fertilizer demand will follow" (p. 27).

Thus while optimism may fuel agro-dealer entry, low barriers to entry facilitates it. As mentioned in Section 3.1, although the government mandates that agro-dealers obtain a TFRA license to sell agricultural inputs, enforcement and compliance remain weak. Using the agro-dealer census, we find that on average only 42.4 percent of agro-dealers had a TFRA license and only 56.7 percent

[19] Growth is defined as opening more business locations, increasing sales at their current location, or increasing the quantity or diversity of products available at their current location.

of the markets studied had *at least* one agro-dealer with this license.[20] Table 1 shows that both of these measures are relatively stable over the study period.

Of the 515 agro-dealers in the census, 57.3 percent consistently had a TFRA license in all rounds; 32 percent had no license in any round. Hence 89.3 percent (i.e., 460 agro-dealers) had the same TFRA license status across all rounds. Despite the high agro-dealer turnover documented previously, agro-dealers' license status appears relatively consistent over time. The remaining 10.7 percent (i.e., 55 agro-dealers) had a TFRA license in some rounds but not in others. One-third of the 55 agro-dealers had a TFRA license upon entry but did not have one in subsequent rounds. The remaining two-thirds did not have a TFRA license upon entry but obtained one in subsequent rounds.

Using the same method captured in Equation 7, the annual entry rates for licensed and non-licensed agro-dealers are 11.2 percent and 22.8 percent, respectively, over the five-year period. This indicates that agro-dealers without a TFRA license enter at double the rate of those with a license.[21]

5.4 Agro-dealer Exit Decisions

If agro-dealers are optimistic and truly committed to the industry, then why do so many firms exit? As a first step toward answering this question, we again draw on the agro-dealer follow-up survey collected in 2022. As reported in Table **??**, roughly one third of agro-dealers (i.e., 30 percent) reported household-level or exogenous shocks as their primary reason for exiting. Nearly six in ten exited agro-dealers (i.e., 57 percent) reported doing so in response to profit losses from supply- or demand-side factors in the marketplace. This suggests that market factors primarily push (rather than pull) agro-dealers out of the sector.

Researchers have used a range of methods to identify the predictors of MSME exit. McKenzie and Paffhausen (2019) use a saturated dummy variable regression model to study firm exit; they control for several owner and MSME characteristics, as well as the number of years since the baseline survey. Kremer et al. (2014) estimate correlations between firm survival and several MSME owner characteristics.

[20]The TFRA license receipt variable for four agro-dealers in round one and five agro-dealers in round three were imputed with the median value of their respective rounds (i.e., no TFRA license). The 42.4 and 56.7 percent measures are weighted averages based on their respective samples and percentages listed in Table 1.

[21]If we exclude the 55 agro-dealers who switched TFRA license status during the study period, the annual entry rates adjust to 14.5 and 29.2 percent, respectively.

We use a linear probability model (LPM) with fixed effects to capture drivers associated with subsequent round agro-dealer exit. Our approach closely resembles Aga and Francis (2017) and Camacho and Rodriguez (2013), who both use probit models with fixed effects. Aga and Francis (2017) include time and country fixed effects while controlling for the varying number of years between survey rounds while Camacho and Rodriguez (2013) include time and firm fixed effects while controlling for the duration a firm has been in the panel. We employ a LPM to facilitate the direct interpretation of the marginal effects of different predictors on the probability of exit. Our results are robust to logit and probit functional forms (see Appendix Tables A.8 and A.9).[22]

The model specification is described by Equation 9.

$$Y_{im(t+1)} = \beta_0 + \beta_1 X'_{it} + \beta_2 Z'_{mt} + \alpha_t + \gamma_m + \epsilon_{imt} \tag{9}$$

$Y_{im(t+1)}$ is a binary indicator variable equal to one if agro-dealer i located in market m exited in round $t+1$. The vectors X'_{it} and Z'_{mt} capture time-variant agro-dealer and market-level controls, respectively, listed in Table 1. Round fixed effects (α_t) control for shocks that affect all markets similarly between rounds. Market fixed effects (γ_m) control for unobserved time-invariant attributes. Standard errors ϵ_{imt} are clustered at the market-level.

Table 5 presents the correlates of agro-dealer exit from the LPM. Columns 1, 2, and 3 show the results when there are no fixed effects, only round fixed effects, and both round and market fixed effects, respectively. Column 3 presents those associated with the full model in Equation 9. Results in Table 5 suggest that agro-dealer exit is not associated with most observable firm characteristics. An exception is agro-dealer licensing: not having a TFRA license is associated with an increased likelihood of subsequent round exit by 6.9 percentage points, holding all else constant. Consistent with this point, using the agro-dealer census and the method captured in Equation 8, we estimate the annual exit rate for agro-dealers with and without a TFRA license. That for non-licensed agro-dealers is double that of licensed agro-dealers (i.e., 11.4 and 6.7 percent).[23]

In our context, MSME age and size (in terms of the number of non-owner employees) are not

[22] Functional form assumptions are not driving our results. Note that we could not perform logit or probit model specifications that included market fixed effects due to convergence issues. There is limited variation in agro-dealer exit within markets. Given the robustness of the results for the LPMs without fixed effects and with round fixed effects, we would assume the results shown in Column 3 of Table 5 would also be robust to logit and probit model specifications if complete separation was not an issue.

[23] Referencing Section 5.3, if we exclude the 55 agro-dealers who switched TFRA license status during the study period, the annual exit rates adjust to 14.3 and 7.9 percent, respectively.

Table 5: Linear Probability Model for Predictors of Agro-dealer Exit

	Subsequent Round Exit		
	(1)	(2)	(3)
Variable	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)
Agro-dealer Characteristics			
Owns a car or truck	-0.075	-0.064	-0.109
	(0.055)	(0.056)	(0.075)
Has organizational certifications displayed	0.024	0.019	0.030
	(0.051)	(0.050)	(0.058)
Uses outdoor signage for advertising purposes	0.029	0.000	0.023
	(0.047)	(0.047)	(0.049)
Number of other locations that sell fertilizer	-0.004	-0.008	-0.016
	(0.035)	(0.034)	(0.043)
Has a license to sell fertilizer	-0.058	-0.052	-0.069*
	(0.039)	(0.037)	(0.038)
Number of additional employees present	0.050**	0.043*	0.022
	(0.022)	(0.023)	(0.029)
Number of years operating at current location	-0.011**	-0.010*	0.001
	(0.005)	(0.005)	(0.006)
Market Characteristics			
Number of agro-dealers operating in market	-0.005**	-0.002	0.048***
	(0.002)	(0.002)	(0.016)
Percent of *other* agro-dealer exits in market	0.054	0.016	-0.604***
	(0.092)	(0.099)	(0.108)
Percent of new market entrants in market cluster	0.027	0.008	0.054
	(0.034)	(0.038)	(0.075)
Round fixed effects	No	Yes	Yes
Market fixed effects	No	No	Yes
R^2	0.030	0.045	0.358
Observations	522	522	522

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parentheses) are clustered at the market-level (Abadie et al., 2023). Column 1 shows results associated with the linear probability model (LPM) with no fixed effects. Column 2 adds round fixed effects and Column 3 adds round and market fixed effects. We winsorize the variable "number of years operating at current location" only for data above the 95th percentile given its long-tailed distribution. In reference to the agro-dealer characteristics presented in Table 1, the "owns a smartphone or mobile phone" and "declared as permanent as compared to seasonal" variables had minimal variation within the sample so they are excluded from the LPM. Also, the variables "has at least one additional employee present" and "number of additional employees present" are highly correlated ($r = 0.743$) since the former is a binary version of the latter. We only include "number of additional employees present" in the LPM because it captures relatively more variation within the sample regarding agro-dealer size.

significant predictors of exit, despite consistent findings from other studies that link these factors to lower exit rates (Aga & Francis, 2017; Kremer et al., 2014; McKenzie & Paffhausen, 2019; Mead & Liedholm, 1998). Instead, results in Table 5 suggest the importance of market factors: agro-dealer exit is correlated with increased market competition and fewer competitor exits.

Market fixed effects control for time-invariant differences across markets, including their overall size or typical level of competition. The coefficient therefore captures how changes in competition within a given market over time affect the likelihood of an agro-dealer exiting: the effect of deviations from the market's typical number of agro-dealers rather than differences across large and small markets. Its positive sign suggests that an increase in the number of competitors within a market raises the probability of subsequent round exit for a given agro-dealer, consistent with heightened competition making survival more difficult.

Specifically, for every additional competitor in an agro-dealer's market, the likelihood of exit in the subsequent round increases by 4.8 percentage points, all else constant. Higher competition intensity within a market raises the probability of agro-dealer exit. Additionally, we find that as the share of an agro-dealer's *within* market competitors that exit increases, the likelihood of that agro-dealer exiting in the subsequent round decreases by 60.4 percentage points, all else constant. This captures a form of persistence in exit dynamics and could indicate that agro-dealer exit relieves competitive pressure: when some agro-dealers exit, the remaining ones may face less competition, making survival easier. Alternatively, agro-dealer exit may signal market distress (e.g., declining demand), with only the most vulnerable agro-dealers exiting first, leaving behind more resilient ones. These results suggest dynamic competitive effects in which the survival outcomes of *other* agro-dealers significantly impact their competitors. In short, higher competition leads to more exits, but once some agro-dealers exit, competition eases, and survivors stabilize.

Our results show that while few observable agro-dealer characteristics predict agro-dealer exit, competition and agro-dealer turnover *within* markets are relevant. In general, existing research does not tend to consider the relationship between market characteristics and MSME survival (Aga & Francis, 2017; Kremer et al., 2014; Liedholm, 2002; McKenzie & Paffhausen, 2019; Mead & Liedholm, 1998). Two studies provide important insights. First, Rudder (2022) finds that in the wake of an adverse environmental shock in Kenya, market-level competition—measured by the number of firms in operation—increases as more firms enter and fewer firms exit, despite the fact that individual firms experience declining sales, profits, and hiring. Second, Klapper and Richmond (2011) find increased competition—as a result of trade liberalization—raises the exit rate of formally-registered firms in Côte d'Ivoire. Our findings align with these patterns because we show that agro-dealer exit is inversely related to the exit of competitors in the same market—suggesting that higher competition may, in some cases, enhance agro-dealer survival.

6 Implications for Consumers

Our theoretical model highlights ways in which firm turnover influences consumer expectations about product quality in a market characterized by information asymmetries. Guided by this theory and noting the high turnover rates observed in the previous section, we now consider the implications of this high turnover for consumers in the market with a specific focus on the relationship between market-level beliefs about fertilizer quality and recent agro-dealer entry and exit.

6.1 Agro-dealer Turnover and Market-Level Beliefs

We begin by estimating Equation 10:

$$Y_{im2} = \beta_0 + \beta_1 Exit_{m(1,2)} + \beta_2 Entry_{m(1,2)} + \beta_3 MarketSize_{m1} + \beta_4 X'_{i2} + \epsilon_{im2} \tag{10}$$

Variable Y_{im2} represents market-level beliefs. $Exit_{m(1,2)}$ is the number of agro-dealer **exits** in market m between rounds one and two, while $Entry_{m(1,2)}$ is the the number of **new market entrants** in market m between rounds one and two. Since $Exit_{m(1,2)}$ and $Entry_{m(1,2)}$ are likely to be highly correlated,[24] we estimate the relationship for each factor independently and concurrently. $MarketSize_{m1}$ controls for the number of agro-dealers in market m in round one and the vector X'_{i2} represents farmer-level controls in round two.

Results are presented in Table 6. Columns 1-3 present the results where beliefs are measured as the number of farmers out of ten that farmer i located in market m in round two believed would receive bad quality fertilizer from market m. In columns 4-6 beliefs are measured as a dummy variable equal to one if the farmer expressed any concern about fertilizer quality in market m (that is, reported at least one farmer would receive a bag of bad quality fertilizer). Columns 1 and 4 report results from a regression estimating the relationship between exit (only) and beliefs, not controlling for entry. Columns 2 and 5 present the relationship between entry (only) and beliefs, not controlling from exit. Finally, Columns 3 and 6 report the estimates conditioning on both entry and exit simultaneously.

[24] Prior literature suggests firm entry rates are highly correlated with firm exit rates within and across sectors. This pattern has been documented among both formal firms (Caves, 1998; Chang, 2011; Dunne et al., 1988) and informal firms (McCaig & Pavcnik, 2021). The pattern implies that markets experiencing above average firm entry rates are likely to exhibit above average exit rates. In our sample, there is a weak correlation between the number of agro-dealer exits and new market entrants in the sample ($r = 0.0945$), ruling out multicollinearity as a major concern.

Table 6: Agro-dealer Turnover and Farmer's Market Quality Beliefs

	Farmers out of Ten Receiving Bad Quality Fertilizer			Concerned About Bad Quality Fertilizer		
	Exit Only (1)	Entry Only (2)	Both (3)	Exit Only (4)	Entry Only (5)	Both (6)
Variable	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)
Baseline market size	0.026	-0.018	0.075	0.010	-0.007	0.011
	(0.047)	(0.063)	(0.066)	(0.006)	(0.008)	(0.008)
Number of agro-dealer exits	-0.266*		-0.291*	-0.056**		-0.057**
	(0.148)		(0.149)	(0.023)		(0.023)
Number of new market entrants		-0.032	-0.055		0.003	-0.002
		(0.052)	(0.055)		(0.006)	(0.006)
Outcome variable mean	3.18	3.18	3.18	0.70	0.70	0.70
Farmer-level controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.025	0.020	0.026	0.022	0.013	0.022
Observations	1,241	1,241	1,241	1,241	1,241	1,241

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parentheses) are clustered at the market-level (Abadie et al., 2023). "Baseline market size" is the number of agro-dealers operating in a market in round one, "number of agro-dealer exits" is the number of agro-dealers that exited a market between rounds one and two, and "number of new market entrants" is the number of new agro-dealers that entered a market between rounds one and two. We use farmer beliefs that are associated with their proximate market. Farmer-level controls from Table 3 include "age," "household size," and "number of acres of land owned" as well as dummy variables for "is female," "no schooling," "secondary school," "vocational training," "university," and "is risk adverse." These results are robust to the following: (1) clustering standard errors at the village-level, (2) winsorizing the variable "number of new market entrants" at the 95th percentile given its long-tailed distribution, (3) winsorizing the variable "baseline market size" at the 95th percentile given its long-tailed distribution, and (4) using the percentage of agro-dealer exits/new market entrants as the independent variable. See Table A.10 for the results of these robustness checks.

We begin with the relationship between firm exit and consumer beliefs about market quality. We focus our discussion on the results of estimating the full specification controlling for both entry and exits simultaneously, but note that the results are consistent when we focus on only exit without controlling for entry. Results presented in Column 3 show that for every additional agro-dealer that exits, the number of farmers out of ten believed to receive bad quality fertilizer *decreases* by about 0.3. The direction and significance of this result is consistent with results in Column 6 showing that for every additional agro-dealer that exits a market, the likelihood that a farmer expresses concerned about the quality of fertilizer sold in that market *decreases* by 5.7 percent. These findings indicate that as agro-dealer exit increases within their market, farmers are less concerned about the quality of fertilizer sold in their market.

In other words, consumer beliefs about the market's overall product quality improve when firms exit in this setting. This empirical finding is consistent with Theorem 1, and suggests exiting firms are typically believed to have sold below-average product quality. Recall that in this setting farmer beliefs are consistently inaccurate - fertilizer quality has been shown to be of higher quality than a typical consumer expects. In this unique context, firm exits seem to play a role in correcting farmers' misconceptions about the market-level fertilizer quality, enabling better informed purchasing decisions.

In contrast to firm exit, we provide no evidence that farmers adjust average beliefs about fertilizer quality in response to a new market entrant. The estimated correlations in Columns 2, 3, 5, and 6 of Table 6 between the number of new market entrants and our beliefs indicators is small and not statistically different from zero. This finding is consistent with Theorem 3, which predicts a new market entrant will moderate consumer beliefs about the market's overall product quality. Our theory suggests the actual affect depends primarily on information signals specific to remaining incumbents. For that, we turn to the next subsection.

6.2 Information Signals through Established Client Relationships

To better understand the effect of a new firm's entry, we return to Theorem's 3.1 - 3.3. Each of these theorems rely on the important insight that revisions to market-level product quality beliefs after the arrival of a new firm, depend on the strength of aggregated information signals for incumbents. If a farmer has strong positive (negative) information about the quality of goods sold by a particular incumbent firm, then the new entrant is expected to lower (improve) consumer beliefs (Theorems 3.1 and 3.2) If no information signals are present in a market, then a new market entrant has no effect on a market's overall product quality (Theorem 3.3).

To test for a differential response to new firms conditional on information about existing firms, we leverage our small sample farmer data. We use data on reported quality beliefs for both an incumbent and a hypothetical new entrant, for both inputs and information, as well as information regarding the strength of relationship between the farmer and the existing agro-dealer. To connect our empirical results to the model, we assume farmers who report to having a consistent and stable relationship with a specific agro-dealer also have strong positive information about the quality of goods sold by that particular incumbent firm.

We estimate the following model with village fixed effects:

$$Y_{iv} = \beta_0 + \beta_1 New + \beta_2 Stable_i + \beta_3 (New \times Stable_i) + \beta_4 X_i' + \mu_v + \epsilon_{iv} \tag{11}$$

Variable Y_{iv} again represents market-level beliefs as stated by farmer i located in village v. Unlike in equation 10, beliefs can refer to either input quality or information quality. New is a dummy variable that equals one if the beliefs are in reference to a hypothetical new agro-dealer, and zero if the beliefs correspond to the current agro-dealer. $Stable_i$ is a dummy variable that equals one if farmer i has a stable relationship with a specific agro-dealer and zero otherwise.[25] The vector X_i' represents farmer-level controls, μ_v represents village fixed effects, and ϵ_{iv} is the error term.

In Equation 11, the coefficient β_0 is the average quality belief for farmers without stable agro-dealer relationships with respect to their current agro-dealer conditional on X_i' and μ_v. The coefficient β_1 is the average difference in beliefs between the current agro-dealer and a hypothetical new agro-dealer for these same farmers (i.e. those without a stable agro-dealer relationship). The coefficient β_2 captures the average difference in beliefs about current agro-dealer quality for farmers with a stable agro-dealer relationship relative to those without. Last, $\beta_3 - \beta_2$ captures the average difference in beliefs between the current agro-dealer and a hypothetical new agro-dealer for those farmers with a stable agro-dealer relationship.

The results are presented in Table 7. For completeness, we show results from estimating

[25] Having a stable relationship is defined as whether farmer i *usually* purchased agricultural inputs from the same agro-dealer over the past five years.

Equation 11 alongside a similar regression omitting the $Stable_i$ dummy and interaction term ($New \times Stable_i$). Results using beliefs about agricultural input quality as the dependent variable are presented in Columns 1-2. Similar findings with respect to information quality are presented in Columns 3-4.

Unlike the results presented in the previous section (which are based on observed market entrants relative to the aggregated market-level beliefs), the results in Table 7 suggest farmers' beliefs differ substantially between a specific known current agro-dealer and a hypothetical new entrant. Column 1 in Table 7 shows farmers have 1.74 point lower average quality expectations if purchasing inputs from an unknown new market entrant compared to a known local agro-dealer. Column 2 shows farmers have 2.04 point lower average quality expectations for information received from an unknown new market entrant compared to a known local agro-dealer.

Column 3-4 unpacks these results to compare expectations for two different types of farmers: those with a pre-existing stable relationship with their agro-dealer, and those whom are uncommitted to a particular agro-dealer. The results suggest this type of heterogeneity across farmers (and agro-dealers) matters. Farmers with a preference for a particular agro-dealer rate agricultural input quality of the current agro-dealer 4.44 points higher than that of a new unknown agro-dealer, holding all else constant. With respect to information, the same farmer's rating is 3.94 points higher for their known agro-dealer relative to a hypothetical new entrant. This finding is consistent with our model's prediction that when *positive* information signals for incumbents dominate a market, consumer beliefs about market-level product quality worsen with firm entry (Theorem 3.1)

In contrast, there's no difference in quality rating for farmers whom don't have a pre-existing stable relationship with their agro-dealer. The average differences presented in Column 1 are entirely driven by farmers with positive information about the agro-dealer from whom they have an established positive working relationship. This is consistent with the model's prediction in the case where no information signals are present in a market. In that case, a new market entrant is expected to have no effect on a market's overall product quality (Theorem 3.3).

Overall, farmers with stable agro-dealer relationships have likely developed substantial trust in their current agro-dealer, reinforced through repeated interactions and positive experiences. This trust may also make them more skeptical of new market entrants. As a result, those with stable agro-dealer relationships primarily drive the overall increase in concerns about agricultural input and information quality following the hypothetical entry of a new agro-dealer.

Table 7: Comparing Quality Rankings for a Known Agro-dealer Relative to a New Entrant

	Agricultural Input Quality Rating (1)	Agricultural Information Quality Rating (2)	Agricultural Input Quality Rating (3)	Agricultural Information Quality Rating (4)
Variable	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)
New market entrant	-1.740*** (0.296)	-2.037*** (0.282)	-0.161 (0.512)	-0.714 (0.496)
Stable relationship			1.918*** (0.392)	1.833*** (0.405)
New market entrant × Stable relationship			-2.520*** (0.613)	-2.110*** (0.591)
Village fixed effects	Yes	Yes	Yes	Yes
Farmer-level controls	Yes	Yes	Yes	Yes
R^2	0.176	0.204	0.239	0.259
Observations	300	300	300	300

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parentheses) are robust. Estimates from Equation 11. These findings are robust to ordered logit model specifications (see Table A.13). Having a stable relationship is defined as whether farmer i *usually* purchased agricultural inputs from the same agro-dealer over the past five years. Farmer-level controls from Table 4 include "age" and "number of acres of land cultivated in the last 12 months" as well as dummy variables for "is female," "no schooling," "primary school," "vocational training," and "university."

7 Conclusion

Agriculture contributes an estimated 17 percent of Sub-Saharan Africa's GDP and accounts for 52 percent of employment (World Bank, 2022, 2023). Despite its central role in the economy, agricultural productivity in the region remains low in relative and absolute terms (Sheahan & Barrett, 2017). One reason for this productivity gap is the low adoption of productivity-enhancing agricultural inputs among small-holder farmers (Asenso-Okyere & Jemaneh, 2012; De Janvry & Sadoulet, 2002; Sheahan & Barrett, 2017; Suri & Udry, 2022). In this paper, we suggest high agro-dealer turnover rates may play an important role in shaping farmer perceptions of agricultural input quality and thus affect related agricultural input adoption decisions.

Agro-dealers supply agricultural inputs and information in local markets and play a critical role in current and future agricultural productivity. Despite their importance for farmer technology adoption and agricultural development, relatively little is known about the operations, dynamics, and constraints of Africa's agro-dealer sector (A. Dillon et al., 2025).

Our paper takes an important step toward addressing this gap by quantifying and analyzing agro-dealer turnover in Tanzania. We document an annual agro-dealer entry rate of 34 percent. Unlike the "reluctant entrepreneurs" described by Banerjee and Duflo (2011), we find evidence of optimistic agro-dealers who report a strong commitment to their businesses and to the sector. Yet, we show that nearly one in five agro-dealers (i.e., 18 percent) exit annually. The rates of entry and exit that we document are more than double the rates found for MSME firms in non-agricultural sectors in similar low-income countries. While few observable agro-dealer characteristics predict exit, higher competition intensity within a market does lead to more agro-dealer exits.

Structural factors may explain the high agro-dealer turnover rates that we document, but this is an area with considerable opportunities for future research. We offer some possible explanations. First, agricultural MSMEs face low barriers to entry, especially when compared to other sectors. As shown in Table 1 and discussed in Section 3.1, a majority of agro-dealers operate without a license to sell fertilizer even though required by the Tanzanian government. Second, barriers to exit are also low and most agro-dealers operate with limited working capital. Third, as mentioned in Section 3.1, the Tanzanian government sets indicative prices for fertilizer. If these prices are too low for agro-dealers to cover operating costs, they may be forced to exit. Fourth, liquidity constraints and a high risk production environment may contribute to high rates of agro-dealer exit. Agricultural production relies on favorable weather and is affected by pests, disease, and other shocks. These shocks not only impact farmers' ability to pay for any agricultural inputs they may have purchased on credit, but also their future demand. More research on these factors and how they jointly affect the agro-dealer sector in low-income settings is needed.

What does high turnover imply for consumers? Broadly speaking, high firm turnover rates are evidence of three key conditions commonly associated with competitive markets: high contestability, market fragmentation, and hyper-localized demand. High contestability implies low barriers to entry and exit within a market. Minimal or unenforceable regulatory constraints and low initial capital requirements allow entrepreneurs to start new businesses with ease; similarly, the ability to close a business with limited financial losses helps to facilitate exit (Asplund & Nocke, 2006; Baumol et al., 1983). This dynamic fosters efficiency by ensuring only firms that can effectively compete and adapt remain in the market. Market fragmentation occurs when market power is evenly spread across numerous firms within a sector. In highly fragmented markets, firms must continuously innovate and differentiate their products and services to maintain a competitive position, or else be pushed out of the market (Asplund & Nocke, 2006; Baldwin & Gorecki, 1998; Caves, 1998). Consumers benefit from continual improvements in product quality, service, and pricing as inefficient firms are replaced or driven out by efficient ones. Hyper-localized demand reflects highly targeted consumer preferences or an emerging local trend. Niche markets develop as new market entrants seek to capitalize on these newly emerging (potential) profit opportunities (Kirzner, 1973, 1979). High levels of firm entry may result in temporary market saturation and overcrowding, especially in sectors with low barriers to entry (M. Carree & Dejardin, 2020; M. A. Carree & Thurik, 1999; Kirzner, 1973, 1979). Firms that are unable to quickly adapt to sudden shifts in technology, consumer behavior, or local market conditions in these niche markets may be forced to exit (Kirzner, 1973, 1979).

Competitive pressure drives each of these conditions, and these conditions simultaneously help maintain competitive markets. As a result, high firm turnover is often observed in competitive markets. Microeconomic theory suggests competitive markets enhance consumer welfare by offering greater product and service variety, improved product and service quality, and more competitive pricing.[26]

But what are the implications of high firm turnover in markets characterized by weak regulation and asymmetric information? A distinguishing feature of the agro-dealer sector is that the products sold are often experience or credence goods, characterized by important information asymmetries. We develop a theoretical model of firm entry and exit under information asymmetries. Our model shows how and why consumer beliefs about market-level product quality can improve or deteriorate when a firm *exits*. The result depends on what consumers believe about the product quality of the exiting firm. The model also explores how consumers revise their beliefs following a new market entrant, which depends on their beliefs about incumbents in their market. Future research might consider applying the model to other markets for experience or credence goods in poorly regulated settings, including veterinary drugs, informal education services, and healthcare provision.

We use the model's predictions to interpret the relationship between agro-dealer turnover and farmer beliefs about agricultural input quality in their local market. In our setting, farmers' perceptions of average market quality improve following a firm's exit—consistent with the idea

[26] Any one of these three underlying conditions, or high turnover more broadly, are not sufficient to imply a competitive market. For example, if more recent new market entrants are more likely to exit than established dominant incumbents, high turnover may actually be explained by a *lack* of competition.

that the departing firm was believed to sell below-average quality products. Given evidence that farmers often hold inaccurate beliefs about fertilizer quality (Hoel et al., 2024; Michelson et al., 2021), our findings suggest that agro-dealer exits may help align farmer beliefs more closely with actual market conditions. Unlike exit, farmers' beliefs do not respond on average to agro-dealers entering the market. However, farmers who regularly purchase agricultural inputs from the *same* agro-dealer have relatively worse quality expectations for a new market entrant.

Our finding that farmers revise their beliefs about agricultural input quality based on agro-dealer exit raises an important question: if exits are common and prompt belief updating, why do inaccurate beliefs persist in the market? High turnover might mean that the market isn't ever stable enough to really shift beliefs. One possibility is that beliefs lag reality because learning is dominated by agro-dealer failure rather than successes. Exits improve beliefs, but learning is slow relative to the turnover in the market. Thus, farmers revise their beliefs around the edits but if new agro-dealers continually enter the market, the net effects might be that beliefs improve locally around exits but do not shift enough to *fix* the incorrect beliefs. Individual agro-dealer exits improve farmer beliefs but the entry of the new agro-dealers prevents a full correction. A second possibility is survivorship bias; agro-dealers who don't exit may be those who are better at establishing and maintaining relationships with farmers. If there are a lot of unreliable entrants, the equilibrium doesn't shift enough to correct beliefs. Finally, farmer belief updating could be slow or asymmetric (Abay, Barrett, et al., 2023; Abay, Wossen, et al., 2023).

Our findings have several implications for policy and market design. Farmers' hesitation to trust new market entrants presents a key challenge for MSMEs operating in weakly regulated environments, where it is difficult to establish credibility or signal quality (Creane & Jeitschko, 2016; Zhang et al., 2022). At the same time, stable relationships between farmers and existing agro-dealers reduce uncertainty in markets with information asymmetries but also may create entry barriers that can contribute to the slow growth and high exit rates observed among new market entrants (Aga & Francis, 2017; McKenzie & Paffhausen, 2019).

Strengthening licensing enforcement could reduce spurious entry and accelerate belief updating, but overly stringent requirements risk dampening competition, increasing costs, and slowing learning. Licensing could serve as a useful quality signal if coupled with complementary measures—such as public quality test results or agro-dealer rating systems. While agro-dealer exits may help correct misinformation, high turnover may also undermine the development of trust, credit relationships, and the provision of agricultural information or advice. Thus, turnover itself may not be the core problem. Instead, the problem may be the perceived entry of low-quality agro-dealers that fails to support a healthy, trusted agro-dealer sector.

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Appendix

This is the detailed proof for Lemma 1 showing the partial derivative of π_{jimt} with respect to α_{jimt}. Yet given the negative sign associated with α_{jimt}, α_{-jimt}, and p_{jmt} in Equation 1, the partial derivative with respect to α_{jimt} yields the same result as that with respect to α_{-jimt} and p_{jmt}.

Since $\pi_{jimt} = \dfrac{1}{1+e^{-(\alpha_{jimt}+\alpha_{-jimt})-p_{jmt}}} = -(1+e^{-(\alpha_{jimt}+\alpha_{-jimt})-p_{jmt}})^{-2}$, we get:

$$\begin{aligned}
\frac{\partial \pi_{jimt}}{\partial \alpha_{jimt}} &= -(1+e^{-(\alpha_{jimt}+\alpha_{-jimt})-p_{jmt}})^{-2}\left(e^{-(\alpha_{jimt}+\alpha_{-jimt})-p_{jmt}}\right)(-1) \\
&= (1+e^{-(\alpha_{jimt}+\alpha_{-jimt})-p_{jmt}})^{-2}\left(e^{-(\alpha_{jimt}+\alpha_{-jimt})-p_{jmt}}\right) \\
&= \pi_{jimt}^2\left(\frac{1-\pi_{jimt}}{\pi_{jimt}}\right) \\
&= \frac{\pi_{jimt}^2-\pi_{jimt}^3}{\pi_{jimt}} \\
&= \pi_{jimt}-\pi_{jimt}^2 \\
&= \pi_{jimt}(1-\pi_{jimt}) > 0 \text{ given that } \pi_{jimt} \in (0,1)
\end{aligned}$$

Thus, $\frac{\partial \pi_{jimt}}{\partial \alpha_{jimt}} = \frac{\partial \pi_{jimt}}{\partial \alpha_{-jimt}} = \frac{\partial \pi_{jimt}}{\partial p_{jmt}} = \pi_{jimt}(1-\pi_{jimt}) > 0$

Table A.8: Logit Model for Predictors of Agro-dealer Exit

	Subsequent Round Exit	
	(1)	(2)
Variable	Coefficient (Std. Error)	Coefficient (Std. Error)
Agro-dealer Characteristics		
Owns a car or truck	-0.383	-0.331
	(0.292)	(0.302)
Has organizational certifications displayed	0.126	0.103
	(0.264)	(0.263)
Uses outdoor signage for advertising purposes	0.140	-0.004
	(0.231)	(0.234)
Number of other locations that sell fertilizer	-0.020	-0.038
	(0.170)	(0.171)
Has a license to sell fertilizer	-0.288	-0.255
	(0.192)	(0.189)
Number of additional employees present	0.251**	0.215*
	(0.107)	(0.110)
Number of years operating at current location	-0.057**	-0.053*
	(0.028)	(0.028)
Market Characteristics		
Number of agro-dealers operating in market	-0.023**	-0.009
	(0.011)	(0.011)
Percent of *other* agro-dealer exits in market	0.244	0.077
	(0.414)	(0.456)
Percent of new market entrants in market cluster	0.125	0.039
	(0.152)	(0.175)
Round fixed effects	No	Yes
R^2	0.026	0.038
Observations	522	522

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the market-level (Abadie et al., 2023). We winsorize the variable "number of years operating at current location" only for data above the 95th percentile given its long-tailed distribution. Columns 1 and 2 show the logit model specifications when there are no fixed effects and only round fixed effects, respectively. We could not perform a logit model specification that included market fixed effects due to convergence issues. There is limited variation in agro-dealer exit within markets. Given the robustness of the results for the LPMs without fixed effects and with round fixed effects, we would assume the results shown in Column 3 of Table 5 would also be robust to a logit model specification if complete separation was not an issue.

Table A.9: Probit Model for Predictors of Agro-dealer Exit

	Subsequent Round Exit	
	(1)	(2)
Variable	Coefficient (Std. Error)	Coefficient (Std. Error)
Agro-dealer Characteristics		
Owns a car or truck	-0.227	-0.194
	(0.168)	(0.175)
Has organizational certifications displayed	0.070	0.059
	(0.158)	(0.158)
Uses outdoor signage for advertising purposes	0.088	-0.001
	(0.139)	(0.141)
Number of other locations that sell fertilizer	-0.020	-0.035
	(0.103)	(0.103)
Has a license to sell fertilizer	-0.169	-0.156
	(0.115)	(0.113)
Number of additional employees present	0.149**	0.127*
	(0.065)	(0.067)
Number of years operating at current location	-0.034**	-0.031*
	(0.017)	(0.017)
Market Characteristics		
Number of agro-dealers operating in market	-0.014**	-0.005
	(0.006)	(0.006)
Percent of *other* agro-dealer exits in market	0.144	0.037
	(0.252)	(0.279)
Percent of new market entrants in market cluster	0.076	0.025
	(0.093)	(0.106)
Round fixed effects	No	Yes
R^2	0.026	0.038
Observations	522	522

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the market-level (Abadie et al., 2023). We winsorize the variable "number of years operating at current location" only for data above the 95th percentile given its long-tailed distribution. Columns 1 and 2 show the probit model specifications when there are no fixed effects and only round fixed effects, respectively. We could not perform a probit model specification that included market fixed effects due to convergence issues. There is limited variation in agro-dealer exit within markets. Given the robustness of the results for the LPMs without fixed effects and with round fixed effects, we would assume the results shown in Column 3 of Table 5 would also be robust to a probit model specification if complete separation was not an issue.

Table A.10: Linear Model for Robustness Checks for the Effect of Agro-dealer Turnover on Farmer Beliefs

	Farmers out of Ten Receiving Bad Quality Fertilizer			Concerned About Bad Quality Fertilizer		
	Exit Only	Entry Only	Both	Exit Only	Entry Only	Both
Variable	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)
(A) Clustering Standard Errors at the Village-Level						
Number of agro-dealer exits	-0.266*		-0.291**	-0.056***		-0.057***
	(0.139)		(0.142)	(0.021)		(0.021)
Number of new market entrants		-0.032	-0.055		0.003	-0.002
		(0.051)	(0.053)		(0.006)	(0.006)
R^2	0.025	0.020	0.026	0.022	0.013	0.022
Observations	1,241	1,241	1,241	1,241	1,241	1,241
(B) Winsorizing "Number of New Market Entrants"						
Number of agro-dealer exits			-0.295**			-0.057**
			(0.147)			(0.023)
Number of new market entrants		-0.115	-0.137**		0.002	-0.003
		(0.069)	(0.068)		(0.011)	(0.011)
R^2		0.022	0.028		0.013	0.022
Observations		1,241	1,241		1,241	1,241
(C) Winsorizing "Baseline Market Size"						
Number of agro-dealer exits	-0.258		-0.264	-0.060**		-0.060**
	(0.160)		(0.162)	(0.024)		(0.023)
Number of new market entrants		-0.025	-0.031		0.002	0.000
		(0.043)	(0.047)		(0.005)	(0.005)
R^2	0.025	0.021	0.025	0.022	0.014	0.022
Observations	1,241	1,241	1,241	1,241	1,241	1,241
(D) Using "Percentage of Agro-dealer Exits/New Market Entrants"						
Percentage of agro-dealer exits	-0.610**		-0.589**	-0.099**		-0.100**
	(0.269)		(0.270)	(0.040)		(0.040)
Percentage of new market entrants		-0.149	-0.129		0.005	0.008
		(0.090)	(0.086)		(0.014)	(0.014)
R^2	0.026	0.021	0.027	0.023	0.016	0.023
Observations	1,198	1,198	1,198	1,198	1,198	1,198
Outcome variable mean	3.18	3.18	3.18	0.70	0.70	0.70
Farmer-level controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each robustness check adjusts the model specification in Equation 10: Panel A clusters standard errors at the village-level, Panel B winsorizes "number of new market entrants" at the 95th percentile given its long-tailed distribution, Panel C winsorizes "baseline market size" at the 95th percentile given its long-tailed distribution, and Panel D uses the "percentage of agro-dealer exits/new market entrants" as the independent variable. Standard errors are clustered at the market-level unless otherwise noted. Panels A, B, and C control for "baseline market size." See the notes under Table 6 for variable definitions and farmer-level controls included. Both the "percentage of agro-dealer exits" and the "percentage of new market entrants" are calculated as the ratio of their respective counts to the "baseline market size." Results in Panel D have a smaller sample size because farmers from markets without agro-dealers in round one are excluded. We use farmer beliefs that are associated with their proximate market. In Panel C, the "number of agro-dealer exits" coefficients -0.258 and -0.264 have associated p-values of 0.110 and 0.106, respectively.

Table A.11: Linear Model for the Effect of Agro-dealer Turnover on Farmer Beliefs by Baseline Market Size

	Farmers out of Ten Receiving Bad Quality Fertilizer			Concerned About Bad Quality Fertilizer		
	Exit Only (1)	Entry Only (2)	Both (3)	Exit Only (4)	Entry Only (5)	Both (6)
Variable	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)
(A) Smaller Markets						
Baseline market size	0.088	-0.117	0.103	0.023	-0.010	0.022
	(0.229)	(0.237)	(0.220)	(0.029)	(0.031)	(0.029)
Number of agro-dealer exits	-0.505**		-0.505**	-0.072**		-0.072**
	(0.199)		(0.200)	(0.029)		(0.029)
Number of new market entrants		-0.067	-0.067		0.008	0.008
		(0.082)	(0.080)		(0.011)	(0.012)
R^2	0.040	0.031	0.041	0.026	0.018	0.026
Observations	851	851	851	851	851	851
(B) Larger Markets						
Baseline market size	-0.013	0.015	0.028	0.004	0.002	0.010
	(0.061)	(0.094)	(0.095)	(0.010)	(0.013)	(0.013)
Number of agro-dealer exits	-0.063		-0.082	-0.048		-0.051
	(0.233)		(0.237)	(0.034)		(0.034)
Number of new market entrants		-0.036	-0.040		-0.003	-0.006
		(0.063)	(0.064)		(0.008)	(0.008)
R^2	0.024	0.024	0.025	0.021	0.013	0.022
Observations	390	390	390	390	390	390
Outcome variable mean	3.18	3.18	3.18	0.70	0.70	0.70
Farmer-level controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the market-level (Abadie et al., 2023). "Baseline market size" is the number of agro-dealers operating in a market in round one, "number of agro-dealer exits" is the number of agro-dealers that exited a market between rounds one and two, and "number of new market entrants" is the number of new agro-dealers that entered a market between rounds one and two. We use farmer beliefs that are associated with their proximate market. Farmer-level controls from Table 3 include "age," "household size," and "number of acres of land owned" as well as dummy variables for "is female," "no schooling," "secondary school," "vocational training," "university," and "is risk adverse." Smaller markets are those that have a size equal to or less than the median number of agro-dealers in round one (i.e., two).

Table A.12: Linear Model for the Effect of Agro-dealer Turnover on Farmer Beliefs by Whether A Farmer is Risk Averse

	Farmers out of Ten Receiving Bad Quality Fertilizer			Concerned About Bad Quality Fertilizer		
	Exit Only (1)	Entry Only (2)	Both (3)	Exit Only (4)	Entry Only (5)	Both (6)
Variable	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)
(A) Farmer is Risk Averse						
Baseline market size	-0.094	-0.169*	-0.021	0.009	-0.022	0.008
	(0.073)	(0.085)	(0.088)	(0.010)	(0.015)	(0.014)
Number of agro-dealer exits	-0.432**		-0.469**	-0.096***		-0.096***
	(0.200)		(0.205)	(0.031)		(0.032)
Number of new market entrants		-0.054	-0.088		0.008	0.001
		(0.061)	(0.059)		(0.013)	(0.012)
R^2	0.055	0.045	0.058	0.046	0.022	0.046
Observations	481	481	481	481	481	481
(B) Farmer is Not Risk Averse						
Baseline market size	0.012	0.004	0.016	0.110*	0.086	0.153*
	(0.009)	(0.009)	(0.012)	(0.060)	(0.078)	(0.089)
Number of agro-dealer exits	-0.037		-0.039	-0.182		-0.205
	(0.028)		(0.028)	(0.167)		(0.169)
Number of new market entrants		-0.001	-0.005		-0.028	-0.045
		(0.009)	(0.009)		(0.067)	(0.071)
R^2	0.010	0.006	0.010	0.021	0.019	0.022
Observations	760	760	760	760	760	760
Outcome variable mean	3.18	3.18	3.18	0.70	0.70	0.70
Farmer-level controls	Yes	Yes	Yes	Yes	Yes	Yes

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are clustered at the market-level (Abadie et al., 2023). "Baseline market size" is the number of agro-dealers operating in a market in round one, "number of agro-dealer exits" is the number of agro-dealers that exited a market between rounds one and two, and "number of new market entrants" is the number of new agro-dealers that entered a market between rounds one and two. We use farmer beliefs that are associated with their proximate market. Farmer-level controls from Table 3 include "age," "household size," and "number of acres of land owned" as well as dummy variables for "is female," "no schooling," "secondary school," "vocational training," and "university." A farmer is "risk averse" if they believe they take much fewer risks or somewhat fewer risks compared to others.

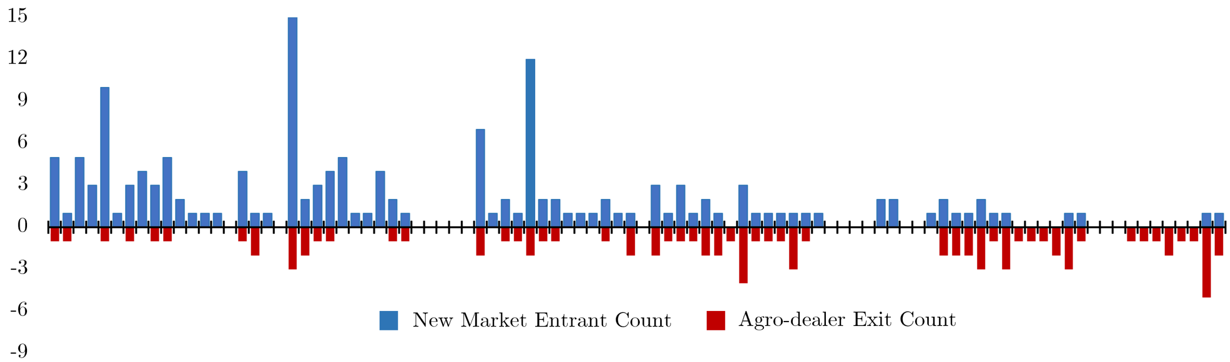

Figure A.4: New Market Entrant and Agro-dealer Exit Count by Market Between Rounds One and Two

Notes: This figures shows the number of agro-dealers that entered and exited each market between rounds one and two. The order of markets on the x-axis of Figure 2 is preserved, except one market is omitted because the farmer sample is distributed across 94 markets, not 95. The figure highlights greater variation in agro-dealer entry across markets compared to agro-dealer exit. Specifically, the sample variance is 5.97 for agro-dealer entry and 1.05 for agro-dealer exit. There is also a higher concentration of markets with low levels of agro-dealer exit compared to entry: 67 percent had zero to one new market entrants, compared to 78 percent having the same range for agro-dealer exits. Lastly, the annual agro-dealer entry and exit rates between rounds one and two exhibit variances of 0.77 and 0.15, respectively. Hence, agro-dealer entry exhibits greater variation than exit, both in absolute and relative terms.

Table A.13: Ordered Logit Model for the Effect of Hypothetical Agro-dealer Entry on Farmer Input and Information Quality Ratings

	Agricultural Input Quality Rating (1)	Agricultural Information Quality Rating (2)	Agricultural Input Quality Rating (3)	Agricultural Information Quality Rating (4)
Variable	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)	Coefficient (Std. Error)
New market entrant	-1.222*** (0.234)	-1.524*** (0.231)	-0.081 (0.367)	-0.597 (0.384)
Loyal			1.468*** (0.318)	1.380*** (0.321)
New market entrant × Loyal			-1.946*** (0.472)	-1.561*** (0.466)
Village fixed effects	Yes	Yes	Yes	Yes
Farmer-level controls	Yes	Yes	Yes	Yes
R^2	0.049	0.057	0.070	0.073
Observations	300	300	300	300

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors are robust. Columns 1 and 2 represent Equation **??** while Columns 3 and 4 represent Equation 11. Having a stable relationship is defined as whether farmer i *usually* purchased agricultural inputs from the same agro-dealer over the past five years. Farmer-level controls from Table 4 include "age" and "number of acres of land cultivated in the last 12 months" as well as dummy variables for "is female," "no schooling," "primary school," "vocational training," and "university."

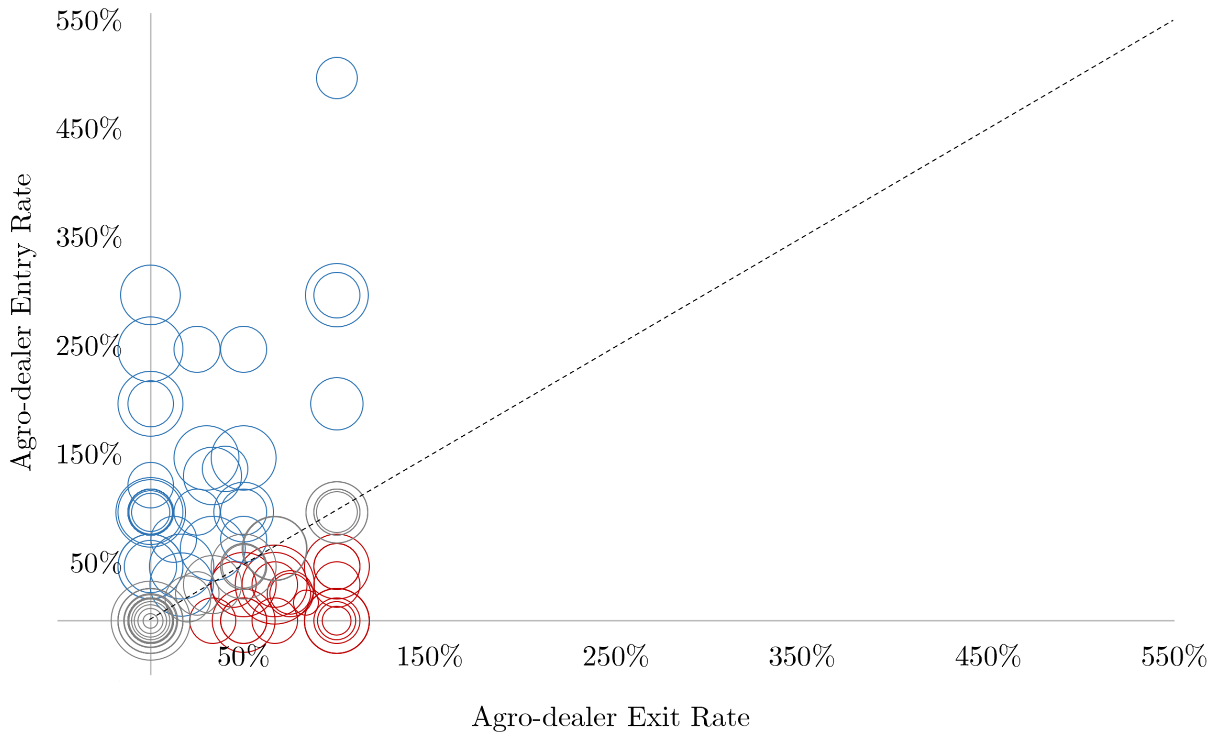

Figure A.5: Farmer Sample Concentration Relative to Market Agro-dealer Turnover Rates

Notes: This figure presents a scatter plot of the farmer sample across markets, depicting agro-dealer turnover rates between rounds one and two. Each bubble represents a market, with its size corresponding to the number of farmers residing in that market in round two. To identify whether a larger portion of the farmer sample resides in markets with a lower agro-dealer entry rate relative to the exit rate, attention is given to bubbles below the $y = x$ diagonal line (where the agro-dealer entry rate equals the agro-dealer exit rate). The area below and to the right of this line highlights markets with lower entry rates than exit rates. Of the 1,241 farmers in the sample, 301 reside in markets below the diagonal (red), 511 reside in those above it (blue), and 429 reside in those on it (gray). This indicates that the majority of farmers are not in markets where the agro-dealer entry rate is lower than the agro-dealer exit rate. Only 94 of the 97 markets are represented in this figure, as the farmer sample only includes those distributed across 94 markets.