Firm Turnover under Asymmetric Information: Tanzania's Agro-dealer Sector*

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Abstract

We analyze firm turnover (i.e., entry and exit) and its consumer implications in a market characterized by asymmetric information. Using a census of agro-dealers in Tanzania's Morogoro Region, we document annual entry and exit rates of 34 and 18 percent, respectively. These rates are more than double those reported for micro-, small-, and medium-enterprises operating in non-agricultural sectors in similar low-income countries. Agro-dealer exit is more common in highly competitive markets and is not well predicted by observable agro-dealer characteristics. Motivated by these patterns, we develop a theoretical model of firm turnover under information asymmetries and test its predictions empirically. We find that farmers' beliefs about agricultural input quality improve following an agro-dealer's exit, consistent with our model's prediction that farmers believe exiting agro-dealers sold low-quality agricultural inputs. Moreover, farmers who regularly purchase agricultural inputs from the same agro-dealer expect new market entrants to provide lower-quality agricultural inputs. These findings suggest that agro-dealer turnover critically shapes farmers' technology adoption decisions. In markets with information asymmetries, repeated transactions with incumbents help farmers manage quality uncertainty.

JEL codes: O12, D82, Q13, L15

Keywords: agro-dealers, Sub-Saharan Africa, agricultural input markets, asymmetric information, technology adoption, firm turnover, product quality beliefs, agricultural input quality, market trust

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1 Introduction

Markets are often characterized by significant information asymmetries between buyers and sellers, limiting buyers' ability to assess product quality before purchase. This is especially pronounced in low-income countries, where markets frequently operate under weak regulatory environments. Agricultural inputs, including seeds, fertilizer, and pesticides, are prone to these asymmetries, as they are typically experience or credence goods whose agronomic quality cannot be easily evaluated until after use. Agricultural input suppliers (i.e., agro-dealers) predominantly operate as micro-, small-, and medium-enterprises (MSMEs) and play a central role in these markets. They sell agricultural inputs to farmers and serve as key sources of agricultural information and advice, which is particularly important in contexts where formal, public extension services are underfunded or absent (Sones et al., 2015; Rutsaert & Donovan, 2020). Just as farmers cannot directly observe the quality of agricultural inputs at the point of sale, they also cannot readily assess the quality of agricultural information and advice supplied by agro-dealers.

Previous research suggests that information asymmetries can partly explain the low adoption of modern agricultural inputs in Sub-Saharan Africa—and, consequently, the region's low agricultural productivity—as farmers reduce investment when uncertain about the quality of agricultural inputs available in their own markets (Ashour et al., 2019; Gilligan & Karachiwalla, 2021; Michelson et al., 2021; Bulte et al., 2023). Considering the challenges posed by weak government regulation and limited enforcement (Kansiime, 2021; Michelson et al., 2025), repeated transactions with the same agro-dealer can help mitigate these information asymmetries by allowing farmers to learn about the quality of their agricultural inputs or information over time. Such relationships can also incentivize agro-dealers to maintain high standards to build a reputation. However, high agro-dealer turnover may disrupt these dynamics, limiting the potential to resolve information-related market failures.

In this paper, we analyze firm turnover (i.e., entry and exit) among agro-dealers and its implications for smallholder farmers. The agro-dealer turnover rates we document are considerably higher than those documented for non-agricultural sectors in the MSME literature. Theoretically, high firm turnover rates suggest three key conditions that are associated with a competitive market: high contestability, market fragmentation, and hyper-localized demand. Each is driven by competitive pressure and each helps sustain competition. Economic theory suggests that high firm turnover enhances competition and benefits consumers, even in imperfectly competitive markets (Asplund & Nocke, 2006; Chang, 2011). For instance, firm entry can stimulate job creation and local economic growth, indirectly benefiting consumers. In contrast, firm exit can reduce consumer choice, impose switching costs as buyers search for alternative suppliers, and lead to job loss. Given this, the net welfare effects of high firm turnover are difficult to assess, even in markets with limited information asymmetries. In markets characterized by information asymmetries, such as the agro-dealer sector, the impacts become even less clear.

We develop a theoretical model of firm turnover in markets with information asymmetries. The model formalizes how consumers form and update beliefs about market-level product quality based on past transactions, information shared by others, and prior market expectations. Our model predicts that when a firm perceived by consumers to be selling below-average quality products exits the market, consumer expectations of market-level product quality improve. Conversely, if a firm perceived to be selling above-average quality products exits, consumer expectations get worse. If most incumbents in the market are perceived to be selling above-average quality products, firm entry reduces consumer expectations of market-level product quality. If instead most incumbents are perceived to be selling below-average quality products, firm entry improves these expectations. When no strong incumbent information signals exist, firm entry has no effect on consumer beliefs.

We test the model empirically using data from Tanzania's Morogoro Region, an important agricultural hub. Our data include a three-round census of all agro-dealers in this region collected between 2015 and 2020. Each agro-dealer operates within one of 97 major markets identified in the region. We merge the agro-dealer census with a survey of 1,242 smallholder farmers collected in 2019. All farmers reside within three to seven kilometers of a market in the agro-dealer census. To further test the consumer implications of our theoretical model, we analyze a smaller cross-sectional dataset of 150 farmers collected in the same region in 2022.

We establish three primary empirical findings. First, agro-dealer turnover rates are substantially higher than those observed for MSMEs operating in non-agricultural sectors in similar low-income settings (Liedholm, 2002; Kremer et al., 2014; McKenzie & Paffhausen, 2019; McCaig & Pavcnik, 2021). Using the three-round agro-dealer census that spans four years, we calculate annual exit and entry rates of 18 and 34 percent, respectively. Our agro-dealer exit rate is up to 4.5 times higher than MSME exit rates previously documented in low-income countries (Kremer et al., 2014; McKenzie & Paffhausen, 2019; McCaig & Pavcnik, 2021), while our agro-dealer entry rate is roughly double (Liedholm, 2002; McCaig & Pavcnik, 2021). These findings suggest that agro-dealers operate in a more dynamic environment relative to MSMEs operating in *other* sectors in low-income countries.

Second, we find that agro-dealer exit is better explained by market dynamics rather than observable firm characteristics. An exception is firm licensing status: agro-dealers without a government-issued license to sell fertilizer are more likely to exit. Operating without such a license may signal limited operational investment or a higher degree of informality. While prior research finds younger and smaller MSMEs are more likely to exit (Mead & Liedholm, 1998; Kremer et al., 2014; Aga & Francis, 2017; McKenzie & Paffhausen, 2019), we instead show that market factors are important: agro-dealer exit is strongly correlated with greater market competition and fewer competitor exits.

Finally, we show that high firm turnover rates have important implications for consumer beliefs in markets characterized by information asymmetries. Empirically, we find that farmer assessments of market-level agricultural input quality improve when agro-dealers *exit* a market. Our theoretical model suggests this happens because consumers assume exiting firms offered below-average quality products. Moreover, we show that, on average, farmers do not adjust their market-level beliefs about agricultural input quality in response to new market entrants. This finding aligns with our model's prediction that firm entry has a moderating effect, anchoring consumer beliefs to market-level priors and leading to no change in beliefs when incumbent information signals are weak or absent. Yet, farmers with an ongoing purchasing relationship with a specific agro-dealer express greater concern about the quality of agricultural inputs and information provided by a new market entrant. This is consistent with our model's prediction that when strong positive incumbent information signals dominate, firm entry can worsen consumer market-level product quality beliefs.

Our findings contribute to three key literatures. First, a substantial body of research explores the constraints that smallholder farmers confront in adopting productivity-enhancing agricultural technologies, including limited information, credit, insurance, or liquidity (Suri and Udry (2022) provide a recent review). However, this literature largely overlooks the role of agricultural input market intermediaries.[1] Agro-dealers are essential to farmers' decisions to adopt agricultural inputs, serving as input suppliers and informal sources of agricultural information. However, as emphasized by A. Dillon et al. (2025), the agro-dealer sector remains understudied at least in part due to difficulties associated with sampling and surveying, its informality, and a longstanding emphasis in development economics on treating farmer technology adoption as a household decision rather than one shaped by market actors. Our study is part of a small but growing set of papers that address this gap. Kariuki et al. (2025) use a randomized controlled trial to examine how margin

[1] Bergquist and Dinerstein (2020) and B. Dillon and Dambro (2017) review the literature on agricultural output (but not input) market intermediaries.

subsidies influence stocking and sales behavior among Kenyan agro-dealers, while results from Dar et al. (2024) show that Indian agro-dealers affect farmers' technology adoption decisions through information provision. By focusing on firm turnover, we provide insight into how the structure and stability of the agro-dealer sector influence market functioning and farmers' beliefs, offering an important foundation for understanding the market-level frictions that limit agricultural technology adoption and, ultimately, agricultural productivity.

Second, we contribute to a literature focused on MSME operations and turnover in low-income countries (Mead & Liedholm, 1998; Liedholm, 2002; Klapper & Richmond, 2011; Kremer et al., 2014; Li & Rama, 2015; Aga & Francis, 2017; McKenzie & Paffhausen, 2019; McCaig & Pavcnik, 2021). Existing research shows MSMEs are mostly informal, under-capitalized, prone to early exit, and constrained by limited access to finance, infrastructure, and managerial capacity (Mead & Liedholm, 1998; Liedholm, 2002; Aga & Francis, 2017). Several studies theorize that high MSME entry rates can facilitate employment growth and structural transformation, whereas high MSME exit rates may lead to labor market instability and inefficient resource allocation (Mead & Liedholm, 1998; Klapper & Richmond, 2011; McCaig & Pavcnik, 2021). Previous research also explores how firm characteristics—including size, age, and entrepreneurial ability—relate to MSME survival and performance; however, evidence on the success of targeted support interventions designed to improve MSME longevity or growth remains mixed (Kremer et al., 2014; McKenzie & Paffhausen, 2019; Aga & Francis, 2017). While this literature has emphasized macro-economic implications of MSME turnover such as employment shifts and productivity changes, it has not directly examined how MSME turnover shapes experiences and outcomes at the consumer-level (Mead & Liedholm, 1998; Liedholm, 2002; Klapper & Richmond, 2011; Li & Rama, 2015; McCaig & Pavcnik, 2021). Our paper provides empirical evidence regarding how MSME turnover impacts consumers directly.

Finally, we analyze the consequences of firm turnover in a market characterized by information asymmetries. Information frictions between firms and consumers can distort firm dynamics: firms that provide low-quality products can persist when consumers cannot accurately evaluate quality, while high-quality new market entrants lacking credible ways to signal their quality may fail to gain traction in the market (Akerlof, 1970; Klein & Leffler, 1981). Many studies underscore how consumer learning and reputation mechanisms shape market selection. Shapiro (1983) shows that firms can build reputations for high quality over time, allowing them to earn price premiums as a reward. In online and healthcare markets, reputational feedback affects consumer behavior in ways that disadvantage lower-quality sellers and providers, such as through reduced sales or poorer matching, which can contribute to their exit (Bai, 2018; Pei, 2023). Interventions designed to improve access to quality signals like targeted outreach or digital labeling can help discipline markets by shifting consumer demand toward suppliers that offer higher-quality products (Bold et al., 2017; Michelson et al., 2021). In some cases, these shifts can induce exit among lower-quality providers (Bao et al., 2024). However, previous research has not explicitly modeled how firm turnover itself can inform consumer belief formation in markets with information asymmetries. Our theoretical model addresses this gap, capturing how consumer learning processes are influenced by market dynamics. The model is relevant to a variety of settings where quality is difficult to observe, including restaurants, healthcare, repair services, and education.

The paper proceeds as follows: Section 2 presents our theoretical model of firm turnover under information asymmetries and derives predictions about how it impacts consumer beliefs. Sections 3 and 4 describe the institutional setting of Tanzania's agro-dealer sector and the data, respectively. Section 5 characterizes the high rates of agro-dealer turnover as well as agro-dealer entry and exit decisions. Section 6 empirically tests our model's predictions by analyzing how agro-dealer turnover affects farmer beliefs about agricultural input and information quality. Section 7 concludes.

2 Model of Firm Turnover Under Information Asymmetries

High firm turnover typically reflects three underlying conditions of competitive markets: high contestability, market fragmentation, and hyper-localized demand. In highly contestable markets, low entry and exit barriers, such as minimal regulatory constraints and low capital requirements, make it easier for firms to enter and exit with relatively low risk (Baumol et al., 1983; Asplund & Nocke, 2006). This condition promotes efficiency by ensuring that only competitive firms survive. Market fragmentation, where market power is distributed across many firms, creates pressure for firms to continuously innovate and differentiate to remain viable (Baldwin & Gorecki, 1998; Caves, 1998; Asplund & Nocke, 2006). Consumers benefit from improvements in product quality, service, and pricing as efficient firms replace inefficient ones. Finally, hyper-localized demand reflects niche opportunities linked to shifting consumer preferences or emerging local trends. It often encourages firm entry as entrepreneurs seek to capitalize on these opportunities (Kirzner, 1973, 1979). Though hyper-localized demand can lead to market saturation, it can also accelerate innovation and market responsiveness, as firms unable to adjust to changes in technology, consumer behavior, or market conditions exit (Kirzner, 1973, 1979; M. A. Carree & Thurik, 1999; M. Carree & Dejardin, 2020).

Competitive pressure drives each of these three conditions; in turn, each condition helps sustain competition within markets. Considering this, high firm turnover is often observed in competitive markets. In such settings, microeconomic theory suggests that competition enhances consumer welfare by expanding product and service variety, improving product and service quality, and reducing prices.[2] But what are the consumer implications of high firm turnover in markets characterized by information asymmetries and weak regulatory enforcement? To address this question, we develop a theoretical 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 t. Specifically, incumbents decide whether to stay in business or exit the market, while potential market entrants decide whether to enter the market or stay out. Once a new market entrant enters a market m in period t, it becomes an incumbent in period $t+1$ if it remains active in market m.

Each firm i_m's true product quality in period t is 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 operating in their 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 (denoted as α_{jimt}) and information based on the experience or interaction with firm i_m by others in market m that are not j (denoted as 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. Therefore, 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 since we assume farmer j_m has no firm-specific information at the time of entry and must take the

[2] Neither high firm turnover nor any single one of these three conditions is sufficient to imply a competitive market. For instance, if more recent market entrants exit while dominant incumbents remain, high firm turnover may instead reflect concentrated market power and a *lack of* competition.

new business at face value. Thus, farmer j_m cannot observe meaningful quality signals or identify similar incumbents from market m for comparison. Over time, however, if the new market entrant remains active, farmer j_m will update their beliefs as firm-specific information becomes available.

In Equation 1, we assume consumer j_m's expectation of the probability that firm i_m sells high-quality products (i.e., 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 firm-specific 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 likely sells 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 likely sells low-quality products. When no firm-specific information signals are available (i.e., $\alpha_{jimt} = 0$ and $\alpha_{-jimt} = 0$), Equation 1 depends solely 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 during the prior 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 firms that choose to exit market m between the end of period $t-1$ and prior to the beginning of period t. Let $\mathrm{I}_{it} \in \{0, 1\}$ indicate whether firm i which operated in market m in period $t-1$ remains active in period t (i.e., $\mathrm{I}_{it} = 1$) or exited prior to period t (i.e., $\mathrm{I}_{it} = 0$). 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 previous period (i.e., $n^{inc}_{mt} \leq n_{m(t-1)}$). Consumer j_m's market-level beliefs can now be defined as follows:

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

As $p_{jmt} \to 1$ all incumbents in market m are expected to sell high-quality products. As $p_{jmt} \to -1$ all incumbents in market m are expected to sell low-quality products. When $p_{jmt} = 0$, either market-level product quality is expected to be a balanced mix of incumbents 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- nor low-quality products.

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

Proof. Mathematically, $\frac{\partial \pi_{jimt}}{\partial \alpha_{jimt}} > 0$, $\frac{\partial \pi_{jimt}}{\partial \alpha_{-jimt}} > 0$, and $\frac{\partial \pi_{jimt}}{\partial p_{jmt}} > 0$.[3]

Figure 1 demonstrates how π_{jimt} adjusts to different beliefs about market-level product quality (i.e., p_{jmt}) and varied firm-specific information signals (i.e., α_{jimt} and α_{-jimt}). For ease of notation, let $\tilde{\alpha}_{jimt} = \alpha_{jimt} + \alpha_{-jimt}$, the combined firm-specific information signals for firm i_m such that $\tilde{\alpha}_{jimt} \in (-2, 2)$. We plot $\pi_{jimt}(\tilde{\alpha}_{jimt})$ for when p_{jmt} is 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}.

The figure illustrates that when prior market-level beliefs are perfectly negative (i.e., $p_{jmt} = -1$), even strong positive firm-specific information signals (i.e., $\tilde{\alpha}_{jimt} \to 2$) result only in modest

[3] Detailed derivations of this proof are in Appendix A.

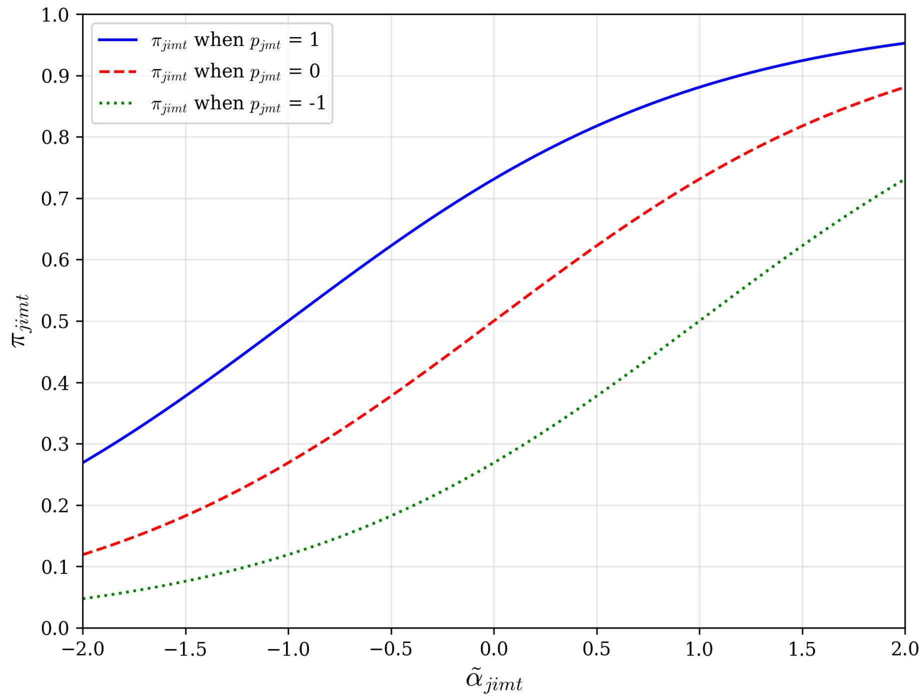

Figure 1: Equation 1 with Varying Parameters

Notes: this graph shows how consumer j_m's belief that firm i_m sells high-quality products (π_{jimt}) changes as a function of combined firm-specific information signals ($\tilde{\alpha}_{jimt}$) for different values of the market-level prior ($p_{jmt} = -1, 0, 1$).

improvements in expected firm product quality. This reflects how consumers anchor to poor market conditions carried over from period $t-1$. Conversely, when prior market-level beliefs are perfectly positive (i.e., $p_{jmt} = 1$), negative firm-specific information signals (i.e., $\tilde{\alpha}_{jimt} \to -2$) have a similarly muted effect. When prior market-level beliefs are neutral (i.e., $p_{jmt} = 0$), firm-specific information signals play a dominant role: expected firm product quality increases or decreases sharply as $\tilde{\alpha}_{jimt}$ moves away from zero. These scenarios highlight Equation 1's key insight: prior market-level beliefs moderate the influence of firm-specific information signals, with strong prior beliefs dampening the responsiveness of expected firm product quality to new information, and weak priors amplifying it.

Thus, the formation of consumer j_m's beliefs about firm i_m can be formally expressed using the following expected value equation:

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

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

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

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

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

Theorem 3.3. *If no information signals for incumbents are present in a market, then a new market entrant has no effect on consumer beliefs about overall product quality for that 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 no information signals for incumbents are present in market m (i.e. $\sum_{i=1}^{n_{mt}^{inc}} \frac{\partial \pi_{jimt}}{\partial \tilde{\alpha}_{jimt}}\Big|_{\tilde{\alpha}_{jimt}} = 0$). This can occur if there are no incumbents, if there are no information signals for any incumbent, or if the aggregated information signals across incumbents equal zero. Under this scenario, the following equality holds: $\frac{1}{n_{mt}^{inc}+1} \left(\sum_{i=1}^{n_{mt}^{inc}} E[q_{jimt}] + E[q_{jEmt}] \right) = \frac{1}{n_{mt}^{inc}} \sum_{i=1}^{n_{mt}^{inc}} E[q_{jimt}]$. Hence consumer j'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 occur simultaneously, our model considers them separately to analyze their potentially distinct effects on consumer beliefs regarding a market's overall product quality. The model predicts that firm exit leads to directional changes in consumer beliefs, depending on the perceived product quality of the exiting firm. However, firm entry has a moderating effect, shifting consumer beliefs toward market-level priors with the extent of that shift based on the strength and direction of incumbent information signals. This differentiation allows us to examine how firm entry and exit independently shape consumer quality perceptions in markets with information asymmetries. Consistent with the model, we separately test the effects of agro-dealer entry and exit on farmers' quality beliefs in Section 6, although we also analyze their joint effects.

3 Setting

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

3.1 Regulatory Environment

Agro-dealers sell a variety of agricultural inputs, including seeds, fertilizer, and pesticides. Fertilizer typically represents the largest share of their sales (Benson et al., 2012; Michelson et al., 2025). As in other Sub-Saharan African countries, the government of Tanzania regulates domestic fertilizer markets in several ways. The Tanzanian government has used bulk procurement for fertilizer imports—nearly all of which is imported (United Republic of Tanzania, 2017)—since 2017, and sets annual import quantities. An analysis by Tanzania's National Audit Office indicated systemic fertilizer shortages during this period (United Republic of Tanzania, 2019).[4] Though our data show a net increase in agro-dealers in this period (see Section 5.1), fertilizer import quantities did not consistently rise. The Tanzanian government also regulates fertilizer transportation. At the time of this study, there were no major government fertilizer subsidy programs for farmers or agro-dealers (Michelson et al., 2025). Two other policies are relevant for the agro-dealers studied in this analysis. As discussed below, these policies influence agro-dealer licensing and pricing decisions.

First, the Tanzanian government requires agro-dealers to obtain a license to sell different types of agricultural inputs, such as seeds, fertilizer, and pesticides. Specifically, a license issued by the Tanzania Fertilizer Regulatory Authority (TFRA) is required to sell fertilizer (United Republic of Tanzania, 2009). This TFRA license is valid for three years and while free of charge, receipt requires submission of one of two document combinations: (1) a Taxpayer Identification Number (TIN) and a TFRA Certificate of Participation received after completing a TFRA training; or (2) a TIN and a college or university certificate or diploma in agriculture, horticulture, or agronomy. Even though required, government enforcement of TFRA registration is weak because of a lack of institutional and human resource capacity (Kansiime, 2021; Michelson et al., 2021). Hence, many agro-dealers operate without a TFRA license. The aforementioned Tanzanian government audit of the agencies and regulations overseeing the country's agricultural inputs system commented:

> "Review of inspections report from TFRA for the year 2018 revealed that, there were [agro]-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 site inspections, the National Audit Office found over 50 percent of fertilizer-selling agro-dealers in Tanzania operated without a TFRA license (United Republic of Tanzania, 2019, p. 78). The audit cites two main reasons for low TFRA registration: a lack of understanding among agro-dealers of the registration procedures and weak enforcement, including infrequent and insufficient inspections of agro-dealers. It further notes that TFRA inspected only about 30 percent of Tanzania's regions annually (United Republic of Tanzania, 2019, p. 79).

Second, the Tanzanian government sets indicative fertilizer prices by transport mode (e.g., rail or road) and distance from the import port in Dar es Salaam. These indicative prices are established prior to the agricultural season and are intended to cap the prices at which agro-dealers may sell fertilizer in each region; they are disseminated through media channels and local government offices. While agro-dealers are free to set prices, they must remain at or below the government's indicative prices. The Tanzanian government audit also reviewed this pricing system and highlighted problems with both communicating the indicative prices to agro-dealers and ensuring compliance:

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

> "...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).

The audit notes multiple failures in communicating and enforcing the indicative pricing policy: prices often did not reach the village-level, agro-dealers frequently failed to display required prices, and inadequate inspections contributed to limited farmer awareness and compliance. In addition to these institutional challenges, many agro-dealers have reported that the government-set price caps are too low to cover their operating and transportation costs (The Citizen, 2021a, 2021b), further discouraging compliance with the indicative pricing regulations.

3.2 Asymmetric Information in the Agro-dealer Sector

Fertilizer sales, and those of other agricultural inputs, are characterized by asymmetric information. Agricultural inputs such as fertilizer, seeds, and pesticides are experience or credence goods because their essential characteristics (i.e., agronomic performance) cannot be evaluated *ex ante*. Moreover, quality signals are often obscured by production stochasticity due to weather and by "fit risk," the potential mismatch between a given technology and the local agronomic conditions (including weather and soil quality) where it is used by a farmer (Heiman et al., 2020). Agro-dealers provide information and advice to farmers on agricultural input selection and use, but the quality of this guidance is similarly difficult for farmers to assess before implementation.

Previous studies (Michelson et al., 2021; Hoel et al., 2024; Michelson et al., 2025) have analyzed fertilizer markets in Tanzania's Morogoro Region, collecting data on fertilizer quality, farmer beliefs about fertilizer, and fertilizer use. Given the information asymmetries present in agricultural input markets and the weak regulatory environment in the agro-dealer sector, farmers have expressed concerns about the quality of agricultural inputs sold by agro-dealers. Specifically, Michelson et al. (2021) and Michelson et al. (2025) provide evidence that on average farmers in the Morogoro Region believe that agro-dealers sell low-quality and agronomically compromised urea fertilizer.

Similar farmer concerns about fertilizer quality have been documented in Uganda (Bold et al., 2017; Hoel et al., 2024) and West Africa (Austin et al., 2013). Yet these concerns are not borne out by the testing of fertilizer samples conducted by academic researchers (Michelson et al., 2023) or the International Fertilizer Development Corporation, which routinely evaluates and advises on the testing of fertilizer quality globally. While testing consistently shows that fertilizer (specifically urea fertilizer) reliably meets industry standards, many farmers continue to believe much of the fertilizer is low-quality.

Why do farmers hold incorrect beliefs about fertilizer quality, and why do they fail to accurately update those beliefs? Hoel et al. (2024) suggest that these misconceptions might arise from misattribution—a cognitive bias in which farmers attribute low yields to fertilizer quality instead of other factors such as weather, incorrect application quantity, fertilizer type, or application timing. As a result, farmers confuse bad luck or poor management with fertilizer quality issues, preventing them from accurately assessing fertilizer performance over time. A randomized controlled trial by Michelson et al. (2025) found that an information campaign in Tanzania's Morogoro Region improved farmer beliefs about fertilizer quality. However, belief updating was incomplete and varied across farmers; although overall concerns about fertilizer quality declined, a substantial share of farmers remained skeptical, suggesting that learning was slow and beliefs were resistant to change.

These misperceptions carry meaningful consequences for farmer investment decisions. A growing body of empirical research shows that suspicion or uncertainty regarding agricultural input quality reduces farmers' willingness to pay, demand, and use (Gharib et al., 2021; Hsu & Wambugu, 2022; Bulte et al., 2023; Miehe et al., 2023; Hoel et al., 2024; Michelson et al., 2025).

Despite evidence that fertilizer quality is reliably high, the persistence of farmer concerns about such quality is central to our study's context, theoretical model, and empirical analysis. Although agro-dealers in our sample are unlikely to be selling fertilizer of objectively low agronomic quality (Michelson et al., 2023), farmers *believe* that low-quality fertilizer is being sold. Of course, farmer perceptions of agro-dealer quality may reflect other relevant dimensions, like the quality of agricultural information provided, the level of customer service offered, and the variety and availability of agricultural inputs. In any case, farmers perceive heterogeneity in fertilizer quality where none exists. Asymmetric information plays a key role in sustaining these beliefs (Hoel et al., 2024).

4 Data

We use three primary datasets related to agro-dealers and smallholder farmers from Tanzania's Morogoro Region. Our agro-dealer turnover analysis in Section 5 uses an agro-dealer census and follow-up survey data that are described in Section 4.1. The smallholder farmer analysis in Section 6 relies on two distinct farmer surveys: one merged with the agro-dealer census to evaluate market-level beliefs, and another used to examine how farmer beliefs vary with the strength of farmer-agro-dealer relationships. Both datasets are described in Section 4.2.

4.1 Agro-dealer Data

We use a unique three-round census of all agro-dealers operating in Tanzania's Morogoro Region. Data were collected in the first quarters of 2016, 2019, and 2020,[5] just before the long rains planting season and associated agricultural input sales.[6] The census identified 97 major markets in the region and surveyed all agro-dealers operating in each market in each round. Following Michelson et al. (2021) and Michelson et al. (2025), these markets are defined administratively, often as clusters of agro-dealers serving a small network of nearby villages or as a recognizable trading hub.

In each round, we collected data on agro-dealer characteristics related to business practices, asset ownership, number of non-owner employees, licensing status, operational scale, years of operation, and shop infrastructure. Columns 1-3 of Table 1 present descriptive statistics from the agro-dealer census by round. This census includes 515 agro-dealers in total. To analyze predictors of agro-dealer exit in Section 5.4, we construct a stacked sample from the census that includes all agro-dealers observed in rounds one, two, or both, yielding 522 observations that correspond to 384 unique agro-dealers. Column 4 of Table 1 reports descriptive statistics for these 384 agro-dealers, using data from the first round in which each appears. To better understand agro-dealer entry and exit decisions (see Sections 5.3 and 5.4, respectively), we conduct a follow-up survey with 202 of the 515 census-identified agro-dealers in the third quarter of 2022. Of these, 54 agro-dealers had exited during or after the census while the remaining 148 were still in business at the time of the survey.[7]

[5] For the 2016 and 2019 rounds, data collection began in the last quarter of the previous calendar year.

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

[7] The agro-dealer follow-up survey is not a census for two reasons: (1) we did not survey any new market entrants and (2) the phone-based survey experienced high attrition due to outdated contact information and non-response. Thus, selection bias may be present as responses reflect only agro-dealers who were reachable and willing to participate.

As shown in Table 1, across all three rounds, nearly all agro-dealers owned a mobile phone, less than one-third owned transportation assets, and around 40 percent had a TFRA license. Most sold fertilizer from a single location, had about one non-owner employee present at the time of interview, and had been in operation at the same location for over four years. The last row of Table 1 reports the share of other agro-dealer exits relative to the previous round, defined as the number of *other* agro-dealers that exited a market between two rounds divided by the total number of agro-dealers present in that market at the start of the previous round.[8] On average, this share ranges from 20 to 32 percent across all rounds. It suggests that between one-fifth and one-third of an agro-dealer's competitors within the same market exit between rounds. While not shown in Table 1, additional descriptive statistics from round one indicate that on average agro-dealers had 1,065 kilograms (kg) of fertilizer in stock at the time of interview, with inventory ranging from 0 to 10,000 kg. On average, they also sold 13,139 kg of fertilizer in the prior year (enough to cover roughly 40 hectares of farmland) though sales ranged from 0 to 90,000 kg.[9] These variables serve as alternative proxies for agro-dealer size.[10]

The average distance between each market and its nearest neighboring market is 6.6 kilometers (km).[11] Ten percent of the 97 markets are less than 1 km from their nearest neighbor, 47 percent are 1–5 km, 25 percent are 5–10 km, and 18 percent are more than 10 km away from their nearest neighbor. Table 2 describes market characteristics across and between rounds. Over time, the share of markets with at least one agro-dealer decreases. The number of agro-dealers per market ranges from 0 to 29, depending on the round, with the average rising from about two to four across rounds. These trends indicate sectoral growth alongside increased concentration of agro-dealers in fewer markets, suggesting intensifying within-market competition.

The last two rows of Table 2 capture agro-dealer turnover within each market between rounds. We define the share of agro-dealer exits relative to the previous round as the number of agro-dealers that exited a market between two rounds, divided by the number of agro-dealers operating in that market at the start of the previous round.[12] On average, this share is 37 percent between rounds one and two and 22 percent between rounds two and three. The share of new market entrants relative to the previous round is defined analogously following the approach of Liedholm (2002). On average, this share ranges from roughly 45 to 70 percent across rounds. These estimates provide initial evidence that markets in this region experience considerable agro-dealer turnover. In Section 5, we expand on these initial estimates to calculate annual agro-dealer entry and exit rates, explore heterogeneity in agro-dealer turnover across markets, and analyze the firm characteristics

[8]This measure is calculated at the agro-dealer-level. For example, if agro-dealer A operates in a market with four agro-dealers in round one (e.g., A, B, C, D), and B and C exit between rounds one and two, then the share of *other* agro-dealer exits for A and D is 66.7 percent (i.e., two out of their three competitors exited), while that for B and C is 33.3 percent (i.e., one out of their three competitors exited). Each agro-dealer's value is based on the exit behavior of their competitors within the same market.

[9]We estimated the 40-hectare coverage using the average amount of fertilizer sold per agro-dealer of 13,139 kg. To approximate how much nitrogen this represented, we obtained the distribution of fertilizer types (e.g., urea, NPK, etc.) sold by agro-dealers in round one. Using nutrient composition data from International Fertilizer Industry Association (2000), we identified the nitrogen content of each type. We then multiplied the 13,139 kg by the proportion of each fertilizer type and by its corresponding nitrogen percentage. Summing across types yielded the total kg of nitrogen sold. Finally, we divided this total by the Tanzanian government's recommended nitrogen application rate of 100 kg per hectare for maize cultivation (Kohler, 2020). This is likely an underestimate of true coverage, as it does not account for other fertilizer nutrients such as phosphorus or potassium.

[10]We winsorize these two variables at the 95th percentile, given their long-tailed distributions, before performing descriptive statistics.

[11]Distances are calculated as great-circle distances using the haversine formula.

[12]This measure is calculated at the market-level. For example, if a market has four agro-dealers in round one (e.g., A, B, C, D), and B and C exit between rounds one and two, the market's share of agro-dealer exits relative to the previous round is 50 percent (i.e., two out of the original four agro-dealers in the market exited).

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

Agro-dealer Characteristics	Round 1 (1)	Round 2 (2)	Round 3 (3)	Unique (4)
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 CNFA/TAGMARK certification displayed	0.23	0.24	0.19	0.20
	(0.42)	(0.43)	(0.39)	(0.40)
Uses outdoor signage for advertising	0.77	0.59	0.89	0.68
	(0.42)	(0.49)	(0.32)	(0.47)
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 at time of interview	0.84	0.80	1.04	0.85
	(0.76)	(0.74)	(0.74)	(0.75)
Years operating at current location	4.18	4.71	4.39	3.31
	(4.33)	(4.68)	(4.99)	(3.76)
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 the previous round		0.32	0.20	0.28
		(0.35)	(0.26)	(0.32)
Observations	224	298	360	384

Notes: each column reports the mean with the standard deviation in parentheses. Agro-dealer owner traits were only available for agro-dealers in round one so they are excluded. Column 4 presents descriptive statistics for the unique agro-dealers in our stacked sample (see Section 5.4). Characteristics for these 384 agro-dealers are associated with the first round in which they appear in the census. The values in the last row capture agro-dealer exit *between* rounds. Specifically, values in Column 2 reflect agro-dealer exit between rounds one and two, while values in Column 3 reflect agro-dealer exit between rounds two and three. A CNFA/TAGMARK certificate is awarded to Tanzanian agro-dealers who completed the TAGMARK training program, which focused on improving agro-dealer professionalism, business practices, and technical knowledge.

and market factors shaping agro-dealer entry and exit decisions.

4.2 Farmer Data

We merge the agro-dealer census with a survey of 1,242 smallholder farmers conducted across Tanzania's Morogoro Region, hereafter referred to as the market-linked farmer sample. These data were collected in the first quarter of 2019, concurrent with the 2019 round of the agro-dealer census. The survey links farmers to agro-dealers through shared markets and all farmers reside within three to seven kilometers of a market in the census. This geographic proximity enables us to later examine the relationship between recent agro-dealer turnover within a market and farmer beliefs about the fertilizer quality in that same market (see Section 6.1).

The majority of farmers in the market-linked sample were male and had completed at most primary school. On average, they were 45 years old, lived in households with approximately five members, and owned about six acres of land (see Column 1 of Appendix Table C.1 for full descriptive statistics). Importantly, the data capture farmers' beliefs about the quality of fertilizer sold by agro-dealers in their proximate market. Following the approach used by Michelson et al. (2021), Ashour

Table 2: Descriptive Statistics for Markets by Round

Market Characteristics	Round 1 (1)	Round 2 (2)	Round 3 (3)
Share of markets with at least one agro-dealer in operation	0.95	0.92	0.89
	(0.22)	(0.28)	(0.32)
Agro-dealers operating in a market	2.31	3.07	3.71
	(2.26)	(3.90)	(4.55)
Share of agro-dealer exits relative to the previous round		0.37	0.22
		(0.39)	(0.31)
Share of new market entrants relative to the previous round		0.68	0.46
		(0.87)	(0.65)
Observations	97	97	97

Notes: each column reports the mean with the standard deviation in parentheses. The values in the last two rows capture agro-dealer turnover *between* rounds. Specifically, values in Column 2 reflect agro-dealer turnover between rounds one and two, while values in Column 3 reflect agro-dealer turnover between rounds two and three.

et al. (2019), Hoel et al. (2024), and others, we asked farmers: "If ten farmers, like you, purchase a one-kilogram bag of fertilizer in your market this week, how many would be high-quality?" Panel A of Table 3 shows farmers believed that on average almost seven out of ten farmers would receive high-quality fertilizer, meaning about three out of ten would receive low-quality fertilizer. A binary version of this variable captures whether the farmer expressed *any* concern about fertilizer quality: 70 percent believed that at least one of the ten farmers would purchase low-quality fertilizer.

The market-linked farmer sample includes information about perceptions of particular markets, but it excludes that about the relationship between farmers and specific agro-dealers. Recognizing the importance of farmer-agro-dealer relationships, we conducted an additional cross-sectional survey with 150 farmers in the third quarter of 2022. Ten farmers were surveyed in each of 15 villages, representative of nine markets.[13] Column 2 of Appendix Table C.1 reports full descriptive statistics for these farmers. Hereafter, this data will be referred to as the supplemental farmer sample.

A key feature of the supplemental survey is that it asked farmers to provide separate quality assessments for both agricultural inputs and information, where agricultural information quality refers to the reliability of advice or expertise related to how or when to apply agricultural inputs, or about different product and brand offerings. In addition, these questions were asked separately for two types of agro-dealers: a farmer's current agro-dealer and a hypothetical new market entrant operating alongside them. Farmer beliefs regarding agricultural input quality were measured on a scale from zero to ten, where ten indicates that *all* farmers would receive high-quality agricultural inputs.[14] Farmer beliefs about agricultural information quality were evaluated using a rating scale of one to ten, where ten denotes the highest perceived quality. Binary versions of these variables capture whether the farmer expressed *any* concern about the quality provided by either agro-dealer type. Descriptive statistics for these responses are shown in Panel B of Table 3. As a preview of our later findings, farmers on average rated both the agricultural input and information quality from their current agro-dealer higher than those from a hypothetical new market entrant. Similarly, based on the binary variables, a greater share of farmers expressed concern about the quality offered

[13]In the market-linked farmer sample, all seven administrative districts in Tanzania's Morogoro Region are represented, while in the supplemental farmer sample only two of these administrative districts are represented.

[14]Farmers were specifically asked to estimate how many out of ten farmers, like themselves, would receive high-quality agricultural inputs from their current agro-dealer and a hypothetical new market entrant, assuming all ten purchased the same agricultural input on the same day.

Table 3: Quality Belief and Relationship Measures for Farmer Samples

(A) Market-linked

	Mean	Std. Dev.	Min	Max
Fertilizer quality beliefs				
Farmers out of ten receiving high-quality	6.82	2.83	0.00	10.00
Share of farmers concerned about quality	0.70	0.46	0.00	1.00
Observations				1,242

(B) Supplemental

	Mean	Std. Dev.	Min	Max
Agricultural input quality beliefs				
Farmers out of ten receiving high-quality				
From current agro-dealer	8.37	2.15	0.00	10.00
From hypothetical new market entrant	6.63	2.94	0.00	10.00
Share of farmers concerned about quality				
From current agro-dealer	0.47	0.50	0.00	1.00
From hypothetical new market entrant	0.66	0.48	0.00	1.00
Agricultural information quality beliefs				
Quality rating				
For current agro-dealer	7.85	2.34	1.00	10.00
For hypothetical new market entrant	5.81	2.53	1.00	10.00
Share of farmers concerned about quality				
From current agro-dealer	0.59	0.49	0.00	1.00
From hypothetical new market entrant	0.84	0.37	0.00	1.00
Share of farmers with a stable agro-dealer relationship	0.63	0.49	0.00	1.00
Observations				150

Note: a stable agro-dealer relationship is defined as *usually* purchasing agricultural inputs from the same agro-dealer over the past five years. The rating scale for agricultural information quality is from one to ten, where ten denotes the highest perceived quality and one denotes the lowest.

by such new market entrants.

The supplemental survey also measured whether farmers *usually* purchased agricultural inputs from the same agro-dealer over the past five years. This question was posed to evaluate both the stability of the farmer-agro-dealer relationship and the farmer's preference for a particular agro-dealer in their proximate market. As shown in Panel B of Table 3, almost two-thirds of farmers reported consistently purchasing from the same agro-dealer over time.

5 Characterizing Agro-dealer Turnover

In this section, we estimate annual agro-dealer turnover rates in Tanzania's Morogoro Region. We also examine heterogeneity across markets and analyze agro-dealer entry and exit decisions.

5.1 Estimating Agro-dealer Turnover Rates

Figure 2 illustrates agro-dealer entry, exit, and continuation across rounds one, two, and three of the census. Of the 224 agro-dealers observed in round one, 138 remained active in round two, while 86 exited. Simultaneously, 160 new agro-dealers entered between rounds one and two, resulting in 298 total agro-dealers in round two. Between rounds two and three, 229 of the 298 round-two incumbents continued, 69 exited, and 131 new agro-dealers entered, resulting in 360 total agro-dealers in round three.

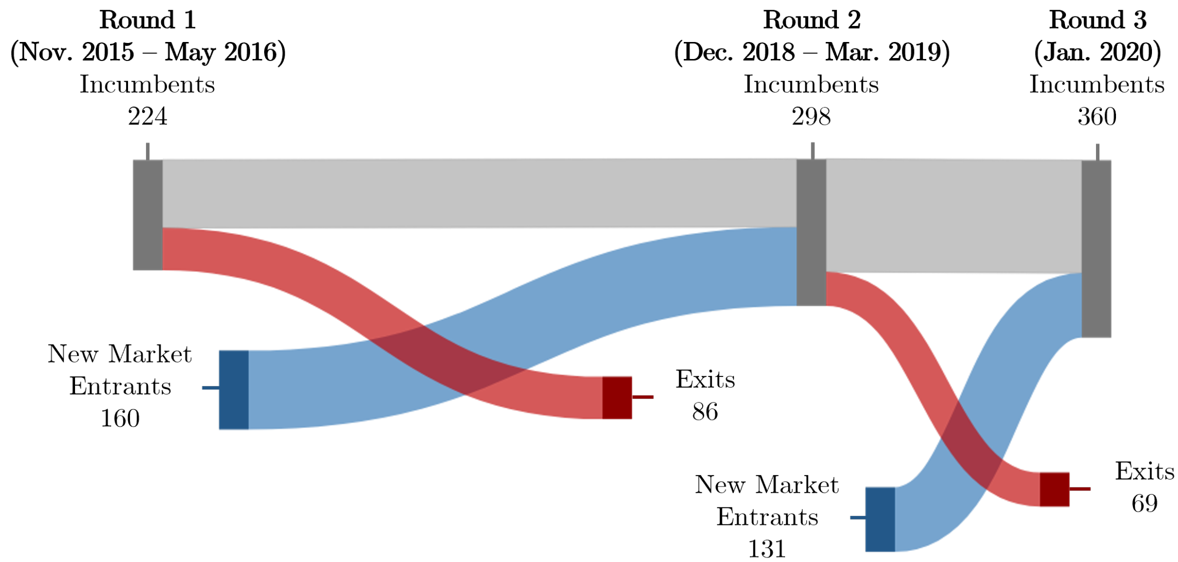

Figure 2: Agro-dealer Turnover Across Rounds: Entry, Exit, and Continuation

Notes: this Sankey diagram visualizes agro-dealer turnover across the three census rounds, capturing the number of agro-dealers that entered, exited, and remained in Tanzania's Morogoro Region over time. The widths of flows are proportional to the number of agro-dealers, while the spacing between rounds reflects the time elapsed between surveys. These transitions form the basis for calculating annual agro-dealer entry and exit rates.

To calculate firm turnover, we define the agro-dealer entry rate between two rounds of the census as the number of agro-dealers that enter a market between rounds divided by the number of agro-dealers present at the start of the previous round. The agro-dealer exit rate is defined similarly. These definitions are consistent with standard approaches used to calculate MSME entry and exit rates in low-income settings (see Liedholm (2002) and Kremer et al. (2014)). To annualize these entry and exit rates, we divide each rate for a pair of rounds by the number of years between rounds. This adjustment ensures comparability across rounds. We then compute a weighted average of the annual rates to produce a single annual rate spanning the full study period. More details regarding our agro-dealer turnover calculations are provided in Appendix B.

We estimate an annual agro-dealer entry rate of 34.0 percent and an annual agro-dealer exit rate of 18.1 percent. The annual agro-dealer exit rate is more than double those reported for MSMEs in non-agricultural sectors in comparable low-income settings. In a seminal study of "firm death" using data from 12 low-income countries, McKenzie and Paffhausen (2019) report an average annual MSME exit rate of 8 percent. Kremer et al. (2014) find even lower rates, between 4 and 6 percent, for Kenyan retail shops. The annual exit rate observed for agro-dealers in our study is most comparable to that of 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 rate of 34 percent is at least one-third higher than, and in some cases roughly double, that observed for non-agricultural MSMEs in prior studies. Liedholm (2002) reports an average annual entry rate of 22 percent across MSMEs in Latin America and Africa, with country-specific rates ranging from 19 to 25 percent. McCaig and Pavcnik (2021) find annual entry rates of 16 to 18 percent among informal MSMEs in Vietnam while Cabal (1995) document slightly higher rates of 21 to 24 percent for informal MSMEs in the Dominican Republic. Altogether, our results suggest that agro-dealers in Tanzania's Morogoro Region operate in a more dynamic environment than MSMEs operating in non-agricultural sectors in low-income countries.

Spurious entry and exit counts could artificially inflate the annual agro-dealer turnover rates we estimate. Such misclassification could potentially stem from sampling design issues or inaccurately defining what constitutes an "active" agro-dealer. For example, seasonal or temporarily inactive agro-dealers may be incorrectly recorded as exits. Entry counts could be inflated by similar forms of misclassification. However, several features of our data collection process give us confidence that these issues are not driving our results. First, our data come from repeated censuses conducted prior to the long rains season, when agro-dealers typically operate in anticipation of peak farmer demand. Second, a consistent team of enumerators conducted the surveys across all rounds, targeting agro-dealers either selling or planning to sell fertilizer in each market during the upcoming season. Third, our census focused on agro-dealers with permanent locations, effectively excluding most seasonal businesses (see Table 1).[15] If anything, these details suggest that our annual agro-dealer entry and exit rates may be lower bounds on the level of firm turnover in the agro-dealer sector more broadly.

One limitation of our study is that it covers a specific four-year window. It is possible this period coincided with an unusually volatile period in agro-dealer turnover. Though we cannot rule out that this period is atypical, the agro-dealer entry and exit patterns we observe are internally consistent across census rounds and are not driven by outliers in specific inter-round periods or markets. These features suggest the observed turnover rates likely reflect long-term market conditions.

5.2 Heterogeneity of Agro-dealer Turnover

We next explore if high agro-dealer turnover varies across markets. The gray bars in Figure 3 depict the annual net agro-dealer turnover rate for each market over the four-year study period, defined as a market's annual agro-dealer entry rate minus its annual agro-dealer exit rate. The figure reveals substantial heterogeneity *across* markets: more than half of the markets experienced net growth in agro-dealers, while about one-quarter experienced net decline.

Figure 3 also illustrates considerable heterogeneity in agro-dealer turnover *within* markets. The blue and red bars represent annual entry and exit rates, respectively, relative to the annual net turnover rate. Within-market heterogeneity is particularly evident among the 15 markets with zero annual net agro-dealer turnover rates. Of those, eight experience no agro-dealer turnover at all, while in the other seven, all existing agro-dealers exited and were replaced by new market entrants—indicating complete turnover despite no net change in agro-dealer count.

Finally, we find no statistical evidence of geographic clustering or dispersion in annual net agro-dealer turnover across markets. To see this, Figure 4 shows a map of Tanzania's Morogoro Region with each circle representing a market. Dark red circles denote markets with high annual net agro-dealer exit, while dark blue circles denote those with high annual net entry; lighter shades

[15] One potential concern is that agro-dealers may close in one market and reopen in another during the study period. However, our census data show no cases of an agro-dealer re-entering the *same* market after exit. Moreover, since we track agro-dealer *shops* rather than the individuals operating them, re-entry into a different market is not pertinent for our analysis. This is because our turnover measures capture market-specific agro-dealer dynamics, not the movement of individuals across markets, so we treat an agro-dealer's exit from one market as a true exit even if the owner opens a new shop elsewhere. Finally, our follow-up survey (see Section 4.1) with agro-dealers who exited during the study period ($N = 54$) indicates that this behavior is uncommon. Specifically, we found no discrepancies between their self-reported entry and exit timing and the census data, further supporting data consistency.

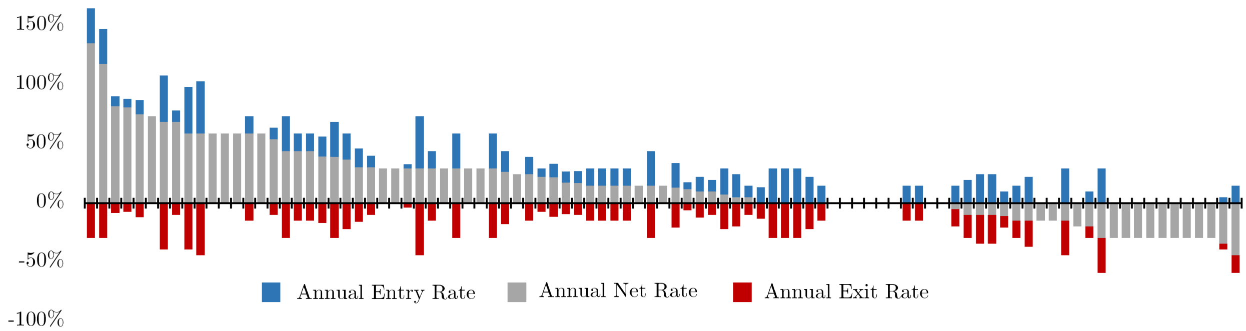

Figure 3: Annual Agro-dealer Turnover by Market: Entry, Net, & Exit Rates

Notes: this figure depicts annual net turnover (gray), entry (blue), and exit (red) rates for agro-dealers across 95 markets over the study period. Two markets are excluded because they only had agro-dealers present in round three, making it impossible to calculate annual net turnover, entry, or exit rates between rounds.

correspond to smaller magnitudes of annual net turnover. Though markets across the region experienced net growth, decline, or no net change over time, no clear spatial pattern emerges. Annual net agro-dealer turnover does not appear systematically concentrated in urban or rural areas. A Moran's I test for global spatial autocorrelation confirms this, yielding a null result ($p = 0.217$) which suggests that annual net agro-dealer turnover does not exhibit significant spatial dependence. We conclude that the high agro-dealer turnover observed in this region is not spatially correlated.

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." Broadly, MSME entry by low-income entrepreneurs is often referred to as "buying a job"—a phrase that describes the willingness to pursue any available work, even if suboptimal, to meet basic needs in the absence of stable income or alternative employment opportunities (Banerjee & Duflo, 2011; Burchell & Coutts, 2019; Sohns & Diez, 2019; Jayachandran, 2021). In such cases, entrepreneurs are *pushed* into the market by necessity, rather than through proactive decision-making. Empirical evidence from Sub-Saharan Africa supports this: Di Falco and De Giorgi (2019) and Rudder (2022) show that MSME start-up activity among farming households increases in response to adverse weather shocks, as households turn to entrepreneurship to help smooth consumption. In this way, MSME entry functions as a coping strategy.

We assess whether this characterization also applies to Tanzanian agro-dealers using data from our follow-up survey (see Section 4.1). Table 4 presents descriptive statistics from this survey. The results in Column 1 suggest that agro-dealers in our sample are *not* "reluctant entrepreneurs" who entered the sector because of a lack of viable outside options. Eighty-six percent of respondents described their decision to enter the agro-dealer sector as a "step up" from their previous primary economic activity. Most cited higher income potential, stronger alignment with their interests and skills, or improved financial security as key motivations. Moreover, fewer than two percent reported entering the sector to temporarily smooth consumption, supplement household income, or due to limited or less desirable alternatives.

These agro-dealers overwhelmingly report entering the sector with the expectation of staying for the long-term. At the time of entry, 96 percent expected to remain in business for more than six

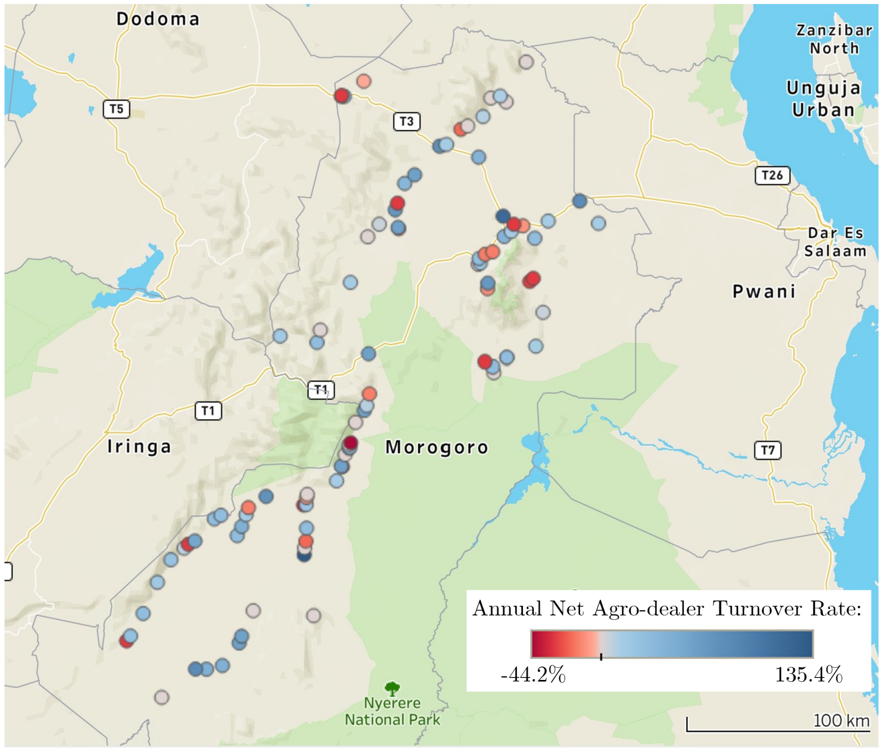

Figure 4: Annual Net Agro-dealer Turnover in Tanzania's Morogoro Region

Notes: this map displays the geographic coverage of the agro-dealer census in Tanzania's Morogoro Region. Circles represent markets, with color shading indicating annual net agro-dealer turnover rates for the four-year study period.

years. Among agro-dealers still operating at the time of our follow-up survey, 93 percent expected to stay in business over the next five years, and 86 percent anticipated growth (i.e. opening additional business locations, increasing sales at their current location, or expanding the quantity or diversity of products offered at their current location) during the same period. Optimism persisted even when presented with a hypothetical scenario involving a more profitable and stable employment opportunity: 84 percent indicated they would *not* exit the agro-dealer sector under such conditions. While hypothetical, this response reflects a high degree of commitment to the business. Altogether, these findings portray agro-dealers as "optimistic entrepreneurs" who view market entry as a long-term investment in a sustainable livelihood strategy; they also corroborate the observations of Benson et al. (2012) 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).

While agro-dealers express long-term optimism about their businesses, their ability to enter the sector is facilitated by relatively low entry barriers. In principle, the Tanzanian government requires agro-dealers selling fertilizer to obtain a TFRA license; though this requirement could constitute a meaningful barrier under strict enforcement, compliance is weak due to limited government capacity (see Section 3.1). Therefore, licensing does little to restrict agro-dealer entry. Using the agro-dealer

Table 4: Descriptive Statistics for Agro-dealer Follow-up Survey

Statement	Sample (1)	Exited (2)	In Business (3)	T-test (4)
Starting my agro-dealer business was a "step-up" from my previous primary economic activity.	0.86 (0.35)	0.89 (0.32)	0.84 (0.36)	0.43
I started this business intending to exit once I made enough money or found a better opportunity.	0.01 (0.12)	0.00 (0.00)	0.02 (0.14)	0.29
When I started this business, I expected to stay in business for more than six years.	0.96 (0.20)	0.96 (0.19)	0.96 (0.20)	0.91
I expect to still be in business five years from now.	—	—	0.93 (0.26)	—
I expect my business to grow over the next five years.	—	—	0.86 (0.35)	—
If offered salaried employment with *higher* income, I would still choose to be an agro-dealer.	—	—	0.84 (0.37)	—
Observations	202	54	148	

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Responses to each statement were coded as one for "yes" and zero for "no." Columns 1-3 report the mean with the standard deviation in parentheses. Column 4 reports the p-values from t-tests comparing mean responses between the 54 agro-dealers who had exited during or after the three-round census and the 148 agro-dealers still in business at the time of the follow-up survey (see Section 4.1). Only agro-dealers still in business responded to the final three statements. A "step-up" refers to an advancement, whether entering a more lucrative business, earning more money, or pursuing work that better aligns with one's interests or skills.

census, we find that on average across rounds only 42.2 percent of agro-dealers had a TFRA license, and just 56.6 percent of markets had *at least one* agro-dealer with a TFRA license. Moreover, 89.3 percent maintained the same TFRA licensing status—whether licensed or unlicensed—throughout the four-year study period, suggesting consistently lax enforcement. Entry patterns reinforce this point: over this period, non-licensed agro-dealers entered at around twice the annual rate (i.e., 22.8 percent) of their licensed counterparts (i.e., 11.2 percent). In short, while optimism may motivate agro-dealer entry, weak regulatory enforcement significantly lowers the cost of doing so.

5.4 Agro-dealer Exit Decisions

If agro-dealers are optimistic and determined, why do so many exit? To address this, we first use data from the agro-dealer follow-up survey. Table 5 shows that one-sixth of agro-dealers (i.e., 16.7 percent) cited household-level shocks as their primary reason for exiting, while a much larger share (i.e., 57.4 percent) reported profit losses due to either supply- or demand-side factors in the marketplace. Compared to our results, previous studies in the MSME literature report higher shares of exits attributed to household-level shocks (26.0 percent (McKenzie & Paffhausen, 2019) and 19.7 percent (McCaig & Pavcnik, 2021)) and lower ones due to profit losses (41.0 percent and 25.3 percent, respectively). Our findings suggest most agro-dealer exits reflect external pressures, particularly market conditions that push (rather than pull) firms out of the sector.

Researchers have employed a range of methods to identify the predictors of MSME exit. McKenzie and Paffhausen (2019) use a saturated dummy variable regression approach, controlling for owner and firm characteristics, as well as the number of years since baseline. By comparison, Kremer et al. (2014) estimate multivariate correlations between MSME survival and owner characteristics. We estimate a linear probability model (LPM) with fixed effects to identify predictors of agro-dealer

Table 5: Distribution of Exit Reasons for Agro-dealer Follow-up Survey Compared to MSME Literature

	Agro-dealer Follow-up Sample		Previous Studies	
	Count	Percent	McKenzie & Paffhausen (2019)	McCaig & Pavcnik (2021)
Profit loss due to…	31	57.4%	41.0%	25.3%
Increased costs	14	25.9%	–	6.7%
Bankruptcy	9	16.7%	–	9.6%
Decreased product demand	4	7.4%	–	–
Increased market competition	4	7.4%	–	4.3%
Other	0	0.0%	–	4.7%
Shocks				
Household-level	9	16.7%	26.0%	19.7%
Exogenous to household	7	13.0%	–	–
Alternative opportunities	1	1.9%	11.0%	27.7%
Other	6	11.1%	22.0%	27.2%
Total	54	100.0%	100.0%	100.0%

Notes: household-level shocks refer to those within the household—such as illness, death, retirement, marriage, or divorce—that lead to business closure. Exogenous shocks originate outside the household and include events like fire or theft. Alternative opportunities are voluntary exits driven by positive prospects, such as pursuing a more lucrative business idea or accepting salaried or higher-paying employment. For the follow-up survey, of the 202 agro-dealers who participated (see Section 4.1), 54 had exited during or after the three-round census.

exit in subsequent rounds using our stacked sample (see Section 4.1). We select an LPM for our descriptive analysis to facilitate direct interpretation of predictors' marginal effects on the probability of exit; however, our results are robust to alternative functional forms, including logit and probit models (see Appendix Tables C.2 and C.3).

Equation 6 presents our LPM specification:

$$Y_{im(t+1)} = \beta_0 + \beta_1 X'_{it} + \beta_2 Z'_{mt} + \alpha_t + \gamma_m + \epsilon_{imt} \tag{6}$$

$Y_{im(t+1)}$ is a binary variable equal to one if agro-dealer i in market m exited by round $t+1$. The vectors X'_{it} and Z'_{mt} include selected time-varying agro-dealer and market-level controls in Tables 1 and 2. Round fixed effects (α_t) account for shocks to all markets between rounds, market fixed effects (γ_m) control for unobserved time-invariant market attributes, and ϵ_{imt} is the error term.

Table 6 reports the correlates of agro-dealer exit estimated using the LPM. Columns 1, 2, and 3 show results with no fixed effects, round fixed effects only, and both round and market fixed effects, respectively. Column 3 corresponds to the full model specification in Equation 6. Overall, the results suggest that agro-dealer exit is not strongly associated with most observable firm characteristics. A notable exception is licensing status: not having a TFRA license is associated with a 6.9 percentage point increase in the likelihood of exit in the subsequent round. Consistent with this finding, we use the agro-dealer census to calculate annual agro-dealer exit rates by TFRA licensing status. Non-licensed agro-dealers exit at roughly twice the annual rate of their licensed counterparts: 11.4 percent versus 6.7 percent.

In our setting, MSME age and size—measured by the number of non-owner employees—are not significant predictors of exit, despite consistent evidence from previous studies linking both factors to lower exit rates (Mead & Liedholm, 1998; Kremer et al., 2014; Aga & Francis, 2017; McKenzie & Paffhausen, 2019). Instead, results in Table 6 underscore the role of market dynamics: agro-dealer

Table 6: Linear Probability Model for Predictors of Agro-dealer Exit

	(1)	(2)	(3)
Agro-dealer Characteristics			
Owns a car or truck	-0.075	-0.064	-0.109
	(0.055)	(0.056)	(0.075)
Has CNFA/TAGMARK certification displayed	0.024	0.019	0.030
	(0.051)	(0.050)	(0.058)
Uses outdoor signage for advertising	0.029	0.000	0.023
	(0.047)	(0.047)	(0.049)
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 at time of interview	0.050**	0.043*	0.022
	(0.022)	(0.023)	(0.029)
Years operating at current location	-0.011**	-0.010*	0.001
	(0.005)	(0.005)	(0.006)
Market Characteristics			
Agro-dealers operating in a market	-0.005**	-0.002	0.048***
	(0.002)	(0.002)	(0.016)
Share of *other* agro-dealer exits relative to the previous round	0.054	0.016	-0.604***
	(0.092)	(0.099)	(0.108)
Share of new market entrants relative to the previous round	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 presents results associated with the linear probability model (LPM) with no fixed effects. Column 2 adds round fixed effects, while Column 3 includes both round and market fixed effects. We winsorize the variable "years operating at current location" only for data above the 95th percentile given its long-tailed distribution. A CNFA/TAGMARK certificate is awarded to Tanzanian agro-dealers who completed the TAGMARK training program, which focused on improving agro-dealer professionalism, business practices, and technical knowledge.

exit is associated with increased competition and fewer competitor exits within markets.

Market fixed effects in Equation 6 account for time-invariant differences across markets, such as their overall size or typical level of competition. As a result, the coefficient on competition reflects how changes in the number of competitors within a given market over time (rather than differences across markets) affect the likelihood of agro-dealer exit. A positive sign indicates an increase in the number of competitors in a market raises the probability that an agro-dealer in that market will exit by the next round, consistent with heightened competition making survival more difficult.

As shown in Column 3 of Table 6, each additional competitor in an agro-dealer's market increases the likelihood of exit in the subsequent round by 4.8 percentage points. This result underscores how higher within-market competition intensity elevates the risk of exit. As the share of exiting competitors within a market increases, an agro-dealer's own likelihood of exit decreases by 60.4 percentage points. When other agro-dealers exit, competitive pressure eases for those remaining, improving their chances of survival. Exit may also reflect selection effects: if the most vulnerable agro-dealers exit first during periods of market distress (e.g., declining demand), more resilient ones survive. These findings point to dynamic competitive effects in which an agro-dealer's survival is shaped by the entry and exit of *others* in their market. In short, greater competition increases the risk of agro-dealer exit, but once competitors leave, market conditions stabilize for survivors.

Our results show that while few observable agro-dealer characteristics predict exit, competition and turnover *within* markets play a significant role. In general, existing research does not tend to consider how market-level dynamics influence MSME survival (Mead & Liedholm, 1998; Liedholm, 2002; Kremer et al., 2014; Aga & Francis, 2017; McKenzie & Paffhausen, 2019). However, two studies provide relevant insights. First, Rudder (2022) shows that in the wake of an environmental shock in Kenya, market-level competition increases—as more MSMEs enter and fewer exit—even as individual firms report declines in sales, profits, and hiring. Second, Klapper and Richmond (2011) show that trade liberalization in Côte d'Ivoire led to increased competition, which in turn increased the exit rate among formally registered MSMEs. Our findings are consistent with these patterns but offer some additional nuance: although rising competition increases the risk of agro-dealer exit, this risk decreases when nearby competitors exit—suggesting that, in some contexts, heightened competition can *improve* agro-dealer survival.

6 Implications for Smallholder Farmers

Our theoretical model shows how firm turnover influences consumer expectations about product quality in markets with information asymmetries. Guided by this theory, we examine the implications of high agro-dealer turnover for smallholder farmers. Section 6.1 analyzes the relationship between market-level beliefs about fertilizer quality and recent agro-dealer turnover using the agro-dealer census and market-linked farmer sample. Section 6.2 uses the supplemental farmer sample to evaluate how farmers' quality beliefs about a hypothetical new market entrant vary based on having an existing relationship with an incumbent.

6.1 Agro-dealer Turnover and Market-Level Quality Beliefs

We begin by estimating the following model specification:

$$Y_{im} = \beta_0 + \beta_1 MarketSize_{m1} + \beta_2 Exit_{m(1,2)} + \beta_3 Entry_{m(1,2)} + \beta_4 X_i' + \epsilon_{im} \tag{7}$$

Y_{im} captures farmer i's market-level beliefs about fertilizer quality in market m. $MarketSize_{m1}$ controls for the number of agro-dealers in market m in round one. $Exit_{m(1,2)}$ 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 entrants in market m between rounds one and two. Because $Exit_{m(1,2)}$ and $Entry_{m(1,2)}$ are likely highly correlated,[16] we estimate their effects separately and jointly. The vector X_i' includes farmer-level controls from Column 1 of Appendix Table C.1 and ϵ_{im} is the error term.[17]

[16] Prior literature suggests that firm entry rates are highly correlated with firm exit rates within and across sectors. This pattern has been documented among formal firms (Caves, 1998; Dunne et al., 1988; Chang, 2011) 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 the market-linked farmer sample, there is a moderate correlation between the number of agro-dealer exits and new market entrants ($r = 0.3031$). The variance inflation factors for these variables are consistently below two, suggesting low multicollinearity and stable coefficient estimates.

[17] A leave-one-out instrumental variables (IV) approach using agro-dealer exits or entry in neighboring markets could serve as a robustness check. However, only ten percent of markets in our sample have a nearest neighboring market within 1 km (see Section 4.1), limiting the instrument's relevance for most farmers. Also, in cases where markets are proximate, spillovers in farmer beliefs across markets are likely, potentially violating the exclusion restriction.

Table 7 reports the results. Columns 1-3 use as the outcome the number of farmers out of ten that farmer i in market m believed would receive high-quality fertilizer from market m. Columns 4-6 use a binary outcome equal to one if farmer i expressed *any* concern about fertilizer quality in market m (i.e., reported at least one farmer would not receive high-quality fertilizer). Columns 1 and 4 estimate the relationship between exit and beliefs, without controlling for entry. Columns 2 and 5 estimate the relationship between entry and beliefs, without controlling for exit. Columns 3 and 6 report the estimates conditioning on both entry and exit simultaneously.

Table 7: Effect of Agro-dealer Turnover on Farmers' Market-level Quality Beliefs

	Farmers out of Ten Receiving High-quality Fertilizer			Concerned About Fertilizer Quality		
	(1)	(2)	(3)	(4)	(5)	(6)
Baseline market size (β_1)	-0.029	0.017	-0.081	0.010	-0.007	0.011
	(0.047)	(0.063)	(0.066)	(0.006)	(0.008)	(0.008)
Agro-dealer exits (β_2)	0.279*		0.305**	-0.056**		-0.057**
	(0.147)		(0.149)	(0.023)		(0.023)
New market entrants (β_3)		0.033	0.057		0.003	-0.002
		(0.052)	(0.055)		(0.006)	(0.006)
Outcome variable mean	6.82	6.82	6.82	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	1,242	1,242	1,242	1,242	1,242	1,242

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parentheses) are clustered at the market-level (Abadie et al., 2023). Columns 3 and 6 estimate Equation 7. "Baseline market size" is the number of agro-dealers operating in a market in round one, "agro-dealer exits" is the number of agro-dealers that exited a market between rounds one and two, and "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 are listed in Column 1 of Appendix Table C.1.

We first examine the relationship between agro-dealer exit and farmer beliefs about market-level fertilizer quality. Our discussion focuses on the full model specification in Equation 7 that controls for entry and exit simultaneously, although the results are similar when we estimate the effect of exit alone. Results in Column 3 of Table 7 show that each additional agro-dealer exit is associated with an *increase* of approximately 0.3 in the number of farmers out of ten that farmer i believes would receive high-quality fertilizer. The significance and interpretation of this result is consistent with that in Column 6, where each additional exit *reduces* the probability that farmer i expresses any concern about the quality of fertilizer sold in their market by 5.7 percentage points. Altogether, these findings suggest that as agro-dealer exit increases within their market, farmers become less concerned about the quality of fertilizer sold in their market.

Consumer beliefs about the market's overall product quality improve following firm exit. This empirical finding is consistent with Theorem 1, which suggests consumers tend to believe that exiting firms are those who sell below-average quality products. As mentioned previously, farmer beliefs in this setting are consistently inaccurate and prior research has shown that fertilizer quality exceeds typical farmer expectations. In this context, agro-dealer exits would seem to help correct farmers' misconceptions about market-level fertilizer quality.

Results in Table 7 are robust to alternative model specifications. These include: (1) clustering standard errors at the village-level; (2) winsorizing the variables "new market entrants" and (3) "baseline market size" at the 95th percentile given their long-tailed distributions; and, (4) using percentages of agro-dealer exits and new market entrants rather than counts as the independent variables (see Appendix Tables C.4, C.5, and C.6, respectively). Furthermore, we find that this relationship between agro-dealer exit and farmer beliefs is stronger in smaller markets and for more risk averse farmers (see Appendix Tables C.7 and C.8, respectively).

In contrast to agro-dealer exit, we find no evidence that on average farmers adjust their market-level beliefs regarding fertilizer quality in response to agro-dealer entry. The estimated relationships between the number of new market entrants and our farmer belief outcomes in Columns 2, 3, 5, and 6 of Table 7 are small and not statistically significant. Additional analyses show that the effect of agro-dealer entry on farmer beliefs does not vary with a variety of farmer characteristics or by baseline market size (see Appendix Table C.7). We also empirically rule out the possibility that the lack of an observed entry effect is driven by lower variation in the number of new market entrants relative to agro-dealer exits across markets or by more farmers residing in markets with lower annual agro-dealer entry relative to exit rates (see Appendix Figures C.1 and C.2, respectively).

This null effect between agro-dealer entry and farmer beliefs is consistent with Theorem 3, which predicts that a new market entrant will moderate consumer beliefs regarding their market's overall product quality. Our model further suggests that the actual entry effect depends primarily on the strength and direction of information signals specific to remaining incumbents, a possibility we explore in the next section.

6.2 Information Signals Through Relationships

To better understand the effect of agro-dealer entry, recall that Theorems 3.1-3.3 build on the insight that shifts in consumer beliefs about market-level product quality following a new market entrant's arrival depend on the strength and direction of aggregated information signals about incumbents. If a farmer holds strong positive (negative) information signals about the quality of products sold by incumbents, agro-dealer entry is expected to lower (raise) their expectations about market-level product quality (Theorems 3.1 and 3.2). If no information signals are present in a market, agro-dealer entry has no effect on farmer beliefs (Theorem 3.3).

To test whether farmers respond differently to new market entrants depending on information signals about incumbents, we analyze data from the supplemental farmer sample. The data include farmers' reported beliefs regarding the quality of both agricultural inputs and information provided by two agro-dealer types: their current agro-dealer (an incumbent) and a hypothetical new market entrant. To connect the empirical results to our model, we assume that farmers who report having a consistent, stable relationship with a particular agro-dealer in their market possess strong positive information signals about that incumbent's product quality.

We estimate the following model specification:

$$Y_{iv} = \beta_0 + \beta_1 New + \beta_2 Stable_i + \beta_3 (New \times Stable_i) + \beta_4 X_i' + \mu_v + \epsilon_{iv} \tag{8}$$

Y_{iv} captures either agricultural input or information quality beliefs reported by farmer i in village v. New is a binary variable equal to one if the beliefs refer to a hypothetical new market entrant, and zero if they refer to farmer i's current agro-dealer. $Stable_i$ is a binary variable equal to one if farmer i reports *usually* purchasing agricultural inputs from the same agro-dealer over the past five years, and zero otherwise. The vector X_i' includes farmer-level controls from Column 2 of Appendix Table C.1, μ_v is village fixed effects, and ϵ_{iv} is the error term.

In Equation 8, β_0 represents the average quality belief about a current agro-dealer for farmers *without* a stable agro-dealer relationship, conditional on X_i' and μ_v. β_1 reflects the average difference in quality beliefs between the current agro-dealer and a hypothetical new market entrant for these same farmers. β_2 represents how quality beliefs about a current agro-dealer differ between farmers with a stable agro-dealer relationship and those without. The interaction term β_3 represents if having a stable relationship with an incumbent modifies the perceived quality of a hypothetical new market entrant relative to that of the incumbent. The sum $\beta_1 + \beta_3$ captures how quality beliefs about a hypothetical new market entrant differ from those regarding the current agro-dealer among farmers with a stable agro-dealer relationship.[18] This sum gives insight into whether strong positive information signals about an incumbent lead farmers to form lower expectations regarding the quality offered by new market entrants. Considering only the quality belief ratings that farmers reported, if $\beta_1 + \beta_3 < 0$, the hypothetical new market entrant is perceived to provide *lower*-quality agricultural inputs or information relative to the incumbent. If $\beta_1 + \beta_3 > 0$, they are perceived to provide *higher*-quality agricultural inputs or information. For the binary versions of these variables that indicate whether a farmer expresses concern, the interpretation is reversed.

Unlike the market-level results reported in Section 6.1, which examine farmers' quality beliefs in relation to observed agro-dealer turnover, the results in this section focus on farmers' stated quality expectations when comparing a specific incumbent to a hypothetical new market entrant. Table 8 presents the results. For completeness, we report estimates from the full model specification in Equation 8 and a reduced model specification that omits $Stable_i$ and its interaction with New. Columns 1-4 use farmers' beliefs about agricultural input quality as the outcome: Columns 1-2 use the number of farmers out of ten that farmer i believed would receive high-quality agricultural inputs, while Columns 3-4 use a binary version equal to one if farmer i expressed *any* concern about agricultural input quality. Columns 5-8 apply the same structure to farmers' beliefs about agricultural information quality.

Column 1 indicates that, on average, farmers expect 1.74 fewer out of ten farmers to receive high-quality agricultural inputs from a hypothetical new market entrant compared to their current agro-dealer. Similarly, Column 3 reports that the probability a farmer expresses *any* concern about agricultural input quality is 18.7 percentage points higher for a hypothetical new market entrant than for their current agro-dealer. Columns 5 and 7 show a similar pattern for agricultural information: farmers rate that of a hypothetical new market entrant on average 2.04 points lower than that of their current agro-dealer, and the likelihood that a farmer is concerned about the quality is 24.7 percentage points higher for a hypothetical new market entrant.

[18] To see this, note the perceived quality belief regarding the current agro-dealer for a farmer with a stable agro-dealer relationship is $\beta_0 + \beta_2$, while that about a hypothetical new market entrant for the same farmer is $\beta_0 + \beta_1 + \beta_2 + \beta_3$. Subtracting the former from the latter yields $\beta_1 + \beta_3$.

Table 8: Comparing Farmers' Quality Beliefs for an Incumbent Relative to a New Market Entrant

	Agricultural Inputs				Agricultural Information			
	Farmers out of Ten Receiving High-quality		Concerned About Quality		Quality Rating		Concerned About Quality	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
New market entrant (β_1)	-1.740***	-0.161	0.187***	-0.036	-2.037***	-0.714*	0.247***	0.018
	(0.258)	(0.404)	(0.051)	(0.079)	(0.310)	(0.357)	(0.059)	(0.070)
Stable relationship (β_2)		1.955***		-0.290***		1.906***		-0.280***
		(0.416)		(0.077)		(0.360)		(0.080)
New market entrant × stable relationship (β_3)		-2.520***		0.355***		-2.110***		0.365***
		(0.487)		(0.092)		(0.406)		(0.080)
$\beta_1 + \beta_3$		-2.681		0.319		-2.824		0.383
Reference group mean	8.37	7.14	0.47	0.66	7.85	6.67	0.59	0.77
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farmer-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.172	0.236	0.108	0.149	0.204	0.263	0.148	0.196
Observations	300	300	300	300	300	300	300	300

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parentheses) are clustered at the village-level (Abadie et al., 2023). Columns 2, 4, 6, and 8 estimate Equation 8. "Reference group mean" reports the outcome variable mean for the baseline group in each model specification: quality beliefs about the current agro-dealer, either for all farmers (Columns 1, 3, 5, and 7) or for farmers without a stable agro-dealer relationship (Columns 2, 4, 6, and 8). Columns 5-6 report responses on a scale from one to ten, where one indicates the lowest perceived quality and ten indicates the highest. A stable agro-dealer relationship is defined as *usually* purchasing agricultural inputs from the same agro-dealer over the past five years. Farmer-level controls are listed in Column 2 of Appendix Table C.1.

Columns 2, 4, 6, and 8 disaggregate the results by farmers with and without a stable agro-dealer relationship. As shown in Table 8, this heterogeneity meaningfully shapes quality beliefs. The sum $\beta_1 + \beta_3$ suggests that farmers with a stable agro-dealer relationship expect, on average, that 2.68 fewer farmers out of ten would receive high-quality agricultural inputs from a hypothetical new market entrant compared to their current agro-dealer. This is reinforced in Column 4, which shows a 31.9 percentage point increase in the probability that these farmers are concerned about a new market entrant's agricultural input quality. A similar pattern emerges for agricultural information quality: these farmers rate that of a hypothetical new market entrant 2.82 points lower than that of their current agro-dealer, and are 38.3 percentage points more likely to express concern. Results are robust to ordered logit model specifications (see Appendix Table C.9). These findings are consistent with our model's prediction: when strong positive information signals about incumbents dominate, firm entry decreases consumer expectations about market-level product quality (Theorem 3.1).

In contrast, among farmers who do *not* have a stable relationship with a particular agro-dealer, there is no statistically significant difference in agricultural input quality beliefs between their current agro-dealer and a new market entrant (see Columns 2 and 4). It seems that the average differences observed in Columns 1 and 3 are entirely driven by farmers with stable relationships, those with strong positive information signals about their incumbent. For agricultural information quality, a similar pattern exists. On average, farmers rate the information quality of a hypothetical new market entrant as significantly worse than that provided by their current agro-dealer, and this difference is predominantly, but not exclusively, influenced by farmers with stable agro-dealer relationships. Columns 7 and 8 reflect comparable patterns. These findings align with our model's prediction that when no strong information signals about incumbents are present, firm entry does not affect consumer market-level product quality beliefs (Theorem 3.3).

Overall, farmers with stable agro-dealer relationships appear to have developed substantial trust in their current agro-dealer, likely reinforced through repeated interactions and positive experiences. This trust may heighten their skepticism toward new market entrants, making them more likely to perceive new market entrants as offering lower-quality products and services by comparison.

7 Conclusion

Smallholder farmers in Sub-Saharan Africa often fail to adopt productivity-enhancing agricultural inputs, contributing to persistently low agricultural productivity in the region (De Janvry & Sadoulet, 2002; Asenso-Okyere & Jemaneh, 2012; Sheahan & Barrett, 2017; Suri & Udry, 2022). This low adoption rate may stem from both demand- or supply-side constraints. Agro-dealers, who serve as the final link in agricultural input supply chains, play an essential role by providing smallholder farmers with access to agricultural inputs and information. Yet, despite their importance, agro-dealers remain understudied and poorly understood (A. Dillon et al., 2025).

In this paper, we establish and analyze a key feature of the agro-dealer sector: high firm turnover. Using three rounds of census data from rural Tanzania, we estimate an annual agro-dealer entry rate of 34 percent. In contrast to the "reluctant entrepreneurs" characterized by Banerjee and Duflo (2011), we find that most agro-dealers are optimistic entrepreneurs, expressing strong commitment to their businesses and agricultural input markets. Despite this optimism, approximately one in five agro-dealers exit annually. Agro-dealers are significantly more likely to exit in markets with greater local competition and fewer exiting competitors. These agro-dealer entry and exit rates are more than twice as high as those documented among MSMEs in non-agricultural sectors in similar low-income countries. While structural factors may explain these observed high agro-dealer turnover rates, further research is needed to fully understand the underlying mechanisms.

To our knowledge, no other study has documented firm turnover in the agro-dealer sector. Future research should quantify and analyze agro-dealer turnover in other contexts.[19] If high turnover is common across settings, it may represent an inherent characteristic of agricultural input supply chains, potentially helping to explain low agricultural technology adoption and agricultural productivity in Sub-Saharan Africa and elsewhere.

Do high firm turnover rates indicate a market failure that could be addressed through stronger regulation? In rural Tanzania, the majority of agro-dealers operate without a government-issued license to sell fertilizer, despite it being a legal requirement. Strengthening enforcement of licensing requirements for *all* agricultural input sales could raise the barriers to entry and potentially reduce information asymmetries, thereby improving market functioning. Licensing reforms could also be paired with complementary interventions, such as publishing quality test results or implementing agro-dealer rating systems (Miehe et al., 2023), to help farmers better evaluate quality. However, any potential benefits must be weighed against the costs. Overly stringent licensing requirements could suppress competition, increase prices, and slow the cumulative learning process among farmers. Additional research on these trade-offs would be valuable to policymakers seeking to develop more robust agricultural input markets.

To better understand the implications of high firm turnover in the agro-dealer sector, we develop a theoretical model of firm entry and exit under information asymmetries. Our model shows that consumers' beliefs about market-level product quality can either improve or get worse following a firm's exit, depending on their perception of the exiting firm's product quality. It also demonstrates how consumers update their beliefs about market-level product quality in response to a new market entrant based on their average expectations of the product quality provided by incumbents. This framework can be extended to other markets for experience or credence goods in weakly regulated settings, such as veterinary pharmaceuticals, informal education services, or healthcare provision—where firm turnover may similarly affect consumer trust and learning.

We use the model's predictions to interpret how agro-dealer turnover influences farmer beliefs about local agricultural input quality. Consistent with our model, we find that farmers' perceptions of market-level fertilizer quality *improve* following an agro-dealer's exit which suggests that farmers believed the exiting agro-dealer sold below-average quality fertilizer. Given prior empirical evidence that farmers often hold inaccurate beliefs about fertilizer quality (Michelson et al., 2021; Hoel et al., 2024), this result implies that agro-dealer exits may help align farmer beliefs more closely with actual market conditions. In contrast, we find no average change in farmer beliefs following agro-dealer entry. Yet, farmers who consistently purchase agricultural inputs from the *same* agro-dealer report lower expectations about the quality of agricultural inputs offered by a new market entrant.

Our finding that farmers revise their beliefs about agricultural input quality in response to agro-dealer exit raises an important question: if exits are frequent and belief updating occurs, why do inaccurate beliefs *still* persist in these markets? We propose two possible explanations. In both cases, misinformation endures not because farmers fail to learn, but because features of agricultural input markets undermine the conditions needed for sustained belief formation.

First, high agro-dealer turnover may prevent the market from stabilizing long enough for farmer beliefs to fully adjust. If belief revision is predominantly triggered by agro-dealer failure rather than success, then learning becomes slow and fragmented. Though individual exits may improve farmer beliefs locally, the frequent entry of new, unfamiliar agro-dealers can offset this process—preventing

[19] Using Ugandan panel data collected by Gilligan and Karachiwalla (2021), we estimate an annual agro-dealer entry rate of 51.0 percent and exit rate of 15.6 percent. These rates, like ours, use data from three survey rounds, but a subset of agro-dealers could not be tracked over time. As such, they are not based on a full census and are not directly comparable to our results. Nonetheless, as a back-of-the-envelope calculation, they suggest similarly high levels of agro-dealer turnover.

broader belief correction. Therefore, ongoing agro-dealer turnover may hinder market-level learning even as exits update beliefs incrementally.

Second, survivorship bias may also play a role: agro-dealers may remain in business not because they supply higher-quality products, but because they are better at establishing trust or maintaining customer relationships. This can make it difficult for farmers to distinguish product reliability from interpersonal rapport. Additionally, belief updating itself may be slow or asymmetric, as farmers are more likely to respond to salient negative signals, such as agro-dealer exit, than to positive signals like consistent performance and the provision of accurate, objective information (Abay, Barrett, et al., 2023; Abay, Wossen, et al., 2023). A similar pattern is observed in another agricultural context, where farmers in Bangladesh overweight salient but noisy signals from recent weather shocks when forming beliefs about climate change (Patel, 2023).

The relevance of our findings extends beyond agricultural input markets to other settings characterized by asymmetric information. Notably, we show high firm exit rates can improve the accuracy of consumer expectations. However, consumers' hesitation to trust new market entrants presents a major challenge for MSMEs operating in weakly regulated environments, where signaling credibility and product quality is difficult (Creane & Jeitschko, 2016; Zhang et al., 2022). This dynamic may contribute to the slow growth and high exit rates frequently observed among new MSME entrants in other sectors in low-income countries (Aga & Francis, 2017; McKenzie & Paffhausen, 2019).

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Appendix

A Supplemental Model Details

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 $\pi_{jimt} = \dfrac{1}{1+e^{-(\alpha_{jimt}+\alpha_{-jimt})-p_{jmt}}} = (1+e^{-(\alpha_{jimt}+\alpha_{-jimt})-p_{jmt}})^{-1}$, 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, $\frac{\partial \pi_{jimt}}{\partial \alpha_{jimt}} = \frac{\partial \pi_{jimt}}{\partial \alpha_{-jimt}} = \frac{\partial \pi_{jimt}}{\partial p_{jmt}} = \pi_{jimt}(1-\pi_{jimt}) > 0$

B Agro-dealer Turnover Rate Estimation Details

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

To annualize these entry and exit rates, we divide each rate for a pair of rounds by the number of years between the rounds in each pair ($T_{(r,r+1)}$). This adjustment ensures comparability across pairs of rounds: rounds one to two, and two to three. We then compute a weighted average of the annual rates to produce a single annual rate spanning the full study period. The weights ($W_{(r,r+1)}$) reflect the proportion of time that each round-pair contributes to the full study period. Time between rounds one and two ($T_{(1,2)}$) is 2.53 years (i.e., 925 days) and time between rounds two and three ($T_{(2,3)}$) is 0.86 years (i.e., 315 days). We calculate these durations by counting the number of days between the day after the last survey date of one round and the day before the first survey date of the next round. The resulting weights are $W_{(1,2)} = \frac{925}{925+315} = 0.75$ and $W_{(2,3)} = 0.25$.

Equations 9 and 10 define the annual agro-dealer entry and exit rates, respectively. In Equation 9, $E_{(1,2)}$ and $E_{(2,3)}$ capture the number of new market entrants between rounds one and two, and two and three, respectively. In Equation 10, $X_{(1,2)}$ and $X_{(2,3)}$ represent the number of agro-dealer exits between rounds one and two, and two and three, respectively. N_1 and N_2 denote the number of agro-dealers at the start of rounds one and two, respectively, while $T_{(1,2)}$ and $T_{(2,3)}$ are the time intervals in years in between each round-pair. The weights $W_{(1,2)}$ and $W_{(2,3)}$ are functions of these time intervals and determine each pair's contribution to the overall annual rate.

$$\text{Annual Agro-dealer Entry Rate} = W_{(1,2)} \left(\frac{\left(\frac{E_{(1,2)}}{N_1}\right)}{T_{(1,2)}} \right) + W_{(2,3)} \left(\frac{\left(\frac{E_{(2,3)}}{N_2}\right)}{T_{(2,3)}} \right) \tag{9}$$

$$\text{Annual Agro-dealer Exit Rate} = W_{(1,2)} \left(\frac{\left(\frac{X_{(1,2)}}{N_1}\right)}{T_{(1,2)}} \right) + W_{(2,3)} \left(\frac{\left(\frac{X_{(2,3)}}{N_2}\right)}{T_{(2,3)}} \right) \tag{10}$$

C Supplemental Tables and Figures

Table C.1: Descriptive Statistics for Farmer Samples

Farmer Characteristics	Market-linked (1)	Supplemental (2)
Is female	0.42	0.27
	(0.49)	(0.45)
Age	44.76	45.08
	(12.46)	(13.25)
Household size	5.42	—
	(2.49)	
Highest level of education		
No schooling	0.10	0.02
	(0.30)	(0.14)
Primary school	0.77	0.66
	(0.42)	(0.48)
Secondary school	0.11	0.27
	(0.31)	(0.44)
Vocational training	0.01	0.02
	(0.09)	(0.14)
University (e.g., diploma, BSc, MSc, PhD)	0.01	0.03
	(0.11)	(0.18)
Acres of land owned	5.68	4.69
	(4.93)	(4.86)
Is risk averse	0.39	—
	(0.49)	
Observations	1,242	150

Note: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Each column reports the mean with the standard deviation in parentheses. We winsorize the variable "acres of land owned" in the market-linked farmer sample only for data above the 95th percentile given its long-tailed distribution.

Table C.2: Logit Model for Predictors of Agro-dealer Exit

	(1)	(2)	(3)
Agro-dealer Characteristics			
Owns a car or truck	-0.383	-0.331	-1.000*
	(0.292)	(0.302)	(0.526)
Has CNFA/TAGMARK certification displayed	0.126	0.103	0.072
	(0.264)	(0.263)	(0.414)
Uses outdoor signage for advertising	0.140	-0.004	0.183
	(0.231)	(0.234)	(0.325)
Other locations that sell fertilizer	-0.020	-0.038	-0.035
	(0.170)	(0.171)	0.286
Has a license to sell fertilizer	-0.288	-0.255	-0.419*
	(0.192)	(0.189)	(0.249)
Number of additional employees present at time of interview	0.251**	0.215*	0.182
	(0.107)	(0.110)	(0.175)
Years operating at current location	-0.057**	-0.053*	0.011
	(0.028)	(0.028)	(0.039)
Market Characteristics			
Agro-dealers operating in a market	-0.023**	-0.009	0.353***
	(0.011)	(0.011)	(0.132)
Share of *other* agro-dealer exits relative to the previous round	0.244	0.077	-4.916***
	(0.414)	(0.456)	(1.273)
Share of new market entrants relative to the previous round	0.125	0.039	0.185
	(0.152)	(0.175)	(0.500)
Round fixed effects	No	Yes	Yes
Market fixed effects	No	No	Yes
R^2	0.026	0.038	0.272
Observations	522	522	452

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 presents results associated with the logit model specification with no fixed effects. Column 2 adds round fixed effects, while Column 3 includes both round and market fixed effects. We winsorize the variable "years operating at current location" only for data above the 95th percentile given its long-tailed distribution. A CNFA/TAGMARK certificate is awarded to Tanzanian agro-dealers who completed the TAGMARK training program, which focused on improving agro-dealer professionalism, business practices, and technical knowledge. Column 3 has a smaller sample size because 29 markets, representing 70 agro-dealers, showed no variation in agro-dealer exit and are dropped when market fixed effects are included.

Table C.3: Probit Model for Predictors of Agro-dealer Exit

	(1)	(2)	(3)
Agro-dealer Characteristics			
Owns a car or truck	-0.227	-0.194	-0.562**
	(0.168)	(0.175)	(0.269)
Has CNFA/TAGMARK certification displayed	0.070	0.059	-0.011
	(0.158)	(0.158)	(0.230)
Uses outdoor signage for advertising	0.088	-0.001	0.095
	(0.139)	(0.141)	(0.191)
Other locations that sell fertilizer	-0.020	-0.035	-0.001
	(0.103)	(0.103)	(0.157)
Has a license to sell fertilizer	-0.169	-0.156	-0.244*
	(0.115)	(0.113)	(0.140)
Number of additional employees present at time of interview	0.149**	0.127*	0.093
	(0.065)	(0.067)	(0.101)
Years operating at current location	-0.034**	-0.031*	0.009
	(0.017)	(0.017)	(0.022)
Market Characteristics			
Agro-dealers operating in a market	-0.014**	-0.005	0.204***
	(0.006)	(0.006)	(0.065)
Share of *other* agro-dealer exits relative to the previous round	0.144	0.037	-2.824***
	(0.252)	(0.279)	(0.673)
Share of new market entrants relative to the previous round	0.076	0.025	0.107
	(0.093)	(0.106)	(0.261)
Round fixed effects	No	Yes	Yes
Market fixed effects	No	No	Yes
R^2	0.026	0.038	0.273
Observations	522	522	452

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 presents results associated with the probit model specification with no fixed effects. Column 2 adds round fixed effects, while Column 3 includes both round and market fixed effects. We winsorize the variable "years operating at current location" only for data above the 95th percentile given its long-tailed distribution. A CNFA/TAGMARK certificate is awarded to Tanzanian agro-dealers who completed the TAGMARK training program, which focused on improving agro-dealer professionalism, business practices, and technical knowledge. Column 3 has a smaller sample size because 29 markets, representing 70 agro-dealers, showed no variation in agro-dealer exit and are dropped when market fixed effects are included.

Table C.4: Robustness Check for the Effect of Agro-dealer Turnover on Farmers' Market-level Quality Beliefs: Clustering Standard Errors at the Village-Level

	Farmers out of Ten Receiving High-quality Fertilizer			Concerned About Fertilizer Quality		
	(1)	(2)	(3)	(4)	(5)	(6)
Baseline market size (β_1)	-0.029	0.017	-0.081	0.010*	-0.007	0.011
	(0.045)	(0.063)	(0.064)	(0.006)	(0.008)	(0.008)
Agro-dealer exits (β_2)	0.279**		0.305**	-0.056***		-0.057***
	(0.138)		(0.141)	(0.021)		(0.021)
New market entrants (β_3)		0.033	0.057		0.003	-0.002
		(0.051)	(0.052)		(0.006)	(0.006)
Outcome variable mean	6.82	6.82	6.82	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	1,242	1,242	1,242	1,242	1,242	1,242

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This robustness check clusters standard errors (in parentheses) at the village-level (Abadie et al., 2023). Columns 3 and 6 estimate Equation 7. "Baseline market size" is the number of agro-dealers operating in a market in round one, "agro-dealer exits" is the number of agro-dealers that exited a market between rounds one and two, and "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 are listed in Column 1 of Appendix Table C.1.

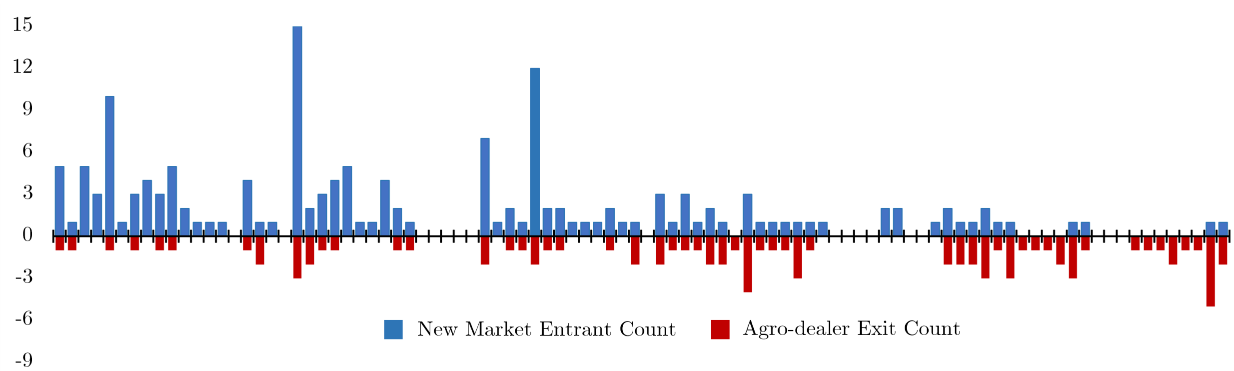

Figure C.1: Number of New Market Entrants and Agro-dealer Exits by Market Between Rounds One and Two

Notes: this figure displays the number of agro-dealers that entered and exited each market between rounds one and two. Market order on the x-axis matches Figure 3, except for one omitted market because the market-linked farmer sample covers 94 markets rather than 95. The figure highlights greater variation in agro-dealer entry across markets relative to exit. Specifically, the sample variance is 5.97 for entry and 1.05 for exit. Also, a larger portion of markets experienced low levels of agro-dealer exit relative to entry: 78 percent had zero to one agro-dealer exit between rounds compared to 67 percent with zero to one new market entrants. Notably, the annual agro-dealer entry and exit rates for these markets exhibit variances of 0.77 and 0.15, respectively. Thus agro-dealer entry shows greater variation than exit, both in absolute terms and relative to market size.

Table C.5: Robustness Check for the Effect of Agro-dealer Turnover on Farmers' Market-level Quality Beliefs: Variable Winzorization

	Farmers out of Ten Receiving High-quality Fertilizer			Concerned About Fertilizer Quality		
	(1)	(2)	(3)	(4)	(5)	(6)
(A) Winsorizing "New Market Entrants"						
Baseline market size (β_1)		0.003	-0.084		-0.005	0.011
		(0.047)	(0.051)		(0.006)	(0.007)
Agro-dealer exits (β_2)			0.309**			-0.057**
			(0.146)			(0.023)
New market entrants (β_3)		0.117*	0.140**		0.001	-0.003
		(0.069)	(0.068)		(0.011)	(0.011)
R^2		0.022	0.029		0.013	0.022
(B) Winsorizing "Baseline Market Size"						
Baseline market size (β_1)	-0.033	0.053	-0.062	0.016	-0.009	0.016
	(0.091)	(0.078)	(0.102)	(0.011)	(0.010)	(0.011)
Agro-dealer exits (β_2)	0.273*		0.279*	-0.060**		-0.060**
	(0.160)		(0.161)	(0.024)		(0.023)
New market entrants (β_3)		0.026	0.032		0.001	0.000
		(0.043)	(0.048)		(0.005)	(0.005)
R^2	0.025	0.020	0.025	0.022	0.013	0.022
Outcome variable mean	6.82	6.82	6.82	0.70	0.70	0.70
Farmer-level controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,242	1,242	1,242	1,242	1,242	1,242

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. These robustness checks address long-tailed distributions by winsorizing "new market entrants" (Panel A) and "baseline market size" (Panel B) at the 95th percentile. Standard errors (in parentheses) are clustered at the market-level (Abadie et al., 2023). Columns 3 and 6 estimate Equation 7."Baseline market size" is the number of agro-dealers operating in a market in round one, "agro-dealer exits" is the number of agro-dealers that exited a market between rounds one and two, and "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 are listed in Column 1 of Appendix Table C.1.

Table C.6: Robustness Check for the Effect of Agro-dealer Turnover on Farmers' Market-level Quality Beliefs: Variable Scaling

	Farmers out of Ten Receiving High-quality Fertilizer			Concerned About Fertilizer Quality		
	(1)	(2)	(3)	(4)	(5)	(6)
Percentage of agro-dealer exits	0.642**		0.620**	-0.099**		-0.100**
	(0.266)		(0.267)	(0.040)		(0.040)
Percentage of new market entrants		0.152*	0.131		0.004	0.008
		(0.090)	(0.086)		(0.014)	(0.014)
Outcome variable mean	6.82	6.82	6.82	0.70	0.70	0.70
Farmer-level controls	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.026	0.021	0.027	0.023	0.016	0.023
Observations	1,199	1,199	1,199	1,199	1,199	1,199

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. This robustness check replaces counts of agro-dealer exits and new market entrants with percentages—calculated as the ratio of each count to the "baseline market size." "Baseline market size" is the number of agro-dealers operating in a market in round one. Each column includes only 1,199 observations because this model specification uses percentage-based measures, requiring the exclusion of 43 farmers from three markets that had no agro-dealers in round one. Standard errors (in parentheses) are clustered at the market-level (Abadie et al., 2023). Columns 3 and 6 estimate Equation 7. We use farmer beliefs that are associated with their proximate market. Farmer-level controls are listed in Column 1 of Appendix Table C.1.

Table C.7: Effect of Agro-dealer Turnover on Farmers' Market-level Quality Beliefs by Baseline Market Size

	Farmers out of Ten Receiving High-quality Fertilizer			Concerned About Fertilizer Quality		
	(1)	(2)	(3)	(4)	(5)	(6)
(A) Smaller Markets						
Baseline market size (β_1)	-0.134	0.086	-0.150	0.023	-0.010	0.022
	(0.225)	(0.237)	(0.215)	(0.029)	(0.031)	(0.029)
Agro-dealer exits (β_2)	0.541***		0.541***	-0.073**		-0.073**
	(0.196)		(0.196)	(0.029)		(0.029)
New market entrants (β_3)		0.069	0.069		0.008	0.008
		(0.082)	(0.080)		(0.011)	(0.012)
R^2	0.040	0.030	0.041	0.026	0.018	0.026
Observations	851	851	851	851	851	851
(B) Larger Markets						
Baseline market size (β_1)	0.013	-0.014	-0.027	0.004	0.002	0.010
	(0.061)	(0.094)	(0.095)	(0.010)	(0.013)	(0.013)
Agro-dealer exits (β_2)	0.062		0.080	-0.049		-0.052
	(0.232)		(0.236)	(0.034)		(0.034)
New market entrants (β_3)		0.035	0.039		-0.003	-0.006
		(0.062)	(0.064)		(0.008)	(0.008)
R^2	0.024	0.024	0.025	0.022	0.014	0.023
Observations	391	391	391	391	391	391
Outcome variable mean	6.82	6.82	6.82	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 (in parentheses) are clustered at the market-level (Abadie et al., 2023). Columns 3 and 6 estimate Equation 7. "Baseline market size" is the number of agro-dealers operating in a market in round one, "agro-dealer exits" is the number of agro-dealers that exited a market between rounds one and two, and "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 are listed in Column 1 of Appendix Table C.1. Smaller markets have a size equal to or less than the median number of agro-dealers in round one (i.e., two).

Table C.8: Effect of Agro-dealer Turnover on Farmers' Market-level Quality Beliefs by Farmer Risk Aversion

	Farmers out of Ten Receiving High-quality Fertilizer			Concerned About Fertilizer Quality		
	(1)	(2)	(3)	(4)	(5)	(6)
(A) Farmer is Risk Averse						
Baseline market size (β_1)	0.089	0.165*	0.015	0.008	-0.022	0.007
	(0.073)	(0.085)	(0.088)	(0.009)	(0.015)	(0.014)
Agro-dealer exits (β_2)	0.438**		0.476**	-0.095***		-0.095***
	(0.200)		(0.204)	(0.031)		(0.032)
New market entrants (β_3)		0.056	0.090		0.008	0.001
		(0.061)	(0.059)		(0.013)	(0.012)
R^2	0.056	0.045	0.059	0.046	0.022	0.046
Observations	482	482	482	482	482	482
(B) Farmer is Not Risk Averse						
Baseline market size (β_1)	-0.113*	-0.086	-0.158*	0.012	0.004	0.017
	(0.061)	(0.078)	(0.090)	(0.009)	(0.010)	(0.012)
Agro-dealer exits (β_2)	0.199		0.223	-0.037		-0.040
	(0.169)		(0.171)	(0.028)		(0.028)
New market entrants (β_3)		0.029	0.048		-0.002	-0.005
		(0.067)	(0.071)		(0.009)	(0.009)
R^2	0.021	0.019	0.022	0.010	0.006	0.010
Observations	760	760	760	760	760	760
Outcome variable mean	6.82	6.82	6.82	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 (in parentheses) are clustered at the market-level (Abadie et al., 2023). Columns 3 and 6 estimate Equation 7. "Baseline market size" is the number of agro-dealers operating in a market in round one, "agro-dealer exits" is the number of agro-dealers that exited a market between rounds one and two, and "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 are listed in Column 1 of Appendix Table C.1; however, "risk averse" is not included as it is used to examine heterogeneity. A farmer is "risk averse" if they believe they take much fewer risks or somewhat fewer risks compared to others.

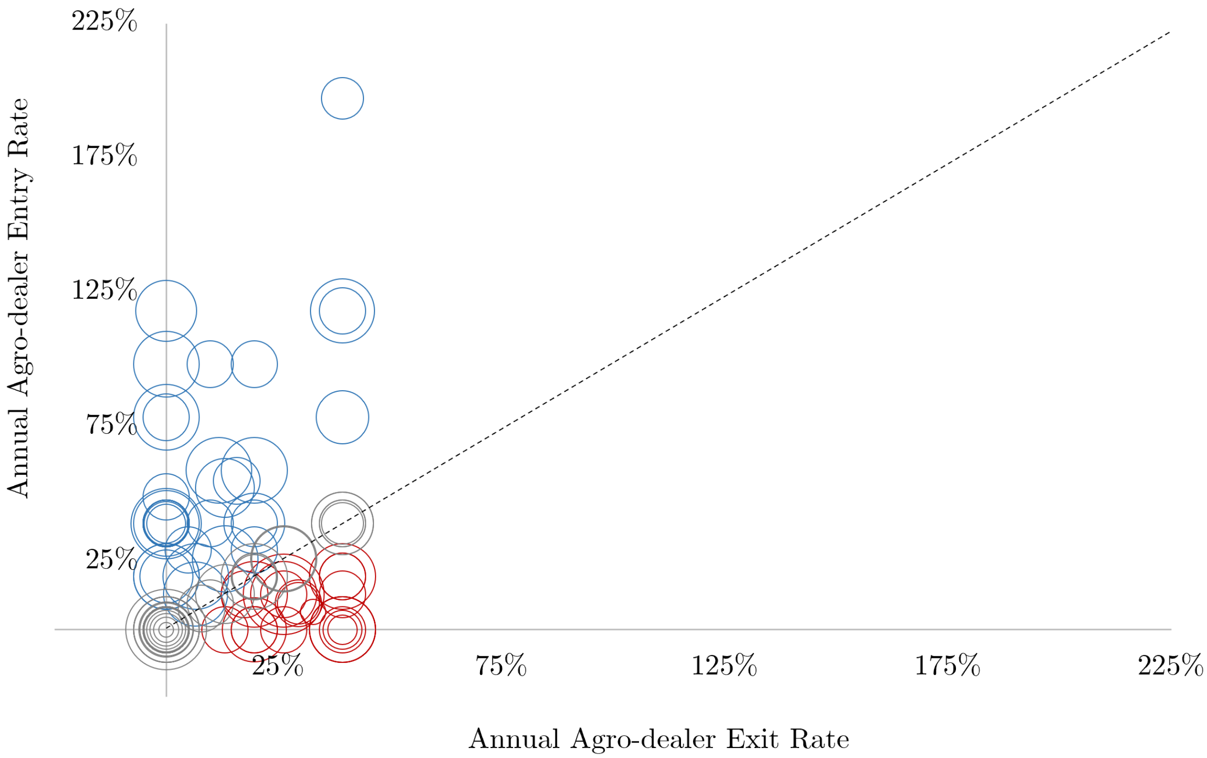

Figure C.2: Market-Linked Farmer Sample Concentration Relative to Annual Agro-dealer Entry and Exit Rates Across Markets

Notes: this figure presents a scatter plot of the market-linked farmer sample across markets, depicting annual agro-dealer turnover rates between rounds one and two. Each circle represents a market, with its size corresponding to the number of farmers residing in that market. To identify whether a larger portion of the market-linked farmer sample resides in markets with a lower annual agro-dealer entry rate relative to exit rate, attention is given to circles below the $y = x$ diagonal line. At this line, the annual agro-dealer entry rate equals the exit rate. The area below and to the right of this line highlights markets with lower entry than exit rates. Of the 1,242 farmers in this sample, 301 resided in markets below the diagonal (red), 511 resided in those above it (blue), and 430 resided in those on it (gray). This indicates that most farmers are not in markets where the annual agro-dealer entry rate is lower than the exit rate. Note that only 94 of the 97 markets are represented in the market-linked farmer sample.

Table C.9: Ordered Logit Model for Comparing Farmers' Quality Beliefs for an Incumbent Relative to a New Market Entrant

	Agricultural Inputs				Agricultural Information			
	Farmers out of Ten Receiving High-quality		Concerned About Quality		Quality Rating		Concerned About Quality	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
New market entrant (β_1)	-1.225***	-0.083	0.835***	-0.167	-1.528***	-0.595*	1.397***	0.110
	(0.190)	(0.286)	(0.228)	(0.355)	(0.256)	(0.312)	(0.346)	(0.416)
Stable relationship (β_2)		1.495***		-1.300***		1.446***		-1.396***
		(0.325)		(0.349)		(0.308)		(0.443)
New market entrant × stable relationship (β_3)		-1.946***		1.617***		-1.583***		2.087***
		(0.390)		(0.440)		(0.302)		(0.452)
$\beta_1 + \beta_3$		-2.029		1.450		-2.178		2.197
Reference group mean	8.37	7.14	0.47	0.66	7.85	6.67	0.59	0.77
Village fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Farmer-level controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.048	0.070	0.084	0.117	0.057	0.075	0.131	0.173
Observations	300	300	300	300	300	300	300	300

Notes: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. Standard errors (in parentheses) are clustered at the village-level (Abadie et al., 2023). Columns 2, 4, 6 and 8 estimate Equation 8. "Reference group mean" reports the outcome variable mean for the baseline group in each model specification: quality beliefs about the current agro-dealer, either for all farmers (Columns 1, 3, 5, and 7) or for farmers without a stable agro-dealer relationship (Columns 2, 4, 6, and 8). Columns 5-6 report responses on a scale from one to ten, where one indicates the lowest perceived quality and ten indicates the highest. A stable agro-dealer relationship is defined as *usually* purchasing agricultural inputs from the same agro-dealer over the past five years. Farmer-level controls are listed in Column 2 of Appendix Table C.1.