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ARTICLE

Firm turnover under asymmetric information: Tanzania's agro-dealer sector

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Abstract

We study firm turnover (i.e., entry and exit) and its consumer implications in a market characterized by asymmetric information. Using a three-round census of agro-dealers in Tanzania's Morogoro Region, we document annual firm entry and exit rates of 33% and 17%, respectively. These rates are more than double those observed for non-agricultural micro-, small-, and medium-enterprises in comparable low-income countries. To analyze how these high rates of entry and exit affect consumers, we develop a theoretical model of firm turnover under asymmetric information and empirically test its predictions for farmers. We find that farmers' market-level beliefs about agricultural input quality are systematically related to agro-dealer turnover, with the relationship depending on farmers' prior perceptions of market quality. Farmers report more favorable beliefs about agricultural input quality in markets with recent agro-dealer exits, consistent with our model when consumers perceive exiting firms as having sold low-quality products. In contrast, farmers who usually purchased agricultural inputs from the same agro-dealer expect new market entrants to provide lower-quality agricultural inputs, suggesting farmers rely on incumbent relationships to manage quality uncertainty in markets with information asymmetries. As a result, agro-dealer turnover may shape and even attenuate farmers' technology adoption.

KEYWORDS
agricultural input markets, consumer beliefs, firm turnover, information asymmetry, Tanzania

JEL CLASSIFICATION
O12, D82, Q13, L15

1 | INTRODUCTION

Markets are often characterized by information asymmetries that prevent buyers from assessing product quality prior to purchase. These information asymmetries are especially pronounced in low-income countries with weak regulatory institutions. Agricultural inputs, including seeds, fertilizer, and pesticides, are prone to these asymmetries because they are typically experience goods whose agronomic quality cannot be readily evaluated until after use. Agricultural input suppliers—known as agro-dealers—primarily operate as micro-, small-, and medium-enterprises (MSMEs) and play a central role in these markets. They not only sell agricultural inputs to farmers but also serve as key sources of agricultural information, particularly in contexts where formal public extension services are underfunded or absent (Rutsaert & Donovan, 2020; Sones et al., 2015).

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. Uncertainty about the quality of agricultural inputs in their own markets leads farmers to reduce investment, even when actual quality variation is limited (Ashour et al., 2019; Bulte et al., 2025; Gilligan & Karachiwalla, 2022; Michelson et al., 2021). Given the challenges posed by weak government regulation and enforcement capacity (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 over time. Such relationships can also encourage agro-dealers to maintain high standards to build reputations. High agro-dealer turnover may disrupt these dynamics, limiting the potential to resolve information-related market failures.

In this paper, we estimate firm turnover (i.e., entry and exit) among agro-dealers and analyze its implications for smallholder farmers. The agro-dealer turnover rates we document are considerably higher than those reported for non-agricultural MSMEs. Theoretically, high firm turnover reflects three underlying conditions of competitive markets: high contestability, market fragmentation, and hyper-localized demand. Each of these conditions both arises from and is reinforced by competitive pressure. Microeconomic theory suggests that high firm turnover enhances competition and benefits consumers, even in imperfectly competitive markets (Asplund & Nocke, 2006; Chang, 2011). Firm entry can stimulate job creation and local economic growth, generating indirect consumer benefits. Firm exit, however, can reduce consumer choice and impose switching costs as buyers search for alternative suppliers. Hence the net welfare effects of high firm turnover are theoretically ambiguous, even in markets with limited information asymmetries. In markets characterized by information asymmetries, such as the agro-dealer sector, the net effects are even less clear.

We develop a theoretical model of firm turnover in markets with information asymmetries that serves as an organizing framework for the structure and interpretation of our empirical analysis. In the model, consumers form and update beliefs about market-level product quality using information from their previous transactions, others' experiences, and prevailing market-level priors. The 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, then consumer expectations worsen. 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 evaluate these predictions using data from Tanzania's Morogoro Region, a major agricultural hub. Our data include a three-round census of all fixed-location agro-dealers in the region collected between 2015 and 2020, covering 515 agro-dealers operating across 97 major markets. We merge the agro-dealer census with a survey of 1242 smallholder farmers collected in the same region in 2019. To further assess the consumer implications of our theoretical model, we analyze a complementary cross-sectional dataset of 150 farmers collected in the same region in 2022.

We establish two 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. Using the three-round agro-dealer census that spans 4 years, we calculate annual exit and entry rates of 17% and 33%, respectively. Our agro-dealer exit rate is up to 4.3 times higher than MSME exit rates previously documented in low-income countries (Cabal, 1995; Kremer et al., 2014; McCaig & Pavcnik, 2021; McKenzie & Paffhausen, 2019) while our agro-dealer entry rate is roughly double (Cabal, 1995; Liedholm, 2002; McCaig & Pavcnik, 2021). These findings indicate that agro-dealers operate in a more dynamic environment relative to MSMEs in other sectors.

Second, high firm turnover shapes consumer belief formation in markets characterized by information asymmetries. Empirically, farmers report more favorable market-level agricultural input quality beliefs in markets with recent agro-dealer exits, consistent with our model's prediction that exit improves beliefs when consumers perceive exiting firms as having offered below-average quality products. Moreover, we show that, on average, farmers' beliefs about market-level agricultural input quality do not systematically vary with agro-dealer entry. 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 those beliefs when incumbent information signals are either weak or absent. However, farmers with an ongoing purchasing relationship with a specific agro-dealer express greater concern about the quality of agricultural inputs offered by a new market entrant. This result 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 related 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, and liquidity (Suri & Udry, 2022). However, this literature often overlooks the role of agricultural input market intermediaries.[1] Agro-dealers are essential to farmers' decisions to adopt agricultural inputs, serving as agricultural input suppliers and unofficial sources of agricultural information. Yet, as noted by Dillon et al. (2025), the agro-dealer sector remains understudied due to difficulties associated with sampling and surveying, its informality, and a longstanding focus in development economics on farmer technology adoption as a household decision rather than one shaped by market intermediaries. Our paper adds to a growing literature that addresses this gap. Kariuki et al. (2025) use a randomized controlled trial to examine how margin subsidies influence stocking and sales behavior among Kenyan agro-dealers while results from Dar et al. (2024) demonstrate that Indian agro-dealers influence farmers' technology adoption decisions through information provision. By focusing on agro-dealer turnover, we shed light on how the structure and stability of the agro-dealer sector help shape market functioning and farmers' beliefs. These insights help provide a foundation for understanding the market-level frictions that constrain agricultural technology adoption and, ultimately, agricultural productivity.

Second, we contribute to an existing literature focused on MSME operations and turnover in low-income countries. Prior research shows that MSMEs are mostly informal, under-capitalized, prone to early exit, and constrained by limited access to finance, infrastructure, and managerial

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

capacity (Aga & Francis, 2017; Liedholm, 2002; Mead & Liedholm, 1998). Several studies theorize that high MSME entry rates facilitate employment growth and structural transformation while high MSME exit rates engender labor market instability and inefficient resource allocation (Klapper & Richmond, 2011; McCaig & Pavcnik, 2021; Mead & Liedholm, 1998). Previous work also explores how firm characteristics—including size, age, and entrepreneurial ability—relate to MSME survival and performance; however, empirical evidence on the success of targeted support interventions designed to improve MSME longevity or growth remains mixed (Aga & Francis, 2017; Kremer et al., 2014; McKenzie & Paffhausen, 2019). Though this literature has emphasized macroeconomic 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 (Klapper & Richmond, 2011; Li & Rama, 2015; Liedholm, 2002; McCaig & Pavcnik, 2021; Mead & Liedholm, 1998). Our paper provides descriptive evidence on how MSME turnover directly impacts consumers.

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. When consumers cannot accurately evaluate product quality, firms that sell low-quality products may persist while high-quality new market entrants lacking credible signals may fail to gain market traction (Akerlof, 1970; Klein & Leffler, 1981). Several studies show how consumer learning and reputation mechanisms influence market selection. Shapiro (1983) finds that firms can build reputations for high quality over time, allowing them to earn price premiums in return. In online and healthcare markets, reputational feedback affects consumer behavior in ways that disadvantage lower-quality sellers and providers—through reduced sales or poorer matching—contributing 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 examined how firm turnover itself can inform consumer belief formation in markets with information asymmetries. Our model helps clarify this relationship by formally linking firm entry and exit to a consumer learning process. 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, which includes predictions about how firm entry and exit shape consumer beliefs. Sections 3 and 4 describe the institutional setting of Tanzania's agro-dealer sector and the data, respectively. Section 5 characterizes the observed high rates of agro-dealer turnover as well as agro-dealer entry and exit decisions. Section 6 empirically tests our model predictions by analyzing how agro-dealer turnover affects farmer beliefs about agricultural input 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, including minimal regulatory constraints and low capital requirements, make it easier for firms to enter and exit with relatively low cost (Asplund & Nocke, 2006; Baumol et al., 1983). 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 (Asplund & Nocke, 2006; Baldwin & Gorecki, 1998; Caves, 1998). Consumers benefit from improvements in product quality, service, and pricing as efficient firms replace inefficient firms. 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, 2015, 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 (Carree & Dejardin, 2020; Carree & Thurik, 1999; Kirzner, 2015, 1979).

Competitive pressure reinforces each of these three conditions and, in turn, each condition helps sustain market competition. Consequently, 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 decreasing 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 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, the firm 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}. Both 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 (α_{jimt}) and information based on the experience or interaction with firm i_m by other consumers from market m that are not j (α_{-jimt}). The information signal α_{-jimt} can be determined by reviews, third-party certifications, or simple word-of-mouth. Information accrues over time, so that both α_{jimt} and α_{-jimt} reflect all past learning. Thus repeated transactions or the accumulation of additional external information 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.

In addition to incumbents, consumers may, in principle, observe firm-specific information signals for new market entrants. For example, a firm owner's reputation in close-knit communities, observable cues—including licenses or infrastructure—and prices may inform information signals. However, we expect such information signals to be limited relative to those available for incumbents. Accordingly, we assume consumers have no reliable firm-specific information about a new market entrant (E_m) at the time of entry. In this case, consumer beliefs about new market entrants (and any firm lacking reliable firm-specific information signals) are anchored to market-level beliefs p_{jmt}. If the new market entrant remains active, consumer 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 (π_{jimt}) can be modeled using a logistic function, ensuring the expected probability remains between 0 and 1:

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

[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.

We define each firm-specific information signal so that as $\alpha_{jimt} \rightarrow 1$ or $\alpha_{-jimt} \rightarrow 1$, consumer j_m's own or others' experience suggest that firm i_m likely sells high-quality products. If $\alpha_{jimt} \rightarrow -1$ or $\alpha_{-jimt} \rightarrow -1$, 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 $\mathrm{I}_{imt} \in \{0,1\}$ indicate whether firm i which operated in market m in period $t-1$ remains active in period t (i.e., $\mathrm{I}_{imt} = 1$) or exited prior to period t (i.e., $\mathrm{I}_{imt} = 0$). 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., $n_{mt}^{inc} \leq n_{m,t-1}$). Consumer j_m's market-level beliefs in period t can now be defined as follows:

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

As $p_{jmt} \rightarrow 1$ all incumbents in market m are expected to sell high-quality products. As $p_{jmt} \rightarrow -1$ 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 (p_{jmt}) and varied firm-specific information signals (α_{jimt} and α_{-jimt}) values. 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 mix, 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., $\tilde{\alpha}_{jimt} \rightarrow 2$) result only in modest 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., $\tilde{\alpha}_{jimt} \rightarrow -2$) 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 in period t can be formally expressed using the following expected value equation:

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

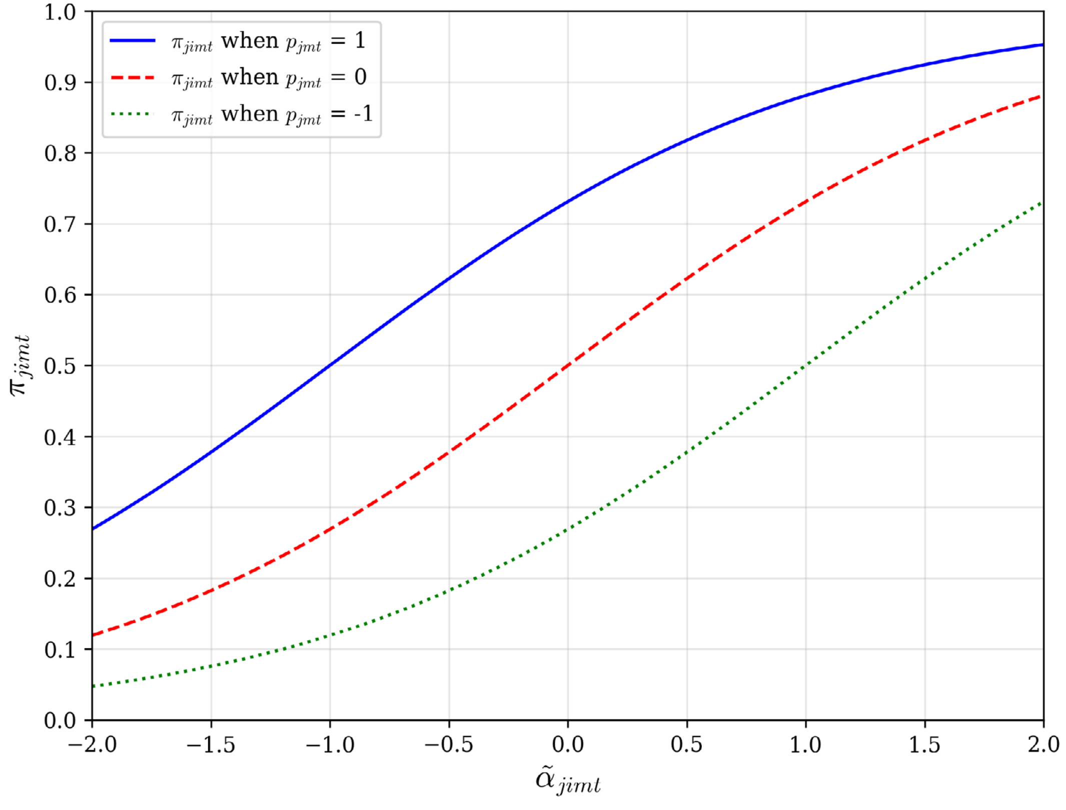

FIGURE 1 Equation 1 with varying parameters. The graph shows how consumer j_m's belief that firm i_m sells high-quality products (π_{jimt}) varies with combined firm-specific information signals ($\tilde{\alpha}_{jimt}$) for different market-level prior values (i.e., $p_{jmt} = -1,0,1$).

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

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 ($E[Q_{jmt}]$) is defined in Equation 4 and reflects consumer j's beliefs about market m's overall product quality in period t.

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

Our theoretical model yields three predictions.

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 believed to sell 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 believed to sell 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.

Our model is agnostic about the accuracy of consumer j_m's beliefs. The conclusions in Theorems 1 and 2 do not require consumer j_m's beliefs to be correlated with firm i_m's true product quality (q_{imt}). Yet, if consumer j_m's beliefs are positively correlated with firm i_m's true product quality, then belief updating in response to firm i's exit may also convey information about market m's true product quality (Q_{mt}).[4] Without this correlation, exit-induced belief updating reflects changes in consumer j_m's expectation $\left(E[q_{jimt}]\right)$ rather than changes in market m's true product quality.

New market entrant E_m is modeled as drawn from the same *believed* product quality distribution as incumbents, with no positive or negative selection into entry. Consequently, firm entry is mean-preserving and does not reveal new information about the market's overall product quality. Instead, firm entry moderates these beliefs by re-weighting beliefs about incumbents' product quality toward the market-level prior p_{jmt}. The direction and magnitude of this moderation depend on incumbent information signals, leading to our third theorem.

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

Proof. A new market entrant E changes market m's overall product quality as follows:

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

For new market entrant E_m, we assume that $\tilde{\alpha}_{jEmt} = 0$,[5] which means that π_{jEmt} only depends on market-level beliefs p_{jmt}. Because p_{jmt} is fixed for all firms (i.e., incumbents and new market entrants) in a given market m, the following is true:

[4]For example, if consumer j_m's beliefs are positively correlated with true product quality, then the exit of a firm i_m that actually sells low-quality products (i.e., $q_{imt} = q_L$) will mechanically raise the market's true product quality (i.e., Q_{mt} increases) and, in turn, *beliefs* about the market's overall product quality (i.e., $E[Q_{jmt}]$ increases).

[5]This assumption may be strong in some settings. If $\tilde{\alpha}_{jEmt} \neq 0$, firm entry would partially shift consumer j_m's beliefs about market-level product quality in the direction of $\tilde{\alpha}_{jEmt}$. In this case, firm entry would no longer solely moderate beliefs toward p_{jmt} as described in Theorem 3. However, as long as incumbent information signals dominate those of the new market entrant, the model's qualitative predictions remain unchanged.

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

The difference between $E[q_{jimt}]$ and $E[q_{jEmt}]$ depends on $\frac{\partial \pi_{jimt}}{\partial \tilde{\alpha}_{jimt}}\Big|_{\tilde{\alpha}_{jimt}}$. Therefore, the effect of firm entry on consumer j_m's market-level product quality beliefs in period t depends on the strength and direction of aggregated information signals for incumbents in market m: $\sum_{i=1}^{n_{mt}^{inc}} \frac{\partial \pi_{jimt}}{\partial \tilde{\alpha}_{jimt}}\Big|_{\tilde{\alpha}_{jimt}}$.

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.

Although firm entry and exit occur simultaneously in all markets, we model them separately to clarify how each margin of firm turnover may affect consumer beliefs about overall market 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 both 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 6.1, 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 rearing, 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 the products they sell to farmers.

3.1 | Regulatory environment

Tanzania's government regulates fertilizer markets in three ways. First, it has centrally procured fertilizer imports since 2017 and sets annual import quantities.[6] While our data show a net increase in the number of agro-dealers during this period (see Section 5.1), fertilizer import volumes did not rise and government audits subsequently reported shortages (United Republic of Tanzania, 2024).[7]

Second, the Tanzanian government requires agro-dealers to obtain licenses to sell different types of agricultural inputs, including seeds, fertilizer, and pesticides. Specifically, agro-dealers that sell fertilizer require a license issued by the Tanzania Fertilizer Regulatory Authority (TFRA), which is valid for 3 years (United Republic of Tanzania, 2009). Obtaining a TFRA license is free but applicants must submit one of two document combinations: (i) a Taxpayer Identification Number (TIN) and a TFRA Certificate of Participation received after completing a TFRA training; or (ii) a TIN and a university certificate or diploma in agriculture, horticulture, or agronomy. Despite these requirements, compliance is limited. Tanzania's National Audit Office (NAOT) found that more than 50% of fertilizer-selling agro-dealers in Tanzania operated without a TFRA license (United Republic of Tanzania, 2019, 78). NAOT attributes low TFRA registration to agro-dealers' limited awareness of registration requirements and procedures as well as weak enforcement, including infrequent and insufficient inspections. United Republic of Tanzania (2019) further notes that TFRA inspected only about 30% of Tanzania's regions annually, indicative of broader institutional and human resource constraints (Kansiime, 2021; Michelson et al., 2021).

Third, the Tanzanian government sets indicative fertilizer prices based on transport mode (e.g., rail or road) and distance from the import port in Dar es Salaam. Established before the agricultural season, these indicatives prices are intended to cap the prices at which agro-dealers may sell fertilizer in each region and are disseminated through media channels and local government offices. While agro-dealers may set their own prices, they must remain at or below these ceilings. However, NAOT has documented multiple failures in both the communication and enforcement of this policy: prices did not often reach the village level, agro-dealers frequently failed to display required prices,

[6]Tanzania imports nearly all of its fertilizer (United Republic of Tanzania, 2017).

[7]An analysis by Tanzania's National Audit Office notes that "for financial years 2020/21 and 2021/22, fertilizers available for domestic utilization were below the demanded fertilizers" (United Republic of Tanzania, 2024, p. 33). These shortages occurred *after* the final round of our agro-dealer census (see Section 4.1).

and inspections were inadequate (United Republic of Tanzania, 2019). In addition to these institutional challenges, agro-dealers have expressed that these prescribed price caps are too low to cover their operating and transportation costs (The Citizen, 2021a, 2021b), further discouraging compliance.

3.2 | Asymmetric information in the agro-dealer sector

Agro-dealers sell a range of agricultural inputs, including seeds, fertilizer, and pesticides, with fertilizer typically accounting for the largest share of their sales (Benson et al., 2012; Michelson et al., 2025). These transactions are characterized by asymmetric information: agricultural inputs are experience goods whose essential characteristics (i.e., agronomic performance) cannot be reliably evaluated before application. Moreover, signals of agricultural input quality are further obscured by weather-driven production stochasticity (Hoel et al., 2024) and by "fit risk," the potential mismatch between a given technology and the local agronomic conditions (including weather and soil quality) under which it is used (Heiman et al., 2020).

Previous research establishes that fertilizer sold in Tanzania's Morogoro Region is of consistently high agronomic quality, with no evidence of adulteration, counterfeiting, or systematic seasonal variation. Similar findings have been documented in other Sub-Saharan African countries (Ashour et al., 2019; Sanabria et al., 2018; Sanabria & Alognikou, 2013; Sanabria & Alognikou, 2019). Synthesizing laboratory and market evidence, Michelson et al. (2023) explain why quality manipulation is unlikely in equilibrium, given both the physical properties of fertilizer and the structure of fertilizer supply chains. Accordingly, fertilizer quality in the region is consistently high and homogeneous.

Even so, studies conducted in Tanzania's Morogoro Region show that farmers hold persistently pessimistic beliefs about fertilizer quality (Hoel et al., 2024; Michelson et al., 2021; Michelson et al., 2025). Similar farmer concerns about fertilizer quality have been documented in both Uganda (Bold et al., 2017; Hoel et al., 2024) and West Africa (Austin et al., 2013). In these settings, these concerns are not supported by the testing of fertilizer samples conducted by academic researchers (Michelson et al., 2023) nor by the International Fertilizer Development Corporation, which routinely evaluates and advises on the testing of fertilizer quality worldwide.

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 misperceptions are explained by 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 evaluating 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.

In theory, prices could help resolve such misperceptions by serving as a signal of fertilizer quality. In practice, however, institutional constraints largely eliminate this channel. As discussed, fertilizer prices in Tanzania are subject to government-set indicative price caps, under which agro-dealers are expected to sell fertilizer at or below their prescribed ceiling. This policy constrains price dispersion, particularly at the upper end of the price distribution. Consistent with this context, our data and previous research in the Morogoro Region (Michelson et al., 2021; Michelson et al., 2025) show very limited price variation within and across markets on a given day, with no systematic relationship between prices and fertilizers' observable characteristics (e.g., clumping or discoloration). While some agro-dealers anecdotally discount older fertilizer with visibly compromised physical condition, such discounts are rare and small in magnitude; thus these discounts do not generate a meaningful relationship between price and agronomic quality in the data.[8] As a result, price does not appear to be a salient nor reliable signal of fertilizer quality in this setting, limiting the scope for price-quality trade-offs to correct farmer misperceptions.

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 (Bulte et al., 2025; Gharib et al., 2021; Hoel et al., 2024; Hsu & Wambugu, 2022; Michelson et al., 2025; Miehe et al., 2023).

The persistence of farmer concern about fertilizer quality is foundational to our study's context, theoretical model, and empirical analysis. While agro-dealers in our sample are unlikely to be selling fertilizer of objectively low agronomic quality (Michelson et al., 2023), farmers still *believe* that low-quality fertilizer is being sold. These perceptions might also reflect other dimensions of agro-dealer quality, including the quality of agricultural information or advice provided, the level of customer service offered, or the quality of other agricultural inputs sold. Asymmetric information plays a key role in sustaining these beliefs (Hoel et al., 2024) and motivates our focus on agro-dealer turnover.

4 | DATA

Our study is based on three primary datasets from Tanzania's Morogoro Region: an agro-dealer census detailed in Section 4.1 and two cross-sectional farmer surveys described in Section 4.2.

4.1 | Agro-dealer data

We use a three-round census of all fixed-location agro-dealers operating within 97 major markets in Tanzania's Morogoro Region at the time of enumeration. Following Michelson et al. (2021) and Michelson et al. (2025), markets are defined as established locations where at least one agro-dealer and other types of businesses operate, forming a recognizable commercial center that serves nearby villages year-round. Data were collected in the first quarters of 2016, 2019, and 2020, just prior to the long rains season and associated agricultural input sales.[9] Enumerators began with extension-based lists and government registries, then conducted full ground-truthing to verify listed agro-dealers and identify any additional active, non-seasonal agro-dealers. This systematic canvassing reduces concerns that observed agro-dealer turnover reflects list artifacts rather than *true* turnover.

In our empirical analysis, a "firm" or "agro-dealer" refers to a single shop location rather than to the broader ownership entity. Each agro-dealer constitutes a distinct point of sale facing farmers in a market and is assigned a unique identifier in the agro-dealer census. Agro-dealer entry and exit therefore correspond to the appearance and disappearance of specific shops within markets over time, which directly affects farmers' local choice sets and learning environments.

In each round of the agro-dealer census, we collected data on agro-dealer characteristics related to business practices, asset ownership, number of non-owner employees, operational scale, years of operation, and shop infrastructure. Columns 1–3 of Table 1 present descriptive

[8]Michelson et al. (2021) find no relationship between urea fertilizer's observable characteristics and its agronomic quality; although observables vary, the underlying nutrient content of urea is consistently 46%, as required.

[9]For the 2016 and 2019 rounds, data collection began in the last quarter of the previous calendar year (see Figure 2). For the 2020 round, data collection concluded in January 2020, before the COVID-19 pandemic reached Tanzania. Michelson et al. (2021) used the 2016 data, while Michelson et al. (2025) used both the 2019 and 2020 data.

TABLE 1 Descriptive statistics for agro-dealer census by round.

Agro-dealer characteristics	Round 1 (1)	Round 2 (2)	Round 3 (3)
Owns a car or truck (1 = yes, 0 = no)	0.22	0.31	0.25
	(0.41)	(0.46)	(0.44)
Owns a smartphone or mobile phone (1 = yes, 0 = no)	0.99	0.99	0.99
	(0.12)	(0.10)	(0.10)
Has CNFA/TAGMARK certification displayed (1 = yes, 0 = no)	0.23	0.24	0.19
	(0.42)	(0.43)	(0.39)
Uses outdoor signage for advertising (1 = yes, 0 = no)	0.77	0.59	0.89
	(0.42)	(0.49)	(0.32)
Number of other locations that sell fertilizer	0.40	0.27	0.27
	(0.79)	(0.59)	(0.58)
Has a license to sell fertilizer (1 = yes, 0 = no)	0.40	0.46	0.40
	(0.49)	(0.50)	(0.49)
Number of additional employees present at time of interview	0.84	0.80	1.04
	(0.76)	(0.74)	(0.74)
Number of years operating at current location	4.18	4.69	4.37
	(4.33)	(4.66)	(4.97)
Permanent as compared to a seasonal business (1 = yes, 0 = no)	0.98	0.96	0.97
	(0.13)	(0.20)	(0.16)
Observations	224	298	360

Note: Each column reports the mean with the standard deviation in parentheses. Owner characteristics were only available for agro-dealers in round one so they are excluded. 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.

statistics by round. The census identified 515 agro-dealers in total. 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.[10]

Table 1 shows that across all three rounds, nearly all agro-dealers owned a mobile phone, fewer than one-third owned transportation assets, and about 40% had a TFRA license. The mean number of additional locations was below one in each round, indicating that most ownership entities operated only a single shop. On average, agro-dealers had approximately one non-owner employee present at the time of interview and had been operating at the same location for over 4 years. While not shown in Table 1, additional descriptive statistics from round one indicate that on average agro-dealers had 1065 kilograms (kg) of fertilizer in stock at the time of interview, with inventory ranging from 0 to 10,000 kg. On average, these same agro-dealers also sold 13,139 kg of fertilizer in the

[10]The agro-dealer follow-up survey is not a census for two reasons: (i) we did not survey any new market entrants and (ii) it was a phone survey that experienced high attrition due to missing or inaccurate contact information and non-response. Of the 515 census-identified agro-dealers, 128 provided no contact information. Among the remaining 387 with contact information, repeated call attempts were made over a multi-month period. Of these, 202 completed the survey while 185 were unreachable or declined to participate. Appendix Table B.1 compares characteristics for agro-dealer follow-up survey respondents and non-respondents. While the groups are similar across many characteristics, respondents are more likely to have CNFA/TAGMARK certification and a license to sell fertilizer, and less likely to use outdoor signage. Selection bias may still be present since responses reflect only reachable and willing agro-dealers.

previous year (enough to cover roughly 40 hectares of farmland) though sales ranged from 0 to 90,000 kg.[11] These variables serve as alternative proxies for agro-dealer size.[12]

The average distance between each market and its nearest neighboring market is 6.6 kilometers (km).[13] Ten percent of the 97 markets are less than 1 km from their nearest neighbor, 47% are 1–5 km, 25% are 5–10 km, and 18% are more than 10 km away from their nearest neighbor. Appendix Table B.2 describes other 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. Together, these patterns suggest increased concentration of agro-dealers in fewer markets, implying greater within-market density.

4.2 | Farmer data

We merge the agro-dealer census with a survey of 1242 smallholder farmers conducted across Tanzania's Morogoro Region, hereafter referred to as the market-linked farmer sample. The data were collected in the first quarter of 2019, alongside the 2019 round of the agro-dealer census.

The survey links farmers to agro-dealers through shared markets, with farmers linked to markets through their village of residence. Farmers reported their beliefs about fertilizer quality for three geographically proximate markets pre-identified by the research team based on regional knowledge of market locations and village-market infrastructure. For each village, one of these three markets was designated as the most central "associated market," located between 3 and 7 km from the village.[14] Our empirical analysis restricts attention to beliefs about the associated market. This geographic proximity enables us to study the relationship between recent agro-dealer turnover within a market and farmer beliefs about the quality of fertilizer sold in that same market (see Section 6.1).

The market-linked farmer survey asked farmers about market visits and fertilizer purchases. Of the 1242 farmers, 49% visited their associated market during the prior year but only 21% purchased fertilizer there during the last long rains season. Farmers who purchased fertilizer from their associated market represented 55% of fertilizer purchasers that season; among the remainder, purchasing elsewhere may partly reflect that associated market assignment could differ from farmers' actual purchase markets (see Footnote 14). Even so, farmers interacted with relatively few markets: 71% visited only one or two markets during the prior year, with the number of markets visited ranging from zero to five. Among fertilizer purchasers, 88% purchased from a single market, with an average of 1.12 markets. Thus, farmers' market engagement was largely concentrated although direct fertilizer purchasing in their associated market was limited.

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 B.3 for full descriptive statistics).

Importantly, the data capture farmers' beliefs about the quality of fertilizer sold by agro-dealers in their associated market. Following the approach used by Michelson et al. (2021), Ashour et al.

[11]We estimated the 40-hectare coverage using the average amount of fertilizer mass sold per agro-dealer (i.e., 13,139 kg). To approximate the nitrogen contained in this aggregate fertilizer mix, we computed the distribution of fertilizer types (e.g., urea, NPK, etc.) sold by agro-dealers in round one and assigned each its nitrogen content using nutrient composition data from the International Fertilizer Industry Association (Reetz, 2016). Multiplying 13,139 kg by the share and nitrogen fraction of each fertilizer type and summing across products yielded about 3968 kg of nitrogen sold per agro-dealer. Dividing this by the Tanzanian government's recommended nitrogen application rate of 100 kg per hectare for maize (Kohler, 2018) implies that an average agro-dealer sold enough fertilizer in a year to cover about 40 hectares. This estimate is conservative since it excludes other crop nutrients such as phosphorus and potassium.

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

[13]Distances are calculated as great-circle distances using the Haversine formula.

[14]Villages located within the 3–7 km radius of *multiple* markets are randomly assigned to a single associated market; this applies to 64 of the 137 villages represented in the market-linked farmer sample. See Michelson et al. (2025) for further details on the village-market matching procedure and sampling design.

TABLE 2 Agricultural input quality belief and relationship measures for farmer samples.

(A) Market-linked				
	Mean	**Std. dev.**	**Min**	**Max**
Fertilizer quality beliefs				
Farmers out of 10 receiving high-quality	6.82	2.83	0.00	10.00
Share of farmers concerned about quality (0 to 1)	0.70	0.46	0.00	1.00
Observations				1242
(B) Supplemental				
	Mean	**Std. Dev.**	**Min**	**Max**
Agricultural input quality beliefs				
Farmers out of 10 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 (0 to 1)				
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
Share of farmers with a stable agro-dealer relationship (0 to 1)	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 5 years.

(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?"[15] Panel A of Table 2 shows farmers believed that almost seven out of ten farmers on average would receive high-quality fertilizer, meaning about three out of ten would receive low-quality fertilizer. A binary version of this variable equals one if the farmer expressed *any* concern about fertilizer quality: 70% of farmers believed that at least one of the ten farmers would purchase low-quality fertilizer.

Given the importance of farmer-agro-dealer relationships and the lack of such information in the market-linked farmer sample, we conducted an additional cross-sectional survey with 150 farmers in the third quarter of 2022, hereafter referred to as the supplemental farmer sample. Ten farmers were surveyed in each of 15 villages, representative of nine markets. While the market-linked farmer sample covers all seven administrative districts in Tanzania's Morogoro Region, the supplemental farmer sample covers only two.[16] We therefore interpret results based on the supplemental farmer sample as informative about the surveyed districts rather than region-wide estimates. Column 2 of Appendix Table B.3 reports full descriptive statistics for these farmers.

The supplemental survey asked farmers to provide a quality assessment for agricultural inputs. This question was 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.[17] A binary version of this variable equals one if the farmer expressed *any* concern with regards to the agricultural input quality provided by either agro-dealer type. Descriptive statistics for these responses are shown in Panel B of Table 2. Consistent with the

[15]Although fertilizer is traded in 50-kilogram bags, it is commonly sold to Tanzanian farmers in smaller quantities drawn from open or repackaged bags by agro-dealers; while this can affect observable characteristics, Michelson et al. (2021) show no difference in nutrient content relative to sealed bags.

[16]The supplemental farmer sample covers two administrative districts: Mvomero and Morogoro Rural.

[17]Farmers were specifically asked to estimate how many out of 10 farmers, like themselves, would receive high-quality agricultural inputs from their current agro-dealer and a hypothetical new market entrant, assuming all 10 purchased the same agricultural input on the same day.

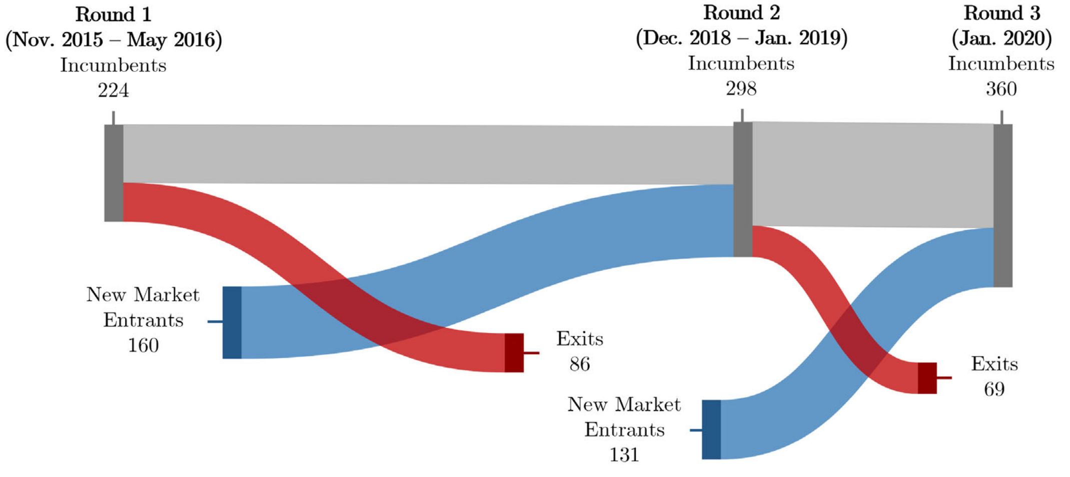

FIGURE 2 Agro-dealer turnover across rounds: Entry, exit, and continuation. The Sankey diagram presents agro-dealer turnover across the three census rounds, capturing the number of agro-dealers that entered, exited, and remained in Tanzania's Morogoro Region over time. The widths of flows are proportional to the number of agro-dealers, while the spacing between rounds reflects the time elapsed between surveys. These transitions form the basis for calculating our annual agro-dealer entry and exit rates.

results presented in Section 6.2, farmers on average rated the agricultural input quality from their current agro-dealer higher than that from a hypothetical new market entrant. The corresponding binary variable indicates that a larger share of farmers expressed concern about the agricultural input quality offered by such new market entrants.

The supplemental survey also measured whether farmers *usually* purchased agricultural inputs from the same agro-dealer over the past 5 years. This question identifies established farmer-agro-dealer relationships.[18] As shown in Panel B of Table 2, 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 presents 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.

[18]This variable should not be interpreted as an exogenous measure of information acquisition. Stable farmer-agro-dealer relationships may arise from information accumulated through repeated transactions, but they may also reflect selection based on pre-existing trust, convenience, or other unobserved relationship-specific factors.

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 obtain a single annual rate that spans the full between-round period. More details regarding our agro-dealer turnover calculations are provided in Appendix C.

We estimate an annual agro-dealer entry rate of 32.5% and an annual agro-dealer exit rate of 17.3%.[19] 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%. Kremer et al. (2014) find even lower rates, between 4% and 6%, 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%) (McCaig & Pavcnik, 2021) and in the Dominican Republic (i.e., 22%–29%) (Cabal, 1995).

Similarly, our estimated annual agro-dealer entry rate of 33% 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% across MSMEs in Latin America and Africa, with country-specific rates ranging from 19% to 25%. McCaig and Pavcnik (2021) find annual entry rates of 16% to 18% among informal MSMEs in Vietnam while Cabal (1995) documents slightly higher rates of 21% to 24% 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 agro-dealers (see Table 1).[20] If anything, these details suggest that our annual agro-dealer turnover 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.

[19]Although agricultural input demand is highly seasonal, our census includes only permanent, fixed-location agro-dealers rather than temporary or itinerant agro-dealers. In round one, 81% reported selling fertilizer in every month of the year, suggesting that observed exit is unlikely to be driven by predictable seasonal closures.

[20]Another potential concern is that agro-dealers may close in one market and reopen in another market during the study period. Yet our census data show no cases of an agro-dealer re-entering the *same* market after exit. As defined in Section 4.1, our firm turnover measures track entry and exit of agro-dealer shop-locations within markets rather than ownership entities; thus, re-entry into a different market is not pertinent for our analysis. Consistent with this, our follow-up survey 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.

5.2 | Heterogeneity of agro-dealer turnover

We next explore agro-dealer turnover variation across markets. The gray bars shown in Figure 3 present 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 that have annual net agro-dealer turnover rates of zero. Of those, eight markets 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 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. Additionally, 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." This phrase describes one's 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; Jayachandran, 2021; Sohns & Diez, 2019). 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. Table 3 presents descriptive statistics from our agro-dealer follow-up survey. The results in Column 1 suggest that agro-dealers in this 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. The majority cited higher income potential, stronger alignment with their interests and skills, or improved financial security as primary motivations. Fewer than 2% reported entering the sector to temporarily smooth consumption, supplement household income, or due to limited or less desirable alternatives.

Follow-up respondents overwhelmingly report entering the sector with the expectation of staying for the long term. At the time of entry, 96% expected to remain in business for more than 6 years. Among agro-dealers still operating at the time of our follow-up survey, 93% expected to stay in business over the next 5 years and 86% anticipated growth (i.e., opening additional shop locations, increasing sales at their current shop location, or expanding the quantity or diversity of products

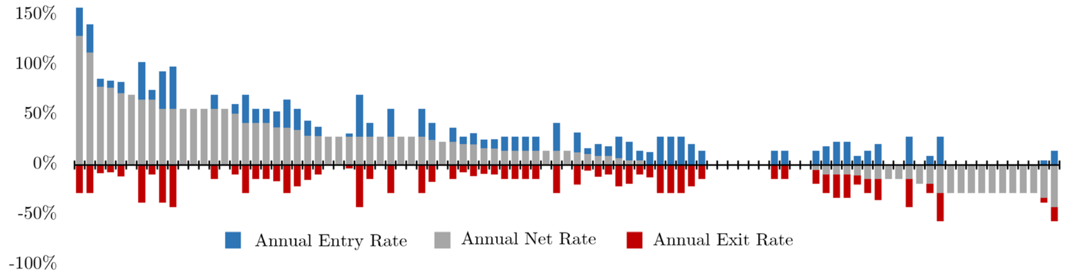

FIGURE 3 Annual agro-dealer turnover by market: Entry, net, and exit rates. The figure depicts annual net turnover (gray), entry (blue), and exit (red) rates for agro-dealers across 95 markets over the study period. Two markets are excluded because they only had agro-dealers present in round three, making it impossible to calculate annual net turnover, entry, or exit rates between rounds.

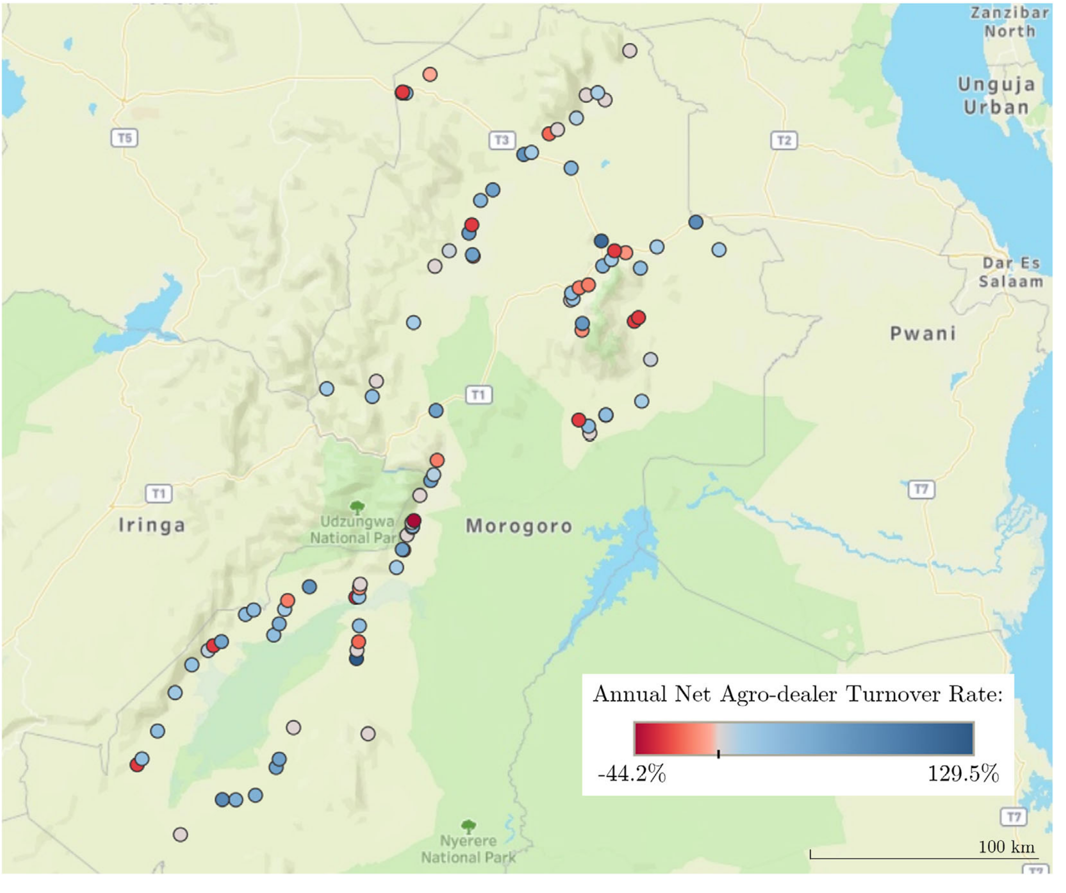

FIGURE 4 Annual net agro-dealer turnover in Tanzania's Morogoro Region. The map presents the geographic coverage of the agro-dealer census in Tanzania's Morogoro Region. Circles represent markets, with color shading indicating annual net agro-dealer turnover rates for the four-year study period.

offered at their current shop location) during the same period. Optimism persisted even when presented with a hypothetical scenario involving a more profitable and stable employment opportunity: 84% indicated they would *not* exit the agro-dealer sector under such conditions. Though hypothetical, this response reflects a high degree of commitment to remaining in the sector. Agro-dealers in

TABLE 3 Descriptive statistics for agro-dealer follow-up survey.

Statement	Sample (1)	Exited (2)	Still in business (3)	Difference (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)	0.04 (0.06)
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)	−0.02 (0.02)
When I started this business, I expected to stay in business for more than 6 years.	0.96 (0.20)	0.96 (0.19)	0.96 (0.20)	0.00 (0.03)
I expect to still be in business 5 years from now.	—	—	0.93 (0.26)	—
I expect my business to grow over the next 5 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	

Note: $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Statement responses were coded as one for "yes" and zero for "no." Columns 1–3 report means with standard deviations in parentheses. Column 4 reports mean differences 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) with standard errors in parentheses. 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.

the follow-up sample therefore appear to be "optimistic entrepreneurs" who view market entry as a long-term investment in a sustainable livelihood strategy. This view corroborates the observations of Benson et al. (2012) in their study of fertilizer supply chains in Tanzania:

> "[Agro-dealers] are generally optimistics…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 operations, 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). Using the agro-dealer census, we find that across rounds an average of 42.2% of agro-dealers had a TFRA license and 56.6% of markets had *at least one* licensed agro-dealer. TFRA licensing status was also highly persistent: 89.3% of agro-dealers retained the same licensing status during the four-year study period. Entry patterns further underscore limited entry barriers: non-licensed agro-dealers entered at roughly twice the annual rate (i.e., 21.8%) of their licensed counterparts (i.e., 10.7%). These patterns indicate that while optimism may motivate agro-dealer entry, weak regulatory enforcement substantially lowers the cost of doing so.

5.4 | Agro-dealer exit decisions

If agro-dealers report optimism and commitment, why do so many exit? To answer this question, we first use data from the agro-dealer follow-up survey. Because these responses are based on only

54 exited agro-dealers, they should be interpreted descriptively and not considered representative of all exited agro-dealers. Table 4 shows that one in six agro-dealers (i.e., 16.7%) cited household-level shocks as their primary reason for exiting while a larger share (i.e., 57.4%) reported exiting due to profit losses driven by either supply- or demand-side factors in the marketplace. Our findings contrast with previous studies that report higher shares of MSME exits attributed to household-level shocks (McKenzie and Paffhausen (2019) report 26% while McCaig and Pavcnik (2021) report 19.7%) and lower shares of exits attributed to profit losses (41% and 25.3%, respectively). These results suggest that reported agro-dealer exits reflect external pressures, particularly market conditions that push (rather than pull) firms out of the sector.

In Appendix D, we use the agro-dealer census to analyze predictors of agro-dealer exit. We find that agro-dealer exit is more strongly associated with market dynamics than observable firm characteristics. An important exception is TFRA licensing status: agro-dealers without a government-issued license to sell fertilizer are significantly more likely to exit in the subsequent round. Consistent with this result, non-licensed agro-dealers exit at nearly twice the annual rate of their licensed counterparts (i.e., 10.9% vs. 6.4%, respectively). Although previous research documents that younger and smaller MSMEs face higher exit risk (Aga & Francis, 2017; Kremer et al., 2014; McKenzie & Paffhausen, 2019; Mead & Liedholm, 1998), we instead find that agro-dealer exit is strongly correlated with greater market competition.

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 analyze the implications of high agro-dealer turnover for smallholder farmers. Section 6.1 analyzes the relationship between beliefs about market-level 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 established relationships with incumbent agro-dealers shape farmers' beliefs about agricultural input quality.

6.1 | Agro-dealer turnover and market-level quality beliefs

We begin by evaluating the relationship between agro-dealer turnover and farmers' beliefs about market-level fertilizer quality. We estimate the following model specification:

$$Y_{im} = \beta_0 + \beta_1 MarketSize_{m,1} + \beta_2 Exit_{m,1\to 2} + \beta_3 Entry_{m,1\to 2} + \beta_4 \boldsymbol{X}_i' + \epsilon_{im} \tag{6}$$

Y_{im} captures farmer i's beliefs about market-level fertilizer quality in market m. $MarketSize_{m,1}$ controls for the number of agro-dealers in market m in round one. $Exit_{m,1\to 2}$ is the number of agro-dealer exits in market m between rounds one and two while $Entry_{m,1\to 2}$ is the number of agro-dealer entries in market m between rounds one and two. Because $Exit_{m,1\to 2}$ and $Entry_{m,1\to 2}$ are likely highly correlated,[21] we estimate their effects separately and jointly. The vector $\boldsymbol{X}_i'$ includes farmer-level controls listed in Column 1 of Appendix Table B.3 and ϵ_{im} is the error term. Standard errors are clustered at the market level.

[21]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; Chang, 2011; Dunne et al., 1988) and informal firms (McCaig & Pavcnik, 2021). The pattern implies that markets experiencing above average firm entry rates are likely to exhibit above average firm exit rates. In the market-linked farmer sample, there is a moderate correlation between the number of agro-dealer exits and entries ($r = 0.3031$). The variance inflation factors for these variables are consistently below two, suggesting low multicollinearity and stable coefficient estimates.

TABLE 4 Exit reason distribution for agro-dealer follow-up sample relative to MSME literature.

	Agro-dealer follow-up sample		Previous studies	
Exit reasons	Count	Percent	McKenzie and Paffhausen (2019)	McCaig and 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%

Note: Household-level shocks refer to those within the household—including illness, death, retirement, marriage, or divorce—that lead to shop 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.

Table 5 reports the results. The outcome variable in Columns 1–3 is 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 variable 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). Since this binary outcome variable is a threshold transformation, Columns 4–6 represent the same underlying belief variation rather than independent evidence. 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.

We first examine the relationship between agro-dealer exit and subsequent farmer beliefs about market-level fertilizer quality. Our discussion focuses on the full model specification in Equation 6 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 5 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. In Appendix B, we show the effect of agro-dealer exit on farmer beliefs is stronger in smaller markets and for more risk averse farmers (see Appendix Tables B.4 and B.5, respectively).

Farmers' fertilizer quality beliefs are more favorable in markets experiencing recent agro-dealer exits. This pattern is consistent with Theorem 1, where consumer beliefs about product quality only improve when the exiting firms are believed to have been selling below-average quality products. If farmers' beliefs about an exiting agro-dealer's fertilizer quality are positively correlated with the true quality of the fertilizer sold by that agro-dealer, then our results are consistent with the exit of an agro-dealer selling low-quality fertilizer and a corresponding improvement in the market's *true* fertilizer quality. Alternatively, in a context where prior research shows that farmers systematically

TABLE 5 Effect of agro-dealer turnover on farmers' market-level fertilizer quality beliefs.

	Farmers out of ten receiving high-quality			Concerned about quality (1 = yes, 0 = No)		
	(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)
Agro-dealer entries (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	1242	1242	1242	1242	1242	1242

Note: *$p < 0.10$, **$p < 0.05$, ***$p < 0.01$. Standard errors (in parentheses) are clustered at the market level. Columns 3 and 6 estimate Equation 6. "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 "agro-dealer entries" is the number of new agro-dealers that entered a market between rounds one and two. We use farmer beliefs that correspond to each farmer's associated market. Farmer-level controls are listed in Column 1 of Appendix Table B.3.

underestimate fertilizer quality, agro-dealer exits may shift beliefs upward and thereby partially correct misperceptions about market-level fertilizer quality.

Appendix Table B.6 qualifies this interpretation. Only 258 of the 1242 farmers (i.e., 21%) purchased fertilizer in their associated market during the last long rains season. Agro-dealer exit estimates are directionally similar but less precise among these recent purchasers, and larger among farmers who did *not* recently purchase fertilizer in their associated market. This suggests that the relationship in Table 5 is not necessarily driven by farmers' own recent purchasing experience. Yet recent non-purchase does not imply lack of exposure: 49% of farmers visited their associated market during the prior year. Thus farmers may form beliefs not only through recent purchases, but also through previous associated market engagement, word-of-mouth, or third-party certifications. In terms of the model in Section 2, these channels suggest farmer j_m's fertilizer quality beliefs may be shaped not only by their own experience α_{jimt} but also by external information signals α_{-jimt}.

However, since we do not observe whether farmers knew about specific agro-dealer exits in their associated market, we cannot establish that this relationship reflects belief updating in response to those exits. Alternative market-level mechanisms could also contribute. For example, markets with more agro-dealer exits may be more competitive or dynamic, and farmers may hold more favorable fertilizer quality beliefs in such markets even without knowledge of specific agro-dealer exits. While our model specification controls for baseline market size, agro-dealer entries, and observed farmer characteristics, other *unobserved* market conditions may be correlated with both agro-dealer exits and farmer beliefs. Therefore, we interpret the estimates in Table 5 as consistent with the model rather than as causal evidence of belief updating.

Results in Table 5 are robust to alternative model specifications. These include: (i) clustering standard errors at the village level; (ii) winsorizing the variables "agro-dealer entries" and (iii) "baseline market size" at the 95th percentile given their long-tailed distributions; and (iv) using percentages of agro-dealer exits and entries rather than counts (see Appendix Tables B.7, B.8, and B.9, respectively). To address potential concerns that farmer beliefs may themselves influence subsequent agro-dealer entry or exit, Appendix E presents a reverse causality analysis. We find no empirical evidence that farmer beliefs predict agro-dealer turnover in a later period. Theoretically, a leave-one-out instrumental variables strategy—that uses agro-dealer entry or exits in neighboring markets as an instrument for *within-market* agro-dealer turnover—could provide a robustness check for the causal interpretation of our estimates. However, only 10% 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. Additionally, in cases where markets are geographically proximate, spillovers in farmer beliefs across markets are likely, potentially violating the exclusion restriction.

In contrast to agro-dealer exit, we find no evidence that on average farmers' market-level beliefs regarding fertilizer quality systematically vary with agro-dealer entry. The estimated relationships between the number of agro-dealer entries and our farmer belief outcomes in Columns 2, 3, 5, and 6 of Table 5 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 B.4). We also empirically rule out the possibility that the absence of an observed entry effect is driven either by lower cross-market variation in the number of agro-dealer entries relative to exits or by farmers' associated markets exhibiting lower annual agro-dealer entry relative to exit rates (see Appendix Figures B.1 and B.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.[22] Our model further suggests that the actual entry effect depends predominantly 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 both the strength and direction of aggregated information signals about incumbents within a market. When strong positive information signals about the quality of products sold by incumbents dominate, firm entry is expected to lower consumers' expectations about market-level product quality (Theorem 3.1). When strong negative information signals dominate, firm entry is expected to raise consumers' expectations (Theorem 3.2). When no information signals are present in a market, firm entry has no effect on consumer beliefs (Theorem 3.3).

To evaluate whether farmers respond differently to agro-dealer entry depending on information signals about incumbents, we analyze data from the supplemental farmer sample. Given the supplemental farmer sample's narrower geographic coverage (see Section 4.2), we interpret the results in this section as suggestive rather than representative of Tanzania's Morogoro Region. Each farmer reported their agricultural input quality beliefs for two agro-dealer types: their current agro-dealer (an incumbent) and a hypothetical new market entrant. These responses are stacked at the farmer-by-agro-dealer-type level, with each farmer contributing two observations. To connect the empirical results to our model, we interpret farmers with a stable agro-dealer relationship as those for whom positive incumbent-specific beliefs regarding agricultural input quality are more likely to dominate when evaluating a hypothetical new market entrant.

We estimate the following model specification:

$$Y_{ijv} = \beta_0 + \beta_1 New_j + \beta_2 Stable_i + \beta_3 \left(New_j \times Stable_i\right) + \beta_4 \boldsymbol{X}_i' + \mu_v + \epsilon_{ijv} \tag{7}$$

Y_{ijv} captures farmer i's beliefs about agricultural input quality provided by agro-dealer type j, with farmer i residing in village v. New_j is a binary variable equal to one if farmer i's beliefs refer to a

[22]Our model maintains the assumption that at the time of entry consumers have no reliable firm-specific information about a new market entrant (i.e., $\alpha_{jEmt} = 0$ and $\alpha_{-jEmt} = 0$; see Section 2). We cannot directly test this assumption with our data. Appendix F provides an indirect check showing that observable agro-dealer characteristics at the market level do not statistically predict farmers' market-level fertilizer quality beliefs. This indirect evidence is broadly consistent with the maintained assumption.

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 5 years and zero otherwise. The vector $\boldsymbol{X}_i'$ includes farmer-level controls listed in Column 2 of Appendix Table B.3, μ_v is village fixed effects, and ϵ_{ijv} is the error term. Standard errors are clustered at the farmer level.

In Equation 7, β_0 captures the average quality belief about a current agro-dealer for farmers *without* a stable agro-dealer relationship, conditional on both X_i' and μ_v. β_1 captures the average difference in quality beliefs between the current agro-dealer and a hypothetical new market entrant for these same farmers. β_2 captures how quality beliefs about a current agro-dealer differ between farmers with a stable agro-dealer relationship and farmers without one. The interaction term β_3 captures whether having a stable relationship with an incumbent modifies the perceived quality of a hypothetical new market entrant relative to that of the incumbent. Finally, $\beta_1 + \beta_3$ captures how quality beliefs about a hypothetical new market entrant differ from those about the current agro-dealer among farmers with a stable agro-dealer relationship.[23] This sum indicates whether these farmers expect lower agricultural input quality from new market entrants, as predicted when positive incumbent-specific information signals dominate. 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 relative to the incumbent. If $\beta_1 + \beta_3 > 0$, they are perceived to provide *higher*-quality agricultural inputs. For the binary versions of these variables that indicate whether a farmer expresses concern about agricultural input quality, 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 6 presents the results using two different outcomes. Columns 1–3 use the number of farmers out of 10 that farmer i believed would receive high-quality agricultural inputs while Columns 4–6 use a binary outcome variable equal to one if farmer i expressed *any* concern about agricultural input quality. Since this binary outcome variable is a threshold transformation, Columns 4–6 represent the same underlying belief variation rather than independent evidence. For completeness, we estimate three model specifications of Equation 7: (i) a reduced model specification that omits $Stable_i$ and its interaction with New_j reported in Columns 1 and 4; (ii) the full model specification reported in Columns 2 and 5; and (iii) the full model specification replacing village fixed effects with farmer fixed effects reported in Columns 3 and 6. The latter model specification serves as a robustness check by exploiting within-respondent differences in beliefs about the incumbent and a hypothetical new market entrant. Under this model specification, coefficients for time-invariant farmer-specific covariates (i.e., β_2 and β_4 of Equation 7) are no longer identified.

Column 1 indicates that, on average, farmers expect 1.7 fewer out of 10 farmers to receive high-quality agricultural inputs from a hypothetical new market entrant than from their current agro-dealer. Column 4 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 2 and 5 show that this difference is concentrated among farmers with stable agro-dealer relationships. The sum $\beta_1 + \beta_3$ suggests that these farmers expect, on average, 2.7 fewer out of 10 farmers to receive high-quality agricultural inputs from a hypothetical new market entrant than from their current agro-dealer (see Column 1) and are 31.9 percentage points more likely to be concerned about a hypothetical new market entrant's agricultural input quality (see Column 5). Results are robust to using farmer fixed effects (see Columns 3 and 6), estimating an ordered logit model specification (see Appendix Table B.10), and redefining the outcome as agricultural *information* quality rather than agricultural input quality (see Appendix G).

[23]To see this, note the perceived agricultural input 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 6 Comparing farmers' agricultural input quality beliefs for an incumbent relative to a new market entrant.

	Farmers out of ten receiving high-quality			Concerned about quality (1 = yes, 0 = No)		
	(1)	(2)	(3)	(4)	(5)	(6)
New market entrant (β_1)	−1.740***	−0.161	−0.161	0.187***	−0.036	−0.036
	(0.289)	(0.473)	(0.645)	(0.052)	(0.083)	(0.114)
Stable relationship (β_2)		1.955***			−0.290***	
		(0.398)			(0.084)	
New market entrant × stable relationship (β_3)		−2.520***	−2.520***		0.355***	0.355**
		(0.575)	(0.784)		(0.105)	(0.143)
$\beta_1 + \beta_3$		−2.681	−2.681		0.319	0.319
Reference group mean	8.37	7.14	7.14	0.47	0.66	0.66
Village fixed effects	Yes	Yes	No	Yes	Yes	No
Farmer fixed effects	No	No	Yes	No	No	Yes
Farmer-level controls	Yes	Yes	No	Yes	Yes	No
R^2	0.172	0.236	0.659	0.108	0.149	0.645
Observations	300	300	300	300	300	300

Note: $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$. Standard errors (in parentheses) are clustered at the farmer level. Columns 1 and 4 report the reduced model specification, omitting the $Stable_i$ and New_j indicators. Columns 2 and 5 estimate Equation 7 while Columns 3 and 6 replace village fixed effects with farmer fixed effects. "Reference group mean" reports the outcome variable mean for the baseline group in each model specification: farmers' quality beliefs about their current agro-dealer, calculated either for all farmers (Columns 1 and 4) or for only farmers without a stable agro-dealer relationship (Columns 2, 3, 5, and 6). A stable agro-dealer relationship is defined as *usually* purchasing agricultural inputs from the same agro-dealer over the past 5 years. Farmer-level controls are listed in Column 2 of Appendix Table B.3.

In contrast, among farmers *without* 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 hypothetical new market entrant (see β_1 in Columns 2 and 5). The average differences in Columns 1 and 4 appear to be concentrated among farmers with stable agro-dealer relationships. Among these farmers, expected agricultural input quality is lower for new market entrants than for incumbents, a pattern consistent with Theorem 3.1 when positive incumbent-specific information signals dominate. Meanwhile, the absence of an entry effect among farmers without a stable agro-dealer relationship aligns with Theorem 3.3: when incumbent-specific information signals are not present, firm entry does not alter consumer market-level quality beliefs.

Overall, farmers with stable agro-dealer relationships evaluate their current agro-dealer more favorably than a hypothetical new market entrant. This pattern may reflect farmers' trust in their current agro-dealer reinforced through repeated interactions and positive experiences. It may also reflect pre-existing trust or other factors that led farmers to form stable agro-dealer relationships in the first place. In either case, strong positive information signals about incumbents may prompt farmers to view new market entrants as offering lower-quality agricultural inputs 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 (Asenso-Okyere & Jemaneh, 2012; De Janvry & Sadoulet, 2002; Sheahan & Barrett, 2017; Suri & Udry, 2022). Low adoption may stem from demand- or supply-side constraints. Agro-dealers, the final link in agricultural input supply chains, play a crucial role in providing farmers with access to agricultural inputs and information. Yet despite their importance, agro-dealers remain relatively understudied (Dillon et al., 2025).

We document and analyze a central feature of the agro-dealer sector: high levels of firm turnover. Using three-round agro-dealer census data from rural Tanzania, we estimate an annual agro-dealer entry rate of 33%. Contrary to the "reluctant entrepreneurs" characterized by Banerjee and Duflo (2011), we find that agro-dealers appear to be optimistic entrepreneurs who are strongly committed to continued operation in agricultural input markets. Nevertheless, exit remains common: about one in six agro-dealers exit annually. These agro-dealer turnover rates are more than double those reported for MSMEs in non-agricultural sectors in comparable low-income countries.

To our knowledge, no other research systematically documents agro-dealer turnover. Available evidence—though limited—suggests that high agro-dealer turnover may be a key characteristic of agricultural input supply chains, with potential implications for agricultural technology adoption and productivity in Sub-Saharan Africa and elsewhere. Several randomized controlled trials of agro-dealers report substantial attrition, providing useful comparative benchmarks for our exit rates. For example, Miehe et al. (2023), Dar et al. (2024), and Kariuki et al. (2025) document attrition rates of 10%–30% across survey rounds. But because these studies do not distinguish business closure from survey non-response, seasonal inactivity, or relocation, these rates represent upper bounds on true agro-dealer exit and are not comparable to our estimates. Evidence from a three-round census of Ugandan agro-dealers by Gilligan and Karachiwalla (2022) suggests annual entry and exit rates of 51% and 15.6%, respectively. Though not based on a *fully* balanced panel, these Ugandan estimates indicate that high agro-dealer turnover is widespread. Future research should build on census-based designs to analyze agro-dealer turnover in other contexts and explore its mechanisms.

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 worsen following a firm's exit, depending on consumers' perceptions of the exiting firm's product quality. The model 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 experience-good markets 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 the relationship between agro-dealer turnover and farmer beliefs about agricultural input quality. Empirically, recent agro-dealer exits are associated with more favorable farmer perceptions of market-level fertilizer quality, consistent with our model if farmers perceived exiting agro-dealers as having sold below-average quality fertilizer. Given prior evidence that farmers often hold inaccurate beliefs about fertilizer quality (Hoel et al., 2024; Michelson et al., 2021), this result suggests that agro-dealer exits may partially correct farmer beliefs toward actual market conditions. In contrast, we find no average change in farmer beliefs following agro-dealer entry. However, farmers who consistently purchase agricultural inputs from the *same* agro-dealer report lower expectations about a new market entrant's agricultural input quality.

If the positive association between agro-dealer exits and farmers' market-level fertilizer quality beliefs reflects exit-induced belief updating, an important question remains: why do inaccurate fertilizer quality beliefs persist despite frequent agro-dealer exits? We propose two possible explanations. In both cases, misperception 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 could offset this process—limiting broader belief correction. Therefore, ongoing agro-dealer turnover may hinder market-level learning even as agro-dealer exits update beliefs incrementally.

Second, belief updating itself may be slow or asymmetric, as farmers are more likely to respond to salient negative signals, like 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). Similar evidence from Bangladesh shows farmers seem to overweight salient but noisy signals from recent weather shocks when forming beliefs about climate change (Patel, 2025).

While our analysis focuses on farmers' beliefs about agricultural input quality, results presented in Appendix G indicate that uncertainty in agricultural input markets also extends to the quality of information provided by agro-dealers. This distinction between product and information quality highlights a critical avenue for future research: understanding how variation in agro-dealer-provided information influences farmer learning, market trust, and technology adoption in settings characterized by information asymmetries. Beyond information provision, heterogeneity across agro-dealers may also stem from differences in product mix. Agro-dealers that sell seeds or pesticides in addition to fertilizer face higher fixed costs related to licensing, storage, and technical knowledge acquisition, leading to greater entry and exit frictions and contributing to distinct turnover dynamics.

The relevance of our findings extends beyond agricultural input markets to other settings characterized by asymmetric information. Notably, our results suggest high firm exit rates may improve consumer expectations. However, consumers' concerns about new market entrants' product quality can create a demand disadvantage and limit firm entry when quality is difficult to observe (Creane & Jeitschko, 2016; Zhang et al., 2022). These information frictions may therefore help explain the slow growth and high exit rates observed among new MSME entrants in other sectors in low-income countries (Aga & Francis, 2017; McKenzie & Paffhausen, 2019).

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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