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IFPRI

IFPRI Discussion Paper 02400

December 2025

Small and Medium Enterprise Development for Climate Adaptation and an Inclusive Food System in Egypt

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ABSTRACT

Rural households in many low- and middle-income countries remain highly dependent on agriculture and related value chain activities, making them particularly vulnerable to the impacts of climate change. As rising temperatures and increasing climate variability reduce agricultural productivity and income stability, small and medium enterprises (SMEs) are increasingly promoted as a path toward rural development and the transformation of the agrifood systems (AFS). Yet, little is known about whether climate change influences rural households' decision to start an enterprise to diversify or switch their income sources away from agriculture-related activities in order to adapt to weather risks. We address this research gap by drawing from nationally representative data from the Egypt Labor Market Panel Survey 2023 and estimating a dynamic duration model to explore how heat stress is linked to households' likelihood to start a (nonfarm) SME. Our findings offer new evidence for climate-responsive rural policy and SME support strategies in vulnerable regions.

Keywords: Small and medium enterprise (SME), agrifood systems, economic transformation, climate change, heat stress, dynamic duration model, Egypt

ACKNOWLEDGMENTS

This work was undertaken as part of the “Future Food Systems” project funded by the International Affairs Office at the Presidential Court of the United Arab Emirates and the Gates Foundation. We thank the funders for their support, and participants of the technical workshop on “Pathways and Priorities for an Inclusive, Resilient, and Low-carbon Food System in Egypt” in the Ministry of Planning, Economic Development, and International Cooperation, Egypt, on September 29, 2025, for their valuable comments on preliminary results of this work.

1 INTRODUCTION

Rural livelihoods in many low- and middle-income countries (LMICs) remain heavily dependent on agriculture, either through direct engagement in farming or through employment in related activities in agricultural value chains (Yi et al., 2025). This dependence increases households' vulnerability to the growing impacts of climate change, as rising temperatures, increased weather variability, and resource stress undermine agricultural productivity and further destabilize income sources that are already characterized by seasonality and informality (de Janvry & Sadoulet, 2020; Wilts et al., 2021; Winsemius et al., 2018).

In response, structural transformation—the reallocation of labor from primary agricultural production toward more stable and higher-value off-farm activities (Johnston & Mellor, 1960)—has become a key strategy to foster rural development. Small and medium enterprises (SMEs)[1] are often viewed as a key instrument in this process, offering opportunities to diversify income and stimulate local economic activity (Fox & Sohnesen, 2016; Hoang et al., 2021). Since employment choices as well as enterprise creation are often linked to existing skills and networks (Breza & Kaur, 2025), the broader agrifood system (AFS) (e.g., processing, distribution, services, and value addition) likely provides a particularly accessible entry point for rural households. In this way, and under the right circumstances, rural SMEs could serve as powerful vehicles of AFS transformation and economic development.

While there is some evidence on the importance of household SMEs for rural livelihoods and poverty reduction (Alemu & Adesina, 2017; Fox & Sohnesen, 2016; Kersten et al., 2017; Manzoor et al., 2021; Oostendorp et al., 2009), much less is known about how weather risks influence the process of enterprise creation. Previous studies show that livelihood diversification is a common coping strategy against climate change impacts (Cruz, 2024; Emerick, 2018; Liu et al., 2023), but the specific link to self-employment and enterprise startup remains unexplored. As a result, it is still unclear whether and how environmental stressors, such as extreme heat, affect rural households' decisions to establish their own enterprises, and what types of enterprises they choose to start (e.g., sector, formality). Understanding this relationship is critical for designing policies that ensure rural SME development supports inclusive growth and climate-resilient transformation of AFS, rather than reinforcing existing vulnerabilities or perpetuating informal subsistence activities.[2]

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[1] In the related literature, similar economic units are often referred to as household enterprises or micro, small, and medium enterprises (MSMEs), typically defined by small employment size, limited capital intensity, and local market orientation. The enterprises in our sample meet these core characteristics and would fall under these alternative definitions. We use the term SMEs throughout the paper for consistency and flexibility, as it allows us to encompass small owner-operated firms as well as enterprises that may grow beyond purely household-based activities. We do not apply any thresholds for employment size or capital intensity in our study, but Section 3.2 ('Variable description') provides summary statistics describing the characteristics of the enterprises in our sample.

[2] Consistent with prior research, informal self-employment in Egypt is defined here by the lack of commercial registration among SMEs. For more details see Section 3.2.

This paper addresses this gap by investigating how weather risks (especially related to temperature) influence the likelihood that rural households in Egypt start a SME. We begin our analysis by developing a conceptual model that stylizes the decision-making process of rural households to establish businesses under weather risks, taking into account the varying upfront investment costs across sectors. For the empirical analysis, we use household and enterprise data from the 2023 round of the Egypt Labor Market Panel Survey (ELMPS), a detailed and nationally representative dataset on labor market conditions (Assaad & Krafft, 2024). We then apply a dynamic duration model framework to examine the effect of heat stress—the most critical climate stressor in Egypt—on the likelihood that households establish an enterprise. We further distinguish between AFS and non-AFS enterprises, as well as between commercially registered and unregistered firms.

Egypt provides an excellent case study for our research objectives: since 2015, the government has launched several large-scale initiatives to support the SME sector. Nevertheless, informality and persistent barriers to financial and institutional support remain significant challenges.

Our results show that weather risks play an important role in shaping rural SME formation in Egypt: both heat stress and temperature variability, though distinct across SME types, accelerate startup rates. Short-term temperature variability has a comparatively large effect on startup rates of SMEs in general as well as AFS SMEs specifically, while longer-term exposure to heat stress is particularly associated with increases in registered SMEs. We also find that sectoral knowledge and remoteness moderates households' decisions to start SMEs: farm households consistently show lower startup rates, households with AFS experience are more likely to establish AFS SMEs, and remoteness moderates the influence of heat stress on SME formation. Taken together, these patterns indicate that SME formation can serve as an adaptation strategy, but one that is highly contingent on households' capabilities and their local structural environment.

By generating new micro-level evidence on the climate-enterprise link, our findings contribute to ongoing policy debates around rural development, climate adaptation, and AFS transformation. If weather risks are already influencing patterns of rural enterprise creation, this has direct implications for how SME support programs, climate finance, and rural industrialization strategies should be designed and targeted.

The reminder of this paper is structured as follows. Section 2 provides some background from the literature and presents a conceptual framework of households' decision-making around SME formation. Then, we describe the data set and introduce our empirical strategy in Section 3. Section 4 presents results, and section 5 concludes.

2 BACKGROUND

2.1 Literature review

There is ample evidence that livelihood diversification serves as an important adaptation strategy for households facing climate-related income risks (Barrett et al., 2001; Cruz, 2024; Kirchberger, 2017; Mueller & Osgood, 2009).

This is particularly true for primary production in the agricultural sector, though other sectors are also vulnerable to weather extremes. For example, construction and other physically demanding occupations are susceptible to disruptions caused by extreme heat or precipitation (Dasgupta et al., 2021; Graff Zivin & Neidell, 2010; Neidell et al., 2021). Diversifying income sources can therefore act as a buffer against sudden income losses resulting from weather shocks. A study by Mueller and Osgood (2009), for example, analyzes how droughts affect wage incomes in Brazil and estimate a recovery period of about five years for impacted households. Their findings also show that the effects are most pronounced for agricultural incomes and that diversifying income sources across sectors can help buffer households against these impacts.

However, especially in rural areas of LMICs, labor markets are often either underdeveloped or characterized by substantial frictions, making it difficult for households to access formal employment opportunities for income diversification (Breza & Kaur, 2025; Donovan & Schoellman, 2023). In such contexts, self-employment (often in the form of SMEs) emerges as a feasible alternative (Donovan et al., 2023). Some studies even suggest that SMEs may be the preferred income source for households, even when wage employment is available (Breza & Kaur, 2025). Nonetheless, most studies exploring the relationship between climate risks and livelihood diversification do not distinguish between self-employment and wage employment. As a result, despite the growing body of research on livelihood diversification, there is limited evidence on the emergence of SMEs as a direct response to climate or weather risks. Most of the literature on the climate–SME nexus focuses on how climate shocks affect the performance and survival of existing SMEs (Crick et al., 2018; McKenzie & Paffhausen, 2019), rather than on the role of climate-related risks in influencing household decisions to start new enterprises.

Another important dimension in this discussion is the type of SME under consideration. While SMEs are commonly portrayed as drivers of innovation and economic growth (Hoang et al., 2021), other studies indicate that many exhibit characteristics more akin to the survival sector, similar to subsistence agriculture (Donovan et al., 2023; El-Haddad & Zaki, 2025). This highlights the need to distinguish between different types of SMEs, particularly with regard to sector and level of formality. Recent research has also raised concerns that conventional labor-sector classifications may fail to adequately capture labor mobility within agrifood systems (Yi et al., 2025). This appears especially relevant in rural areas, as evidence suggests that although many households partially exit primary agricultural production, much of their labor remains within agricultural value chains. Similar patterns may emerge in household decisions about which sector to enter when starting a new SME.

In summary, understanding how climate risks influences the establishment of rural SMEs is a critical addition to the literature on climate adaptation and structural change. This knowledge is vital for designing policies that promote inclusive and resilient agri-food systems, as it reveals whether households pursue enterprise creation as an adaptive strategy, in which sectors, and under what conditions. Insights into the nature and formality of these enterprises can help policymakers assess their potential to contribute to economic transformation, rural employment, and long-term climate resilience. Moreover, such evidence can inform targeted interventions that not only support adaptive SME development but also strengthen agrifood systems as drivers of inclusive and sustainable rural growth.

2.2 Study context

In Egypt, SMEs play a central role in the economy, accounting for over 90 percent of all businesses, nearly 60 percent of employment, and around 75 percent of national value added (AfDB, 2016). By 2023, micro, small, and medium enterprises (MSMEs) collectively provided 73 percent of all private sector wage employment within establishments (El-Haddad & Zaki, 2025). Their economic significance has made SMEs a key target for policies aimed at promoting employment, private-sector growth, and economic diversification.

Over the past decade, Egypt has introduced several institutional and legal reforms to support MSME development. The establishment of the Micro, Small, and Medium Enterprises Development Agency (MSMEDA) in 2017 consolidated various support functions under a single agency (Assaad et al., 2019; OECD, 2025). Regulatory changes, including Investment Law 72/2017 and Law 176/2018, aimed to lower barriers for small firms through cost-reduction incentives and expanded access to non-bank financial services (El-Haddad & Zaki, 2025). The most comprehensive effort came with Law No. 152/2020, which unified MSME definitions and introduced a package of tax and non-tax incentives, simplified licensing procedures, and improved access to finance. It also promoted the development of supporting institutions such as incubators, accelerators, and specialized lenders (OECD, 2025).

Despite these reforms, a large share of SMEs, especially in rural areas, remain informal and effectively excluded from government support programs. Micro-enterprises constitute 96 percent of all businesses in Egypt, and most household firms operate at a very small scale, often as single-person ventures (El-Haddad & Zaki, 2025). By 2023, nearly three-quarters of SMEs continued to operate informally, a modest improvement since 1998, despite initiatives aimed at reducing the costs of formality.

This widespread informality has important implications for access to finance. Most SMEs rely on self-financing, and many are ineligible for formal credit, not only due to their informality but also because of how eligibility criteria are structured. While Law No. 152/2020 brought MSME definitions closer to those of the Central Bank of Egypt by relying on turnover, capital, and activity type, employment size is not a criterion. As a result, small, labor-intensive, and informal enterprises, particularly in rural areas, are often excluded from financial programs and broader support schemes (Amer & Selwaness, 2022; El-Haddad & Zaki, 2025). This limits the reach and effectiveness of policies intended to promote inclusive enterprise development and rural economic transformation.

A particularly relevant subset of this landscape is agrifood SMEs, which are disproportionately concentrated among micro and small firms. As of 2015, they accounted for over 90 percent of Egypt's agrifood production and export businesses, more than 90 percent of sectoral employment, and over 75 percent of agrifood exports (Abu Hatab et al., 2021). These enterprises play a vital role in food security, rural livelihoods, and the functioning of agricultural value chains. However, they also face significant structural constraints including limited scale, low productivity, weak financial access, and undiversified income streams, which heighten their exposure to external shocks, including climate-related risks (Abu Hatab & Hess, 2013).

Extreme heat, aridity, and more frequent droughts are the most common and severe impacts of climate change in the Middle East and North Africa (MENA) region (Waha et al., 2017). In Egypt, rising temperatures represent one of the most significant climate risks, deepening an already severe water deficit in a context of minimal rainfall and heavy dependence on the Nile and groundwater resources (Monem et al., 2022; UNESCWA, 2017). As the country remains far from self-sufficient in food production, higher temperatures and increased evapotranspiration are expected to widen the gap between water demand and available supply, contributing to expanding desertification, harvest losses, and declining productivity across key agroecological zones (Ahmed et al., 2021; Lewis et al., 2018). Greater climate and temperature variability also places additional stress on crops and livestock, heightening vulnerability to pests and diseases and further undermining the resilience of rural livelihoods (Monem et al., 2022). These compounding pressures are anticipated to intensify socioeconomic strain in rural areas and accelerate rural–urban migration (Waha et al., 2017), directly shaping the environment in which agrifood SMEs operate and amplifying their exposure to climate-related risks.

Against this backdrop, agrifood SMEs occupy a critical position within both the rural economy and climate-sensitive sectors, placing them at the intersection of vulnerability and transformation. Yet their potential to serve as effective adaptation pathways for rural households is constrained by structural challenges including informality, limited access to finance, and institutional exclusion. Addressing these barriers will require targeted policy interventions that integrate agrifood SMEs into broader strategies for inclusive rural development, climate resilience, and structural economic change.

2.3 Conceptual framework

The goal of this study is to better understand the link between weather risks and SME formation in rural areas. To guide our analysis and motivate our empirical strategy, we draw on a dynamic economic model to give some intuition of the mechanisms of households' decision-making to start SMEs under weather risks.

We assume that the decision to establish a SME is typically a long-term strategic choice made by households, rather than a short-term or recurrent one. That is, once the decision is made, households generally do not revisit it on a regular (e.g., annual) basis. Instead, the formation of an SME represents a permanent expansion of the household's livelihood portfolio. Given the lasting nature of this decision, understanding when it is made often provides deeper insight than simply analyzing the binary choice of whether to start an SME. Thus, moving beyond a static binary framework toward a dynamic perspective—one that emphasizes the timing of SME entry—allows for a more nuanced analysis of the determinants of SME formation. Accordingly, in the spirit of Samuelson's discounted utility model (Samuelson, 1937), we conceptualize SME formation as an *optimal timing problem*, in which households assess the evolving costs, benefits, and uncertainties of starting an SME over time. Crucially, this includes examining whether and how external factors, such as weather, influence household perceptions of risk and opportunity, thereby shaping the timing of SME startup decisions.

To formalize this decision problem, we define two key components.

The first component is an income function denoted $Y_s(t, l)$ in year t and at location l, where $s \in \{0, 1\}$. $s = 0$ corresponds to a household without an off-farm SME, and $s = 1$ to a household with an off-farm SME (Eq. (1)).

$$Y_s(t, l) = \omega(t, l)L_s(t, l) + D_s \times \pi^{SME}(t, l) \quad (1)$$

For simplicity, a household's income is defined as the sum of two parts:[3] wage employment, ωL, and the profits from an SME, π^{SME} (Eq. (2)).

$$\pi^{SME}(t, l) = p(t, l)q(t, l) - c(t, l)a \quad (2)$$

where q denotes the quantity of output produced by the SME, p is the price per unit of output, and c represents the cost per unit of input a.

The indicator D_s in Eq. (1) is a bivariate variable, taking the value of 1 for a household with a SME. For a household without a SME, $D_s = 0$ and the right-hand side of the income function in Eq. (1) reduces to only income from wage employment.

Note that the income function depends on both time t and household location l, capturing variation across time and space. Since the primary variable of interest is weather risks, we make the simplifying assumption that all spatial variation l is exclusively driven by weather variability. In other words, aside from variation in weather conditions, space is treated as homogeneous—an assumption we later relax in the analysis. For the moment, this abstraction allows us to isolate some stylized effects of climate-related factors on household income.[4]

Accordingly, both wage employment and SME profits are assumed to be sensitive to weather conditions. In the Egyptian context, this sensitivity is particularly shaped by temperature extremes and variability. We therefore allow wages (ω) and household labor allocation (L) to vary with weather, as do SME output (q), output prices (p), and input costs (c). For example, high temperatures can reduce labor productivity, disrupt working hours, and increase health-related absences, thereby affecting wage employment (Neidell et al., 2021; Zanobetti et al., 2012). Similarly, operational costs for household SMEs may rise due to increased cooling requirements, higher spoilage risk, or shifts

[3] Households often have more than two income sources (e.g., wages from multiple off-farm activities) and in the rural context, farming is an important self-employed activity as well. For simplicity, we however abstract to only two income sources, and ωL should be rather unterstood as an aggregated measure of income including all activities except for off-farm self-employment (SME activity).

[4] In the empirical model, we add a set of controls to capture other sources of spatial heterogeneity.

in consumer demand, particularly in climate-exposed sectors such as agriculture, food processing, and informal services.

The second component needed to describe a household's decision problem is the one-time investment cost, $C(t)$, required to establish an off-farm SME in year t. We assume that C generally does not depend on temperature (l) and is mainly defined by t. That is, a certain technology or machinery needed for the household SME might become cheaper with time, for example, but costs would not vary across space at a given time.

Based on the income function $Y_s\,(t, l)$ and a one-time installation cost $C(t)$, the household determines the optimal timing for starting an SME by comparing the expected present value of net returns at a given time T, $V(T, l)$ (Eq. (3)), with the expected present value of delaying the decision by one period, $V(T + 1, l)$ (Eq. (4)).

The first summation in Eq. (3) captures the discounted stream of future income the household would obtain after starting the SME, while the second term subtracts the one-time installation cost $C(T)$. The final summation represents the discounted income stream the household would have earned had it remained without an SME. The present value $V(T, l)$ therefore reflects the expected gain from switching from state $s = 0$ to $s = 1$ in year T, considering both the long-term income difference between the two states and the fixed cost of entry. Discounting through $\delta(h)$ ensures that future income flows are weighted appropriately over time, consistent with a dynamic decision framework.

$$V(T, l) = \sum_{h=0}^{\infty} Y_1(T + h, l)\delta(h) - C(T) - \sum_{h=0}^{\infty} Y_0(T + h, l)\delta(h) \tag{3}$$

Analogous to Eq. (3), the expression in Eq. (4) defines the present value of net returns for delaying the SME startup decision by one year. Thus, the first two terms capture the income the household earns without a SME in year T and the discounted income stream with a SME beginning in year $T + 1$, net of the installation cost $C(T + 1)$, which is also discounted. The final terms subtract the corresponding income stream associated with entering in year T, allowing $V(T + 1, l)$ to represent the expected gain (or loss) from postponing SME formation by a single year relative to immediate entry.

$$\begin{aligned} V(T + 1, l) = Y_0(T, l) + \sum_{h=1}^{\infty} Y_1(T + h, l)\delta(h) - C(T + 1)\delta(1) - Y_1(T, l) \\ - \sum_{h=1}^{\infty} Y_0(T + h, l)\delta(h) \end{aligned} \tag{4}$$

Conceivably, a household could optimize by comparing $V(T, l)$ against the value of starting the SME at multiple future time periods (i.e., after one, two, three years, etc.; see literature on optimal stopping problems or stochastic dynamic optimization (Dixit & Pindyck, 1994)). However, given the uncertainties and constraints often faced by rural households, assuming a shorter decision horizon appears more realistic and facilitates the subsequent modeling steps. That means, we model rural households as revisiting their decision to start an SME on an annual basis until the enterprise is established.

Thus, assuming that households time their decision to start a SME based on the present values denoted Eq. (3) and (4), two criteria have to be fulfilled for SME startup in T.

First, the expected present value of starting a SME in T cannot be negative (Eq. (5)).

$$V(T,l) \geq 0 \tag{5}$$

Second, the expected present value of starting a SME in T must at least be equal or larger than the expected present value of waiting for another year $(T+1)$ (Eq. (6)). In other words, there is no value in waiting. The derivation of Eq. (6) can be found in the appendix.

$$\begin{aligned} V(T,l) \geq V(T+1,l) \Leftrightarrow L_1(T,l) + \frac{p(T,l)}{\omega(T,l)}\, q(T,l) - L_0(T,l) \\ \geq \frac{C(T) - C(T+1)\delta(1)}{2\omega(T,l)} + \frac{c(t,l)a}{\omega(T,l)} \end{aligned} \tag{6}$$

The left-hand side of Eq. (6) represents the immediate net income gain from switching from no SME ($s = 0$) to having a SME ($s = 1$) in year T. This includes the difference in labor income, $L_1(T,l) - L_0(T,l)$, as well as the ratio of SME revenues normalized by the wage rate, $\frac{p(T,l)}{\omega(T,l)} q(T,l)$. The latter reflects the relative profitability of SME activity compared to wage employment. The right-hand side captures the discounted advantage of postponing SME formation by one period. This includes the difference between the startup costs in years T and $T+1$, adjusted by the discount factor, and the ratio of the SME input costs to the wage rate, $\frac{c(T,l)a}{\omega(T,l)}$. That means, a household would start a SME if the gains from the SME in terms of wage rate are disproportionately higher than the one-time startup costs and SME input costs in T.

Since we assume that most elements of the household's decision problem are influenced by location-dependent weather risks l, we can now consider how temperature may shift the balance presented in Eq. (6). Climate shocks affect both sides of the inequality by altering wages, labor productivity, and SME profitability. For example, extreme temperatures can reduce labor productivity or limit available working hours, thereby lowering wage income $\omega(T,l)\, L_s(T,l)$ and increasing the relative attractiveness of allocating labor to SME activities. At the same time, higher temperatures may reduce SME revenues through declines in output $q(T,l)$, raise spoilage risk, or increase operational and input costs $c(T,l)$, particularly in temperature-sensitive sectors.

This also highlights how SME formation can differ by sector and level of formality. Households with lower entry costs such as those operating in familiar sectors (e.g., AFS) are more likely to satisfy Eq. (6) earlier, leading to quicker entry. Conversely, forming a registered or more capital-intensive SME involves higher fixed costs $C(T)$, meaning that the threshold for immediate startup is harder to meet and that households may delay entry until expected returns increase or investments costs fall (i.e., when technology becomes cheaper with time).

So far, we have assumed that weather risks are the only spatially varying factor influencing household SME formation in location l. However, previous studies show that labor allocation and household decision-making are also shaped by access to markets and economic centers (Christiaensen et al., 2013; Steinhuebel-Rasheed et al., 2025). In other words, beyond spatial weather variation, household remoteness (also dependent on l) is likely to influence both the timing of SME entry and households' responsiveness to weather risks. This is particularly relevant in the Egyptian context, where economic activity is strongly concentrated in the Delta region and around Cairo as the primary economic hub and where the Nile has long structured the spatial distribution of settlements and economic opportunities. Remoteness can alter several elements of the inequality in Eq. (6) by reducing expected revenues $q(T, l)$ through weaker market access, raising input and transport costs $c(T, l)$, and shaping wage opportunities $\omega(T, l)$ depending on local labor demand. It may also increase the investment or startup costs captured in $C(T)$, implying that these costs should explicitly be written as $C(T, l)$ to reflect spatial disparities in market access and administrative reach.

3 DATA AND METHODS

The household's decision regarding the optimal timing to establish an SME can be empirically analyzed using a duration model framework. If we observe a sample of households along with the timing of their first SME startups, we can estimate the probability that a given household i will initiate an SME in the next period h, given that it has not done so by time t. This probability, referred to as hazard rate, $\lambda_{\mathrm{i}}(t)$, reflects the likelihood of transitioning from a non-SME to a SME status at time t (see Eq. (7)). Here, T is a nonnegative random variable representing the duration until SME entry, with the non-SME spell ending when $T = t$.

$$\lambda_i(t) = \frac{\lim_{h \to 0} \Pr(t \leq T^* < t + h | T^* \geq t)}{h} \tag{7}$$

In a duration model framework, it is possible to regress the hazard rates on a set of independent variables, x_i', as in the Cox model (Cox, 1972) presented in Eq. (8). Specifically, we assume that a household's hazard rate, $\lambda_i(t)$, consists of two components: the baseline hazard, $\lambda_0(t)$, that is common to all households and depends only on time t, and the effects of covariates x_i' measured at the household level i.

$$\lambda_i(t) = \lambda(t, x_i) = \lambda_0(t) \exp(x_i' \beta) \tag{8}$$

Note that duration models require specific preparation of the dataset. Therefore, in the subsequent sections, we first present the data sources and the steps taken for data preparation, followed by a description of the key variables, namely SME formation ($\lambda_i(t)$) and covariates (x_i') including measures of weather risks. We then provide a more detailed account of the duration model specifications estimated to address the hypotheses defined in the conceptual framework.

3.1 Data sources and processing

Data sources: For our empirical analysis, we draw from and combine three data sources: the Egypt Labour Market Panel Survey (ELMPS) 2023 (OAMDI, 2024), the ERA5 climate reanalysis data (Copernicus Climate Change Service, 2020), and World Development Indicators (World Bank, 2025).

The ELMPS 2023 is the fifth wave of a nationally representative household survey to capture household income and labor market dynamics in Egypt. It is implemented by the Economic Research Forum (ERF) in collaboration with the Central Agency for Public Mobilization and Statistics (CAPMAS) and the Ministry of Planning and Economic Development, covering all 27 governorates of the country. In addition to standard socioeconomic modules, the more recent rounds also introduced a dedicated section on enterprises owned by households, collecting detailed recall information on the year of SME startup, sectoral classification, formality status, and related enterprise characteristics (Assaad & Krafft, 2024). From the 2023 sample, we consider a total of 16,664 households[5] (3,205 with household SME). As we are primarily interested in rural SME patterns, we use a subsample of 10,372 rural households in the subsequent analysis. We moreover drop all households who started their first SME before 1990 and end up with a final sample of 10,357 households who started their first SME after 1990 or have not started one yet. This restriction is mainly for technical and data reasons as several of the critical control variables are not (reliably) available for the period prior. Furthermore, we are mainly interested in drivers of SME formation in recent history, and those focus on decision-making of current household heads (current generation). We also drop households who report self-employment in the past but no longer have a SME. This ensures that we only consider first-time SME formation in the period of observation and do not bias our results with households who exited the SME sector. Figure 1 presents the distribution of existing rural household SMEs in the final sample as of 2023.

As illustrated in Figure 1, the ELMPS data include disaggregated spatial identifiers down to the village level (admin3), which enables us to link household and enterprise information to disaggregated climate data. To capture weather risks, we rely on data published by the European Centre for Medium-Range Weather Forecasts (ECMWF) as part of the AgERA5 data set. AgERA5 is a pre-processed product based on the hourly ECMWF ERA5 surface-level reanalysis and provides daily agrometeorological indicators at high spatial resolution (0.1° grid). ERA5

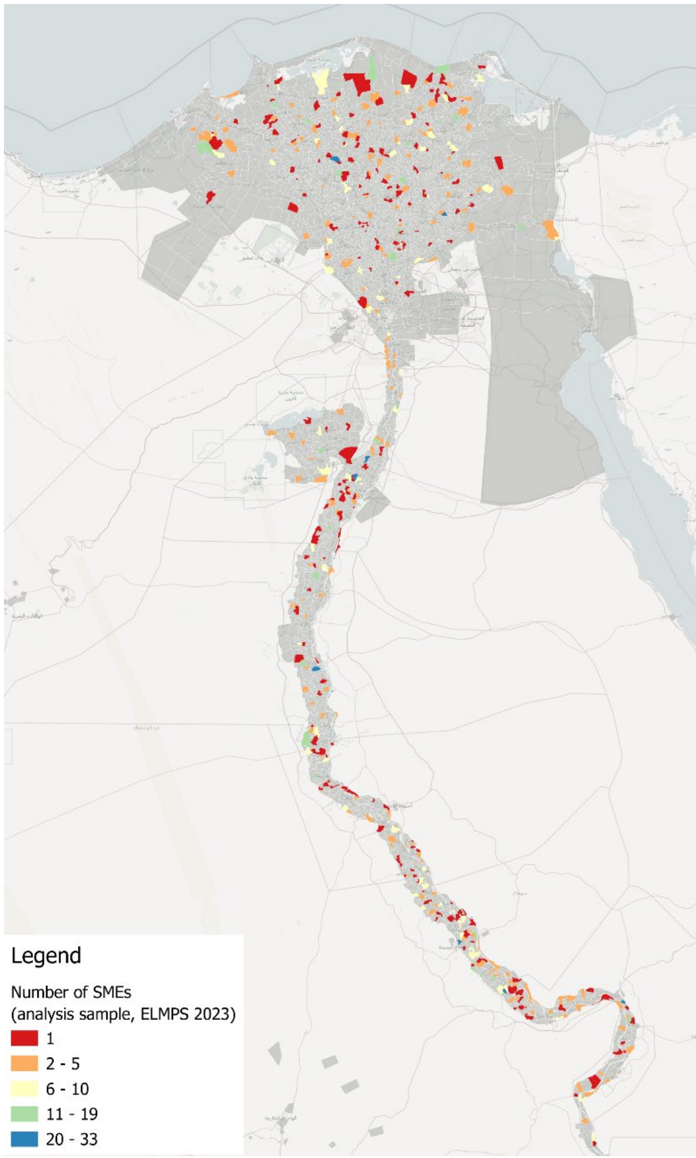
[5] Data are available from 17,784 households (Assaad & Krafft, 2024). However, in preparing the dataset we had to drop households with missing observations in the main variables of interest or lack of spatial identifiers.

indicators are not direct measurements but are derived from ECMWF's fifth-generation global atmospheric reanalysis, which combines a physically based numerical weather prediction model with the assimilation of diverse historical observations. Unlike simple spatial interpolation, this approach enforces physical consistency through atmospheric dynamics and can provide reliable estimates in data-scarce environments such as Egypt by propagating information from surrounding observations and large-scale circulation patterns. All assimilated observations are subject to systematic quality control and bias correction, whereby erroneous data are screened, and instrument- or platform-specific biases are adjusted to ensure a temporally consistent and physically realistic climate record. As a result, ERA5-based products are widely used as a standard source for spatially disaggregated and comparable climate information (Kotz et al., 2021). Given that temperature is generally perceived as the most critical climate/weather risks in Egypt (see section 'Study context'), we obtained aggregated daily mean and maximum temperature information for the years 1985 to 2023 on a 0.1° grid. Afterward, we use administrative boundary shapefiles (see Figure 3 and Figure 4) to match temperature data to the village level coinciding with the ELMPS spatial identifiers. The result is a daily time series for every village unit in Egypt.

Lastly, we also include time series data from the World Development Indicators (World Bank, 2025) in our analysis data set. That is, we use GDP at $t-1$ and inflation rate of consumer prices in t to control for economic and investment climate over the past three decades.

Data processing: As the dependent variable in a duration model is the time until an event occurs, the dataset for analysis requires to be structured in so-called *time spells*. Thus, we must define entry and exit points for each household in the sample. We include only households whose current household head either started their first SME after 1990 or has not yet started one until the end of the observation period (2023). We assume that the spell for each household begins at the earliest when the current household head reaches age 15. For individuals already older than 15 in 1990, the observation is left-truncated (i.e., delayed-entry); for those who turned 15 after 1990, entry into the sample occurs in the year they reach that age. From that point onward, the household remains under observation until a SME is started or until the observation window ends. In addition to the entry and exit variables, an indicator variable captures whether a SME was started in a given year before 2023 ($d_{SME} = 1$) or not ($d_{SME} = 0$).

In the classical duration model, each household would contribute a single observation defined by its entry and exit times and an event indicator variable. For our analysis, however, we expand the dataset into yearly time spells for each household. Accordingly, each household has as many yearly observations as the number of years from sample entry to exit (or until 2023), with the event indicator (d_{SME}) capturing SME formation in each year. Once the indicator takes a value of 1—signifying the year in which a SME is started—no further observations are recorded for that household. Splitting the data into yearly spells offers the advantage of incorporating time-varying covariates. This allows us to link variables such as annual temperature data or national economic indicators (possibly lagged) to each household-year observation and to examine the temporal relationship between these factors and SME formation. For time-invariant variables such as region or gender of household head, the same value is assigned to all yearly observations (see section 'Variable description' for more details).



Source: ELMPS 2023, authors' calculation.

Figure 1. Distribution of household SMEs on village level (2023)

3.2 Variable description

Measurement of SME formation: For our analysis, we consider that formation of household SMEs overall but are also specifically interested in drivers of AFS and formally registered SMEs. In total our sample contains 1,912 SMEs[6] (Table 1).

For each enterprise the economic activity according to the International Standard Industrial Classification (ISIC4) (United Nations, 2008) is reported, and we rely on 4-digit disaggregation to identify AFS activities. The list of activities considered AFS for this study is presented in Table 9 in the appendix. Note that this also includes

[6] With complete data available (e.g., year of formation, economic activity)

agricultural activities. The ELMPS module on SMEs asks specifically for nonfarm enterprises but some of the reported enterprises seem to be agricultural businesses. To achieve a clear distinction between farming and nonfarm AFS SMEs, we drop all enterprises which have an 'agriculture' economic activities and state field/plot as location of the enterprise. Remaining 'agriculture' enterprises located in shops or inside the family home are considered as AFS SMEs in the analysis. As an additional dimension, we also split the enterprise sample by whether it is commercially registered, which is recorded in the ELMPS. This commercial registration is the prerequisite for access to government support and we use it as a proxy for the formalization of enterprises (Assaad & Krafft, 2024).

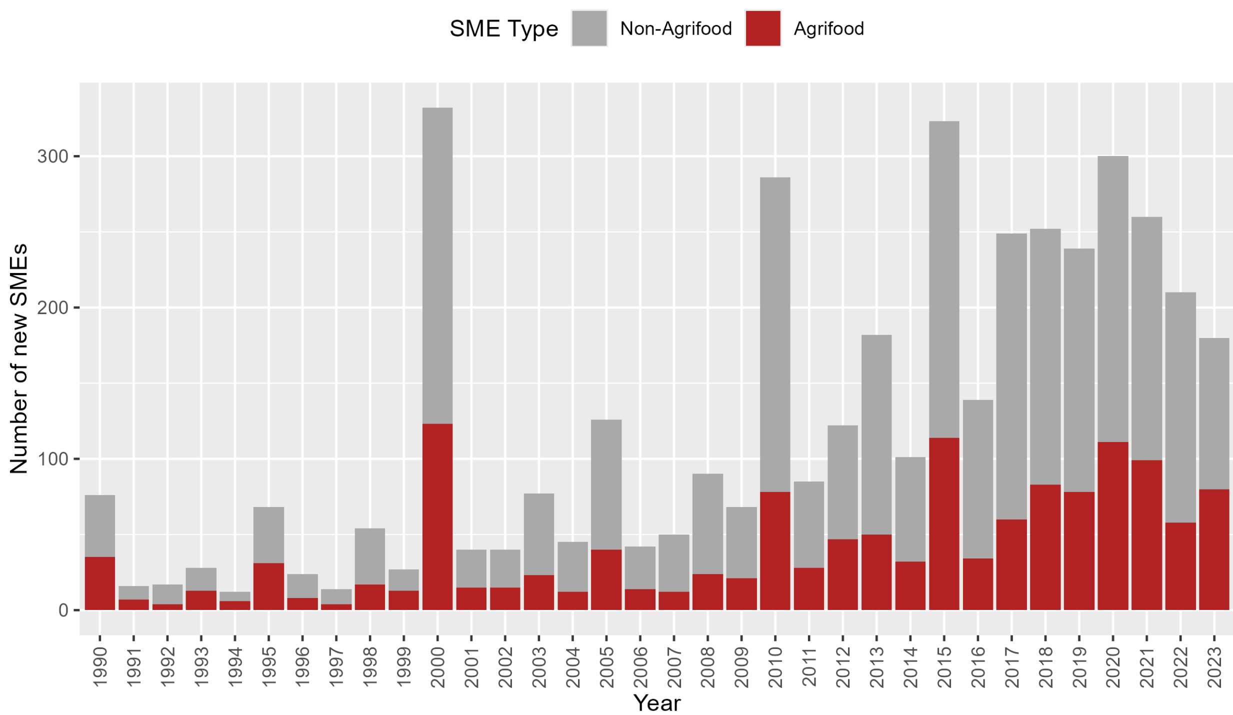
Table 1. Cross-tabulation of rural SMEs

	AFS[a] SMEs	Non-AFS SMEs	TOTAL
Registered SMEs	122	225	**347**
Not-registered SMEs	485	1,080	**1,565**
TOTAL	**607**	**1,305**	**1,912**

Note: [a]AFS=Agrifood System.
Source: ELMPS 2023, authors' calculation.

In Table 1, we present the distribution of first-time SMEs (as of 2023) in the sample against the AFS and formalization categories. About one-third of the SMEs in our sample fall into the AFS sector, with a slightly higher share of commercial registration (though the difference is not statistically significant). That is, overall 18 percent of all SMEs are commercially registered compared to a share of 20 precent only for AFS SMEs. Of all registered SMEs in the sample, 35 percent fall in the AFS sector.

Most SMEs rely exclusively on household labor, with only about 12 percent employing outside labor. The main source of capital to start SMEs is from saving, while financing through loans, for example, from relatives or formal institutions, is rare (below 10 percent). Overall, enterprises appear to be rather small and informal, with around 40 percent reporting a value of current capital smaller than EGP 5,000 (~US$100).



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Source: ELMPS 2023, authors' calculations.

Figure 2. Number of new SMEs between 1990 and 2023 started by households without prior experience of self-employment

On average, household SMEs reported in 2023 are approximately 9.5 years old. Figure 2 provides an overview of new SME formation over time based on the ELMPS subsample. The figure indicates that SME formation has become more frequent during the last ten years of the observation period. It also suggests potential recall issues for older enterprises, as there appears to be some heaping—that is, a reporting bias resulting from rounding of time periods—around certain years such as 2000. However, the fact that observations in adjacent years are not systematically lower suggests that such reporting errors are limited. To address potential biases in subsequent analyses, we conduct sensitivity tests using our key variables of interest (e.g., weather risks), aggregating data over the past several years (see Table 2).

Measurement of weather risks: To capture weather risks, we rely on the daily ERA5 temperature data to build indicators for temperature intensity and variation. Both are common indicators in the literature and recent studies have shown that temperature is often an even better predictor for economic development than rainfall, for example (Burke et al., 2015; Kotz et al., 2021). Next to increased heat intensity, changes in temperature variation also has been shown to be an important determinant of human wellbeing and economic development (Kotz et al., 2021; Zanobetti et al., 2012). Resulting uncertainty from increasing temperature variation for farm and rural households can very likely lead to adjustments in livelihood portfolios. Thus, we create four different temperature measures (Table 2). First, we calculate the number of heat days on a yearly basis as a general indicator of heat stress. A heat day is a day with maximum temperatures above 44°C in the summer months (May to August) or above 37°C in the remaining months. Second, as another and more seasonal heat stress indicator, we also consider only heat days during the summer season. Third, we follow the approach by Kotz et al. (2021) to create yearly measures of temperature variation. Thus, we compute monthly temperature variability as the standard deviation of daily mean temperatures and then average these monthly values over each year. Fourth, the final indicator is the yearly maximum temperature variation.

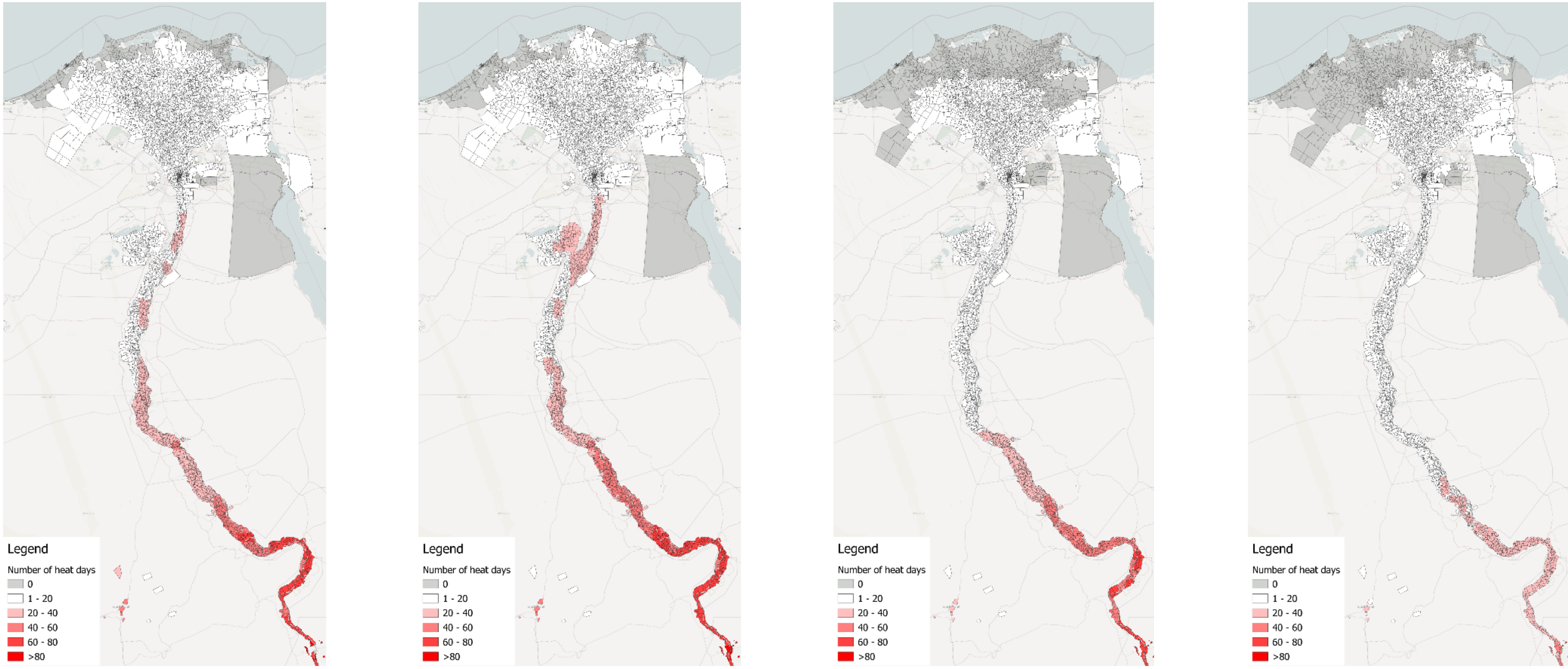
As a sensitivity test, we calculate all four indicators for the year of observation t, the yearly average of the past three years, $t_3 \in [t-3, t)$, and the yearly average of the past five years, $t_5 \in [t-5, t)$.

Table 2. Descriptive statistics for weather risks variables

Variable	N	Mean	St. Dev.	Min	Max
Heat Days (#)					
Current year – t	10,357	16.078	16.604	0	97
Yearly average of past three years – t_3	10,357	16.018	17.172	0	80.667
Yearly average of past five years – t_5	10,357	14.913	17.557	0	80
Summer Heat Days (#)					
Current year – t	10,357	1.417	3.179	0	34
Yearly average of past three years – t_3	10,357	1.105	2.193	0	22
Yearly average of past five years – t_5	10,357	1.672	2.786	0	21.2
Average Monthly Day-to-Day Temp. Variation (SD °C)					
Current year – t	10,357	1.821	0.278	1.068	2.82
Yearly average of past three years – t_3	10,357	1.87	0.238	1.14	2.574
Yearly average of past five years – t_5	10,357	1.859	0.24	1.117	2.51
Max. Monthly Day-to-Day Temp. Variation (SD °C)					
Current year – t	10,357	2.945	0.589	1.642	4.98
Yearly average of past three years – t_3	10,357	3.545	0.374	1.891	4.463
Yearly average of past five years – t_5	10,357	3.378	0.327	1.913	4.267

Note: N = number of households. Averages for 2023 or year of SME formation.
Source: ERA5 reanalysis data, authors' calculations.

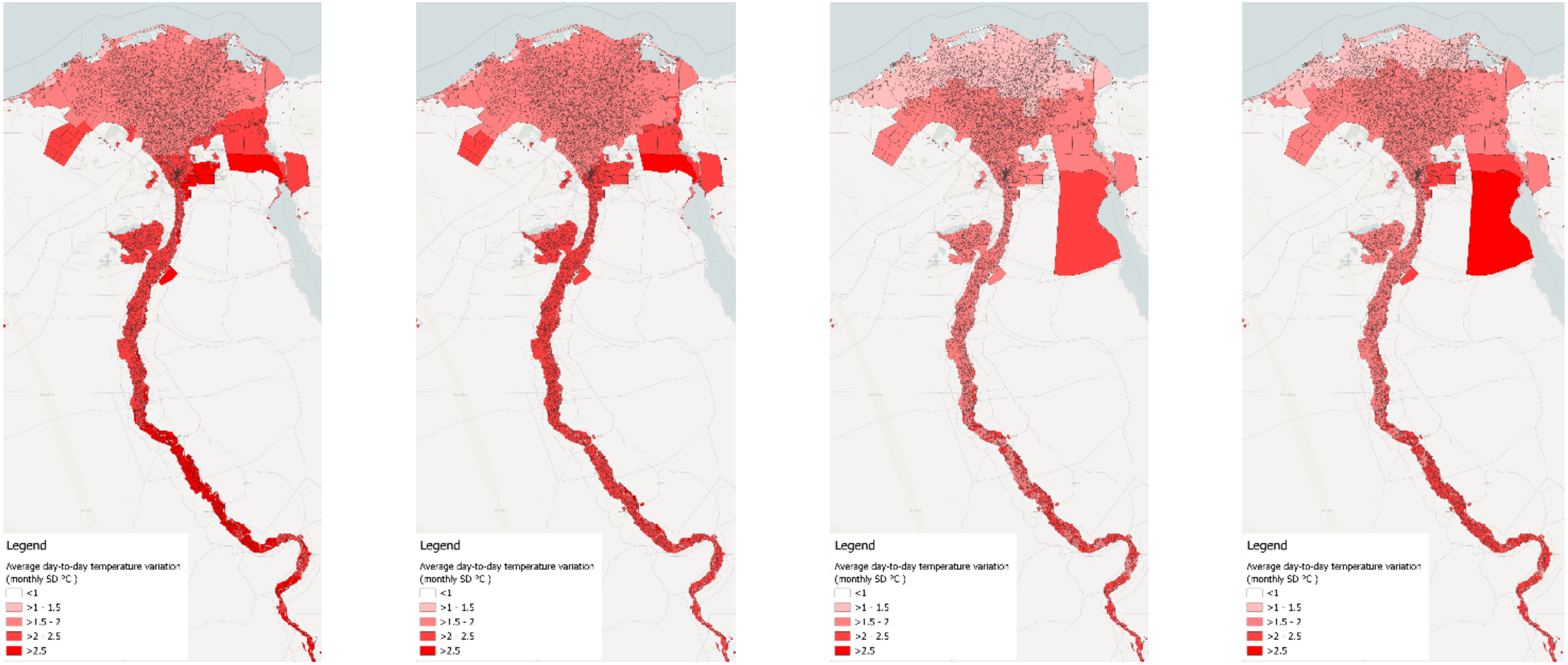
The values presented in Table 2 are the sample means for all rural households in our ELMPS sample, indicating an average 16 heat days for households per year and an average monthly temperature variation of close to 2°C. However, looking at the range of the different variables (Min and Max in Table 2), it becomes evident that there is substantial variation in the temperature patterns across sample households and Egypt.



a) 2010 **b) 2015** **c) 2020** **d) 2023**

Source: ERA5 reanalysis data, authors' calculations.

Figure 3. Heat days at the village level across the years



a) 2010 **b) 2015** **c) 2020** **d) 2023**

Source: ERA5 reanalysis data, authors' calculation.

Figure 4. Average monthly day-to-day temperature variation at the village level across the years

Thus, in Figure 3 and Figure 4, we present the spatial variation of heat days and mean temperature variation respectively for selected years during the observation period. The panels show that weather risks generally seem much more pronounced in the southern part of Egypt (Upper Egypt), but there is variation between years. For example, in 2015, the number of heat days (Panel b in Figure 3) as well as temperature variations (Panel b in Figure 4) seem to have increased in more northern parts of Egypt, compared to years before and after. Note, however, while there is variation in the weather risks variables between different years, there seems to be no visible trend of increasing or decreasing heat stress or temperature variation (time series of national averages are presented in Figure 6 and Figure 7 in the appendix).

Control variables: In addition to the weather risks variables, we also include a set of additional and control variables in our analysis. This includes household characteristics such as the gender and age of the household head and households' relative wealth status (wealth quantiles).

We furthermore also control and investigate remoteness and spatial controls, namely households' location in Upper Egypt and distance to the Nile River. Upper Egypt is generally poorer than the northern parts of Egypt, which is magnified by its distance from Cairo, the major economic center of the country. In the water constrained environment of Egypt, the Nile is the major source of water necessary for many economic activities. Thus, location in Upper Egypt and distance to the river is an important proxy and control of spatial heterogeneity. About 50 percent of households in our sample are located in Upper Egypt.

As a third household-level variable group, we include a set of variables capturing available household labor and skills/sector knowledge of the household. We use the number of adults (older than 15) in 2023 as an indicator for available household labor through the years. Since our observation period is long, it is likely that there have been changes throughout the years, with household members leaving or dying, or still being children. Nonetheless, we assume that the overall number should be relatively constant throughout the years with both in- and outflows. However, estimated coefficients should only be interpreted as associations. On average households have 2–3 adults available for income generation. We, furthermore, introduce a dummy variable for farm households (accounting for 14 percent of the sample). This variable relies on information about whether a household has been involved in crop or livestock farming in the past 12 months in 2023. Assuming that farming is the traditional occupation in rural areas in Egypt, we assume that households farming in 2023 also pursued farming activities in the years before. Note, however, that this variable does not account for households who dropped out of farming in the years before. The ELMPS includes past occupation on the individual levels with only very few individuals reporting activities prior to the current. Thus, we can safely assume that the potential bias due to farm drop out is limited. In a similar fashion, we create the dummy variable whether the household head has any experience in the AFS sector (39 perfect), considering current employment in 2023 and reported employment history. As a last labor-related variable, we aim to capture the weather risks through labor market links and calculate the yearly average temperature variation from villages for which a household member reports income activities.

Finally, to capture the economic and investment climate at the national level, we also consider the current inflation rate and GDP of the past year ($t-1$) as controls. These variables are constant across household, but vary based on the year under observation (x_t).

Table 3. Descriptive statistics for control variables

Variable (*Time-varying)	N	Mean	St. Dev.	Min	Max
<u>Household variables</u>					
Female Hh (0/1)	10,357	0.22			
***Age Hh (year)[a]**	10,357	43.579	15.759	16	98
Wealth Quantiles					
1	10,351	0.302			
2	10,351	0.25			
3	10,351	0.197			
4	10,351	0.152			
5	10,351	0.098			
<u>Remoteness variables</u>					
Upper Egypt (0/1)	10,357	0.532			
Distance to Nile (km)	10,357	13.756	18.749	0.024	110.482
<u>Labor-related variables</u>					
Household Labor (# adults)	10,357	2.493	1.183	1	11
Farm Household (0/1)	10,357	0.143			
Hh employed in AFS(0/1)	7,049	0.39	0.488	0	1
***Average Temp. Variation (t) in Linked Villages[b]**	10,357	0.722	0.901	0	2.774

Note: [a]Age in 2023 or at time of SME formation; [b]Linked villages: At least one household member employed in this village; Hh = Household head.
Source: ELMPS 2023, authors' calculations.

3.3 Model specifications

To better and more flexibly capture the underlying time dynamics in SME formation over the last three decades, we extend the Cox model presented in Eq. (9) by introducing a smooth function of time to parameterize the baseline hazard. This is implemented using restricted cubic splines following Royston and Parmar (2002), which entails modeling the log cumulative hazard, $H_i(t)$, rather than the instantaneous hazard rate, $\lambda_i(t)$. The flexible functional form is particularly suitable given the long observation period of the analysis, during which structural changes and unobserved year-specific effects may influence SME startup behavior. That means, in addition to the time-varying covariate described in the previous section, we can also capture the year-specific effect on the cumulative hazard to start a SME. Thus, this approach enables the baseline hazard to capture gradual temporal shifts without imposing restrictive parametric assumptions.

$$\ln H_{i,k}(t) = s(\ln t\,; \gamma) + x_i'\beta \tag{9}$$

where $H_i(t)$ denotes the cumulative hazard function four household i to start a SME of type $k = \{all\ SME, AFS\ SME, registered\ SME\}$, $s(\ln t\,; \gamma)$ represents a spline function of log time with parameters γ, and β captures the vector of coefficients associated with the covariates of interest x_i'. This specification allows the hazard rate to vary nonlinearly over time while maintaining a proportional structure across explanatory variables. That is, the coefficients β are interpreted as proportional effects on the cumulative hazard, reflecting differences in the accumulated risk of SME formation over time, rather than on the instantaneous hazard at a given point in time.

To explore the hypotheses from the conceptual framework and consider the different types of variables in our dataset, we follow three steps.

In the first step is a model specification excluding covariates, focusing only the baseline hazard (Eq. (10)). This allows us to better understand how the cumulative hazard for the formation of different SME types developed during the observation period. For more flexibility, we model the cubic spline with five knots in this specification, but reduce the number to three in the remaining specifications to reduce model complexity and more efficient estimation.

$$\ln H_{i,k}(t) = s(\ln t\,; \gamma) \tag{10}$$

In the second step, we add the weather risks variables ($c_i'(t)$) and all control variables (x_i, $x_i(t)$, and $x(t)$). The primary goal of estimation of the model specification in Eq. (11) is to assess the most relevant climate proxies related to the formation SME type k. Therefore, we estimate model specifications including different combinations of the temperature variables introduced in Table 2. This includes the combined and interacted considerations of heat intensity and variation as well as past and current temperature measures.

$$\ln H_{i,k}(t) = s(\ln t\,; \gamma) + c_i'(t)\theta + x_i'\beta_1 + x_i'(t)\beta_2 + \mathrm{x}'(t)\beta_3 \tag{11}$$

In the third and last step, we aim to explore different mechanisms that might influence the link of temperature risk and SME start up by including interaction effects between climate variables $c_i'(t)$ and control variables for sector knowledge (Eq. (12)) and remoteness (Eq. (13)).

In the conceptual framework, we argue that sector-specific knowledge can lower the entry costs or increase the productivity for SMEs within the same sector. Since our analysis focuses on AFS transformation and related SMEs, we estimate two specifications that interact the weather risks variables with indicators of household sector experience. Specifically, we capture whether the household is active in farming or whether the household head has prior experience in the AFS through employment ($d_{\text{sector}} = \{d_{\text{farm}}, d_{\text{AFS}}\}$). This allows us to assess how sector knowledge might moderate households' responsiveness to weather risks when deciding to start a SME.

$$\ln H_{i,k}(t) = s(\ln t\,; \gamma) + (c_i'(t) \times d_{sector})\theta + x_i'\beta_1 + x_i'(t)\beta_2 + \mathrm{x}'(t)\beta_3 \tag{12}$$

Similarly, our conceptual framework suggests that access to markets is likely to affect the costs and benefits of SME formation. To capture this, we examine two dimensions of remoteness (d_{remote}). First, we interact weather risks with households' location in Upper Egypt, representing broader remoteness at the national level ($d_{\text{remote}} = d_{\text{Upper}}$) (i.e., distance from major economic centers such as Cairo and Alexandria). Second, we consider distance to the Nile, which reflects local remoteness and access to water as well as infrastructure and services (e.g., roads and electricity) that are generally concentrated along the river ($d_{\text{remote}} = d_{\text{Nile}}$).

$$\ln H_{i,k}(t) = s(\ln t\,; \gamma) + (c_i'(t) \times d_{remote})\theta + x_i'\beta_1 + x_i'(t)\beta_2 + \mathrm{x}'(t)\beta_3 \tag{13}$$

In all model specifications, standard errors are clustered on the district (*kism*) level. As a robustness check, we also run specifications including governorate fixed effects.[7] However, since results are consistent, we rely on the more parsimonious specification for the rest of the analysis.

4 RESULTS

Following the hypotheses outlined in the conceptual framework, we present the estimation results in three steps. First, we examine overall SME dynamics over the observation period by analyzing the baseline hazard (Eq. (10)). Second, we assess the relationship between weather risks and the likelihood that households start a SME, with particular attention to AFS-related SMEs and commercial registration (i.e., formalization). Finally, in the third subsection, we explore potential mechanisms and spatial patterns—specifically sectoral knowledge and remoteness—that may moderate the climate-related effects observed in the estimation results of Eq. (11).

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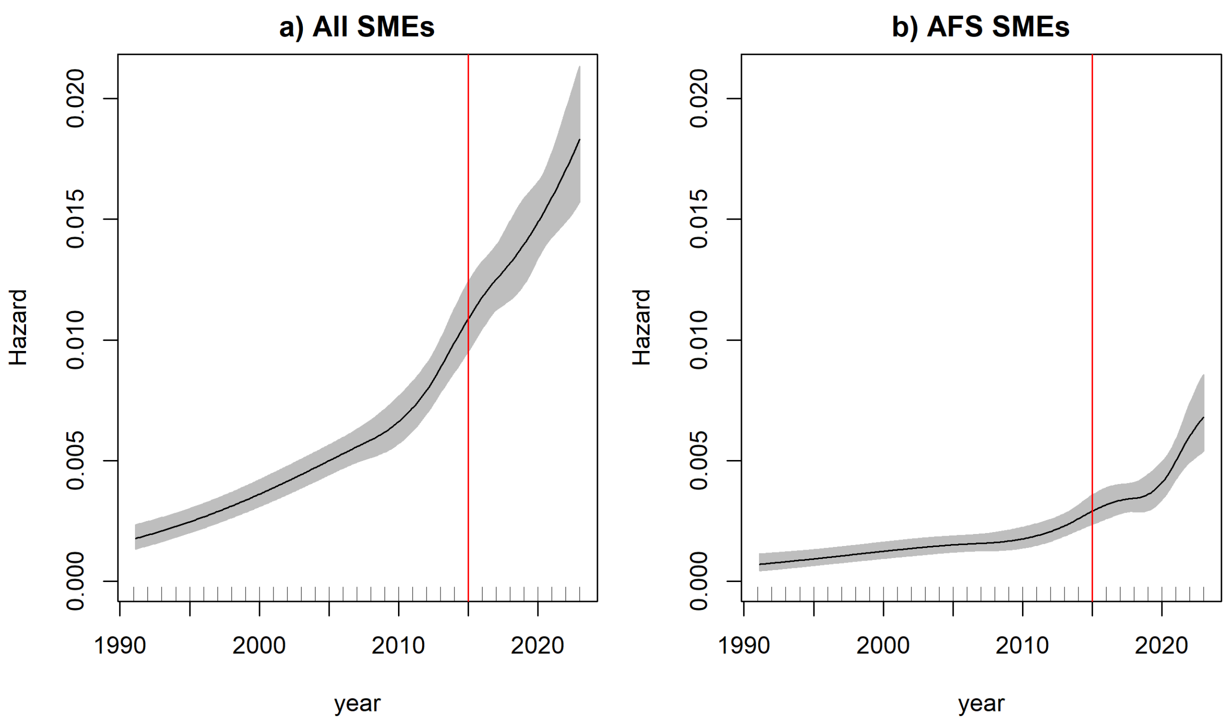
[7] Results are available on request.

4.1 Baseline hazard and SME dynamics

Figure 5 presents the estimated baseline hazard for the formation of SMEs overall (Panel a) and for AFS SMEs specifically (Panel b). The two graphs can be interpreted as showing the average event probability—that is, the likelihood that a rural household in the ELMPS sample starts a first SME of the respective type at a given point in time, conditional on not having done so previously (the instantaneous risk). Since AFS SMEs are a subset of all SMEs, it is expected that Panel a generally shows higher baseline hazard estimates. Nonetheless, even for the "All SMEs" model, the estimated hazards remain relatively low. For instance, the highest hazard in 2023, around 0.017, corresponds to an approximately 1.7 percent chance that a household without a SME at that time will start one.

Both baseline hazards display a continuous upward trend, indicating that SME formation has become more likely in recent years. For SMEs overall (Panel A in Figure 5), the rate of SME formation appears to take off around 2010, with the slope of the hazard rate becoming steeper. In contrast, while also increasing, the takeoff of AFS SMEs seems to occur somewhat later, primarily in the late 2010s.



Source: ELMPS 2023, authors' estimations.

Figure 5. Estimated baseline hazard for rural (AFS) SMEs (Eq. (10))

Although the results shown in Figure 5 do not allow us to directly identify the underlying drivers, they indicate that the formation of non-AFS SMEs has historically been more common in rural areas of Egypt, as evidenced by higher hazard levels in Panel A compared with Panel B. This pattern contrasts with the expectation that entry barriers for non-farm AFS activities are lower in rural settings. A plausible explanation is that agricultural value chains in Egypt have historically been limited in scope (Breisinger et al., 2019), with concerted efforts to strengthen secondary and tertiary AFS sectors—through government and development initiatives aimed at improving productivity and value addition—emerging in recent years (OECD, 2025). Moreover, large-scale (infrastructure) programs such as Haya Karima focus on building human capital and enhancing the connectivity of rural and remote communities to economic centers (Raouf et al., 2023), potentially facilitating (AFS) SME formation.

4.2 Temperature effects on SME formation

To explore the relationship between weather risks and SME formation, we test a variation of model specifications (Eq. (11)) including temperature variables separately (Columns 1 and 2 in Table 4), combined (Column 3), with interaction effects between heat intensity and variation (Column 4), and with interaction effects for current and past temperature variables (Columns 5 and 6 for heat days and temperature variation, respectively). Table 4 presents the estimated hazard ratios of the temperature variables for overall SME formation, while Table 10 in the appendix reports results for AFS SMEs only. A hazard ratio greater than 1 indicates an acceleration of SME formation at a given point in time, whereas a hazard ratio below 1 reflects a slowdown in households' decisions to start an SME. For example, a hazard ratio of 1.33 implies a 33 percent higher rate of SME formation at any given time. Taking the example from above, where the baseline hazard in 2023 is 1.7 percent, this would correspond to an increase in the likelihood of a household starting a SME that year to approximately 2.3 percent.

In Table 2, we presented four different climate measures: two for heat stress and two for temperature variability. Running exploratory models with all four variables, total yearly heat days and mean temperature variation generally produced better model fit than the remaining proxies for heat stress and temperature variability. Thus, the reminder of this paper only presents results using total heat days and average temperature variation, but estimation results with other climate variables are available upon request. We report the Akaike information criterion (AIC) for all model specifications to identify the best combination of temperature variables with the best model fit.

Table 4. Comparison of different model specifications for the hazard ratios of temperature variables on startup rate of rural SMEs

	All SME					
	(1)	(2)	(3)	(4)	(5)	(6)
HD (# in year t)	1.005*		0.999	0.985	1.040***	
	(1.00, 1.01)		(0.99, 1.01)	(0.95, 1.02)	(1.03, 1.05)	
HD (Average # in t_5)					1.008	
					(1.00, 1.02)	
Average TV. (t)		2.370***	2.426***	2.219***		1.453
		(1.77, 3.17)	(1.75, 3.37)	(1.53, 3.21)		(0.21, 10.07)
Average TV (t_5)						0.43
						(0.06, 3.24)
HD (t) × TV (t)				1.007		
				(0.99, 1.02)		
HD (t) × HD(t_5)					0.999***	
					(1.00, 1.00)	
TV (t) × TV (t_5)						1.347
						(0.49, 3.67)
AIC	17937.65	17893.20	17895.05	17895.79	17863.14	17894.85
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Governorate FE	No	No	No	No	No	No
N (households)	10,357					
N (enterprises)	1,912					

Note: 95% confidence intervals in parentheses (Std. errors clustered at village level); ***p < 0.01, **p < 0.05, *p < 0.1; HD = Heat days; TV = Day-to-day Temperature variation; t_5.= Yearly average over past five years.
Source: ELMPS 2023 and ERA5 reanalysis data, authors' estimations.

When including heat stress (heat days in t) and climate variability (temperature variation in t) separately, both yield statistically significant and positive effects on the SME formation rate (Columns 1 and 2 in Table 4). This suggests that increased heat stress and temperature variability accelerate households' decisions to start a SME. However, when both variables are included in the same model (Column 3), only temperature variation remains statistically significant. Given the correlation between the two variables ($\rho = 0.63^{***}$), this is likely related to some degree of multicollinearity. Nonetheless, since the AIC for the model including temperature variation (in t) (Column 2) is lower than that for heat days (in t), current temperature variation appears to be an important factor in households' decision-making regarding livelihood portfolios and self-employment.

Beyond these different dimensions of weather risks, previous studies also show that the timing and frequency of climate extremes can have important implications for household decisions and coping mechanisms (Ansah et al., 2021; Newman & Tarp, 2020; van Asselt et al., 2026). Therefore, we also estimate models including current (t) and past (t_5) temperature variables (Columns 5 and 6 in Table 4). Interestingly, accounting for the time dimension of temperature variability does not appear to be relevant (Column 6). In contrast, for heat intensity, longer exposure to heat stress emerges as an important factor influencing SME formation. Notably, the AIC for the model specification in Column 5 of Table 4 is even lower (indicating a better model fit) than that for the temperature variation specification in Column 2. These patterns are consistent with the estimations focusing exclusively on AFS SMEs, as reported in Table 10 in the Appendix.

Table 5. Hazard ratios of temperature extremes and variation on the startup rates of different types of rural SMEs

	(1) All SME	(2) AFS SME	(3) Registered SME
HD (# in *t*)	1.030***	1.041***	1.045**
	(1.02, 1.04)	(1.02, 1.06)	(1.01, 1.09)
HD (Average # in t_5)	1.004	1.013	1.036**
	(0.99, 1.02)	(0.99, 1.04)	(1.00, 1.07)
Heat Days (t) × Heat Days (t_5)	0.999***	0.999***	0.999**
	(1.00, 1.00)	(1.00, 1.00)	(1.00, 1.00)
Average Temp. Variation (*t*)	1.800***	1.707**	1.696
	(1.27, 2.55)	(1.00, 2.91)	(0.79, 3.64)
AIC	17847.71	6686.77	4238.28
Controls	Yes	Yes	Yes
Governorate FE	No	No	No
N (households)	10,357	10,357	10,357
N (enterprise)	1,912	607	347

Note: 95% confidence intervals in parentheses (Std. errors clustered at village level); ***p < 0.01, **p < 0.05, *p < 0.1; HD = Heat days; TV = Day-to-day Temperature variation; t_5.= Yearly average over past five years.
Source: ELMPS 2023 and ERA5 reanalysis data, authors' estimations.

The specification with the best model fit includes current and past heat days (with interaction) and current temperature variation. In Table 5, we present the respective estimated hazard ratios for all three SME types. Results for current heat days (t) and the interaction effect of present and past heat days is consistent across all SME types. That is, on average one extra heat day in the current year t increases the rate of SME formation between 3 and 5 percent. However, if a household has also experienced higher numbers of heat days in past years (interaction effect), this slightly decreases the effect (0.1 percent). Moreover, the influence of longer time heat stress appears to be especially important for the formation of registered SMEs. The effect size of one extra heat day in the past-5-year average on the formation rate is almost as large for current heat stress (3.6 percent). Note, however, that the magnitude of the hazard ratios for both heat stress variables is relatively small. On average, households experience 16 to 17 heat days a year, so that for big influence on the formation rate the number of days had to increase substantially.

In contrast, estimated hazard ratios for temperature variation are larger but only yield statistically significant results for overall and AFS SMEs. If monthly day-to-day temperature variation (i.e., monthly standard deviation) would increase by one degree Celsius (°C), the formation of overall and AFS SME in any given year would happen up to 80 percent. Considering an average temperature variation of 2.5°C and maximum values around 4°C, a jump by one full degree might be unlikely, but even half an extra degree would be associated with as high an increase in the formation rate than around 10 extra heat days.

These results have two important implications: first, longer term exposure to increasing heat stress potentially leads to households starting SMEs faster. The fact that this is especially linked to registered SMEs is remarkable and likely indicates a planned and less ad-hoc decision (i.e., not a survival decision) to shift income portfolios to self-employment. Note, however, that this effect is reduced when there is long-term exposure and heat stress in the time period of decision-making. Households might decide to wait for another year until conditions a more favorable (see concept of value of waiting in the 'Conceptual framework'). Second, the response to temperature variability and inherent increases in uncertainty seem rather linked to SME formation without registration or in the AFS sector. This might imply that increasing weather uncertainty, while linked to SME formation, might rather be related to informal and 'survival' enterprises.

In summary, while there is the motivation to start a registered SME and adaptation to weather risks might be linked to increasing formalization of self-employment in the secondary and tertiary sectors, more stable and enabling environments appear critical for households to accept the risk of starting a new business (Amer & Selwaness, 2022; Beck & Demirguc-Kunt, 2006; Campos et al., 2023). This is an important finding as it suggests that climate change adaptation has the potential to facilitate the formal SME and private sector in rural areas, but only if conditions are good enough. In the sense of structural change and economic development, this could have the potential for great welfare benefits of rural communities.

4.3 Mechanisms: Sectoral knowledge and remoteness

While the results presented in the previous section suggest that enabling environments can help to facilitate SME development as adaptation strategy against weather risks and uncertainty, with potential to also support structural change and transformation in rural areas more broadly, the mechanisms further facilitating SME formation in the context of climate change adaptation strategy need to be better understood.

In the conceptual framework, we hypothesize that there are several factors that could reduce startup costs and thus shift the income optimization decision with a household SME to earlier rather than later. More specifically, we focus on two factors. The first relates to human capital and more specifically the notion that sector knowledge is likely to reduce the costs since households already have networks, can likely negotiate better prices, and are able to more easily find suppliers and buyers. Since we are especially interested in the role of the AFS sector in the SME dynamics in Egypt, the first mechanism we explore is whether farm households (i.e., experts in the primary AFS sector) or households with a head employed in the AFS sector (not self-employment) respond to weather risks differently (Eq. (12)). The other mechanisms repeatedly linked to structural change and development patterns are remoteness and market access (Minten et al., 2013; Steinhübel & von Cramon-Taubadel, 2021; Steinhuebel-Rasheed et al., 2025; Vandercasteelen et al., 2018). Therefore, we explore remoteness a) on the national level (household location in Upper Egypt) and b) on the local level (distance to the Nile) (Eq. (12)).

4.3.1 Sectoral knowledge

The specification with interaction effects between weather risks and farming activities does not yield statistically significant results, and the AIC does not imply an improved model fit (see Table 11 in the appendix). Thus, we do not find an indication that farm households approach SME formation differently than households when it comes to climate change adaptation. However, results from our main specification without any interaction effects show that, overall, farm households have much lower SME formation rates on average (Table 6). This is particularly pronounced for AFS and registered SMEs, where farm households have a formation rate of 60 percent and 75 percent lower in any given year, respectively. But, holding all else equal for farm households, even for SMEs overall, formation rates are 50 percent lower on average, even for SMEs overall. This might be linked to financial constraints as farm households in Egypt often belong to the poorest part of communities (Sattar et al., 2024). Another explanation might also be that primary agricultural production requires high labor inputs, especially without the adoption of modern technologies, and farm households might have limited labor resources to reallocate to SME self-employment (Bustos et al., 2016).

This is supported by the statistically significant and positive hazard ratios for the variable of household labor. Every additional available adult in a household is linked to 10–12 percent faster formation of all three SME types. This links to literature indicating that in many LMIC contexts household labor is not fully exhausted (Breza & Kaur, 2025). The unemployment rate in Egypt based ELMPS data over the last years remains relatively constant—around 8 percent of the total labor force, with unemployment among women especially high (up to 17 percent) (Assaad & Krafft, 2024). Thus, starting SMEs is likely easier for larger households with more excess labor. Note, however, that we do not find the same results for registered SMEs (Column 3 in Table 6).

Rather than focusing solely on the direct effect of weather risks on rural households and their decisions to start an SME, we also examine a potential indirect channel operating through labor-market linkages. Specifically, we assess whether temperature variability and uncertainty in the locations where household members are employed influence SME formation at home. In other words, do households shift toward self-employment when external employment becomes increasingly insecure? Interestingly, despite earlier studies emphasizing the relevance of labor-market links (Breza & Kaur, 2025), our findings suggest that this mechanism does not drive SME creation in our sample. Across all SME types considered, exposure to temperature variability through labor-market connections is associated with lower rates of household SME formation. One possible interpretation is that this measure primarily captures whether households have labor-market links in the first place (i.e., extensive-margin effect) rather than the intensive-margin effect of temperature variability within those links.

Table 6. Hazard ratios of labor market variables on the startup rates of different types of rural SMEs

	(1) All SME	(2) AFS SME	(3) Registered SME
Farm households (0/1)	0.501***	0.404***	0.244***
	(0.42, 0.60)	(0.30, 0.54)	(0.15, 0.39)
Household Labor (# adults)	1.124***	1.106***	1.118*
	(1.07, 1.18)	(1.03, 1.19)	(0.98, 1.28)
Average TV (*t*) in Linked Villages	0.763***	0.914*	0.847**
	(0.72, 0.81)	(0.83, 1.01)	(0.74, 0.96)
Hh[a] head AFS employee (0/1)	0.866**	4.766***	1.541**
	(0.76, 0.99)	(3.70, 6.14)	(1.08, 2.20)
Controls	Yes	Yes	Yes
Climate variables[a]	Yes	Yes	Yes
Governorate FE	No	No	No
N (households)	10,357	10,357	10,357
N (enterprise)	1,912	607	347

Note: 95% confidence intervals in parentheses (Std. errors clustered at village level); ***p < 0.01, **p < 0.05, *p < 0.1; [a]As defined in Table 5; TV = Temperature variation; Hh = Household.

Source: ELMPS 2023 and ERA5 reanalysis data, authors' estimations.

The final variable capturing sector knowledge is whether the household head has been employed in AFS wage employment. We find that AFS wage employment on average reduces the rate of overall SME startup by about 13 percent, keeping everything else equal. However, when only focusing on AFS SMEs (Column 2 in Table 6), an increased startup rate by over 350 percent in any given year. Thus, it appears having experience in the AFS sector drastically increases the likelihood of households starting an AFS SME, which likely illustrates the lowered entry costs hypothesis detailed in the 'Conceptual framework' section.

We continue and estimate a model allowing interactions between temperature variables and AFS wage employment to explore if there is also a difference in terms of SME startup in response to weather risks (i.e., beyond a pure base effect). Only the specification with the interaction effect between the heat day variables and AFS wage employment yielded and improved model fit (Table 7). The interaction effects are statistically significant only in the specifications for all SMEs and for registered SMEs, while no significant interaction is found for AFS SMEs themselves. Although the baseline (main) effect of AFS affiliation is strong and positive, indicating that households engaged in or close to the agricultural and food system are generally more likely to start an SME, the interaction terms do not improve model fit, as reflected in the unchanged AIC values. As the interaction effect is positive for overall and registered SMEs, this suggests that while weather risks may encourage diversification into nonagricultural self-employment, households with experience in the AFS sector may be less likely to establish new AFS-related SMEs in response to climate pressures. A plausible explanation is that AFS activities themselves are highly exposed to weather risks, and individuals with sector-specific knowledge may also possess greater awareness of these vulnerabilities, leading them to pursue alternative business opportunities as an adaptation strategy. Thus, while reduced entry barriers likely contribute to the strong positive baseline effect for AFS-related SMEs, this advantage does not appear to translate into higher formation rates under increasing climate variability, as sector-specific knowledge may also internalize climate-related risks.

Table 7. Interaction effects (hazard ratios) of heat stress and AFS wage employment on the startup rates of different types of rural SMEs

	(1) All SME	(2) AFS SME	(3) Registered SME
HD (# in *t*)	1.028***	1.038***	1.027*
	(1.01, 1.04)	(1.01, 1.07)	(1.00, 1.06)
HD (Average # in t_5)	0.997	1.003	1.026
	(0.98, 1.01)	(0.97, 1.03)	(0.99, 1.06)
Heat Days (t) × Heat Days (t_5)	1.000***	0.999**	0.999**
	(1.00, 1.00)	(1.00, 1.00)	(1.00, 1.00)
Average TV (*t*)	1.788***	1.700*	1.632
	(1.26, 2.53)	(1.00, 2.90)	(0.76, 3.52)
Hh head AFS employee (0/1)	0.677***	3.955***	0.87
	(0.55, 0.83)	(2.65, 5.90)	(0.48, 1.56)
HD (t) × Hh head AFS employee (0/1)	1.005	1.003	1.048*
	(0.99, 1.02)	(0.97, 1.03)	(1.00, 1.10)
HD (t_5) × Hh head AFS employee (0/1)	1.020**	1.014	1.032
	(1.00, 1.04)	(0.98, 1.05)	(0.98, 1.08)
HD (t) × HD (t_5) × Hh head AFS employee (0/1)	1.000*	1	0.999**
	(1.00, 1.00)	(1.00, 1.00)	(1.00, 1.00)
AIC	17843.09	6691.06	4233.78
Controls	Yes	Yes	Yes
Governorate FE	No	No	No
N (households)	10,357	10,357	10,357
N (enterprise)	1,912	607	347

Note: 95% confidence intervals in parentheses (Std. errors clustered at village level); ***p < 0.01, **p < 0.05, *p < 0.1; HD = Heat days; TV = Day-to-day Temperature variation; t_5.= Yearly average over past five years.
Source: ELMPS 2023 and ERA5 reanalysis data, authors' estimations.

4.3.2 Remoteness

Similar to the findings for AFS experience, we also observe evidence that remoteness plays a critical role in moderating the effect of weather risks—particularly heat stress—on SME startup rates. This pattern is most pronounced when using the Upper Egypt indicator, our national-level measure of remoteness (Table 8). Although distance to the Nile also slightly improves model fit and yields statistically significant coefficients, the effect sizes are small (Table 12 in the Appendix). We therefore focus the discussion in this subsection on the hazard ratios associated with household location in Upper Egypt.

Looking first at the baseline effects, we do not find statistically significant hazard ratios for SMEs overall or for AFS SMEs (Columns 1 and 2 in Table 8). In contrast, startup rates for registered SMEs are, on average, 70 percent lower for households located in Upper Egypt in any given year. This provides an initial indication that remote households—those with limited access to the large urban and economic centers concentrated in northern Egypt—are less likely to start SMEs that are typically associated with structural transformation and greater formality.

Turning to climate-risk interactions, we find that SME formation rates overall are 7 percent lower for households in Upper Egypt for every extra heat day they experience in a given year. However, patterns for prolonged exposure differ (triple interaction effect): for households in Upper Egypt, longer-term heat stress is associated with a modest acceleration in SME and registered-SME formation—an increase of about 2 percent for each additional heat-stress day. Notably, this pattern does not hold for AFS and registered SMEs, whose formation rates appear less sensitive to remoteness.

Table 8. Interaction effects (hazard ratios) between heat stress and household location in Upper Egypt (remoteness) on the startup rates of different types of rural SMEs

	(1) All SME	(2) AFS SME	(3) Registered SME
HD (# in *t*)	1.114***	1.083	1.067
	(1.04, 1.19)	(0.96, 1.22)	(0.95, 1.20)
HD (Average # in t_5)	1.061	1.057	1.035
	(0.98, 1.14)	(0.93, 1.20)	(0.92, 1.16)
Heat Days (t) × Heat Days (t_5)	0.978***	0.99	0.980*
	(0.96, 0.99)	(0.97, 1.01)	(0.96, 1.00)
Average TV (*t*)	1.806***	1.665*	1.981*
	(1.27, 2.57)	(0.97, 2.84)	(0.91, 4.33)
Upper Egypt (0/1)	0.924	1.366	0.310**
	(0.61, 1.41)	(0.73, 2.55)	(0.13, 0.77)
HD (t) × Upper Egypt	0.928**	0.961	0.999
	(0.87, 0.99)	(0.86, 1.08)	(0.89, 1.12)
HD (t_5) × Upper Egypt	0.95	0.958	1.018
	(0.88, 1.03)	(0.85, 1.09)	(0.90, 1.15)
HD (t) × HD (t_5) × Upper Egypt	1.022***	1.009	1.018
	(1.01, 1.04)	(0.99, 1.03)	(0.99, 1.04)
AIC	17827.56	6691.96	4226.53
Controls	Yes	Yes	Yes
Governorate FE	No	No	No
N (households)	10,357	10,357	10,357
N (enterprise)	1,912	607	347

Note: 95% confidence intervals in parentheses (Std. errors clustered at village level); ***p < 0.01, **p < 0.05, *p < 0.1; HD = Heat days; TV = Day-to-day Temperature variation; t_5.= Yearly average over past five years.
Source: ELMPS 2023 and ERA5 reanalysis data, authors' estimations.

5 CONCLUSIONS

This paper investigated how weather risks influence the timing and likelihood of rural SME formation in Egypt, with a particular focus on the role of heat stress, temperature variability, sectoral characteristics, and spatial factors.

Several key findings emerge from the analysis. First, baseline hazards show a continuous increase in SME startup rates over the observation period, with non-AFS SMEs accelerating earlier than AFS SMEs. This suggests that SME formation has become more common over time, although AFS-related activities appear to have expanded more recently. Second, weather risks are an important determinant of SME formation. Both heat stress and temperature variability accelerate startup rates, but they do so through different channels: short-term temperature variability has a comparatively large effect on the formation of overall and AFS SMEs, while longer-term exposure to heat stress plays a particularly notable role in the formation of registered SMEs. Third, sectoral characteristics shape households' ability to respond to weather risks through enterprise creation. Farm households exhibit substantially lower startup rates across all SME types, whereas households with prior AFS sector experience have markedly higher rates of establishing AFS SMEs, consistent with lowered entry costs. However, this advantage does not extend to increased responsiveness to temperature shocks. Fourth, remoteness and particularly household location in Upper Egypt moderate climate effects. While current heat stress dampens SME formation for remote households, sustained exposure to heat stress is associated with modest increases in the formation of registered SMEs, suggesting context-specific adaptation patterns.

Taken together, the results suggest that SME formation is a relevant, yet highly conditional, adaptation strategy. Households appear more likely to establish SMEs in response to weather risks when uncertainty is short-lived (temperature variability) or when long-term pressures increase the incentive to diversify (sustained heat stress). However, structural constraints related to sectoral knowledge, household labor availability, and remoteness limit the extent to which climate pressures translate into more formal or transformative types of SME activity.

The findings underscore the importance of policies that lower the costs and risks associated with SME formation in rural areas under increasing climate stress. Enhancing access to finance, reducing administrative burdens for registration, and expanding rural infrastructure and connectivity can support households in shifting from short-term, informal coping strategies toward more stable SMEs. Strengthening support systems in the AFS sector—such as extension services, skills development, and improved market access—can reduce entry barriers and improve the viability of AFS-related enterprises, particularly for households with relevant experience. Finally, targeted interventions in remote regions, especially Upper Egypt, are essential to address structural disadvantages that weaken the adaptive potential of SME formation. By improving the broader enabling environment, policies can enhance the role of SMEs as a climate adaptation pathway while supporting longer-term rural economic development.

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7 APPENDIX

Derivation of Equation (6)

$$V(T,l) \geq V(T+1,l)$$

$$\Leftrightarrow V(T,l) = \sum_{h=0}^{\infty} Y_1(T+h,l)\delta(h) - C(T) - \sum_{h=0}^{\infty} Y_0(T+h,l)\delta(h) \ \geq \ V(T+1,l)$$

$$= Y_0(T,l) + \sum_{h=1}^{\infty} Y_1(T+h,l)\delta(h) - C(T+1)\delta(1) - Y_1(T,l)$$

$$- \sum_{h=1}^{\infty} Y_0(T+h,l)\delta(h)$$

$$\Leftrightarrow Y_1(T,l) - C(T) - Y_0(T,l) \geq Y_0(T,l) - Y_1(T,l) - C(T+1,l)\delta(1)$$

$$\Leftrightarrow Y_1(T,l) - Y_0(T,l) \geq \frac{1}{2}[C(T) - C(T+1,l)\delta(1)]$$

$$\Leftrightarrow \ \omega(T,l)L_1(T,l) + p(T,l)q(T,l) - c(T,l)a - \omega(T,l)L_0(T,L) \geq \frac{1}{2}[C(T) - C(T+1,l)\delta(1)]$$

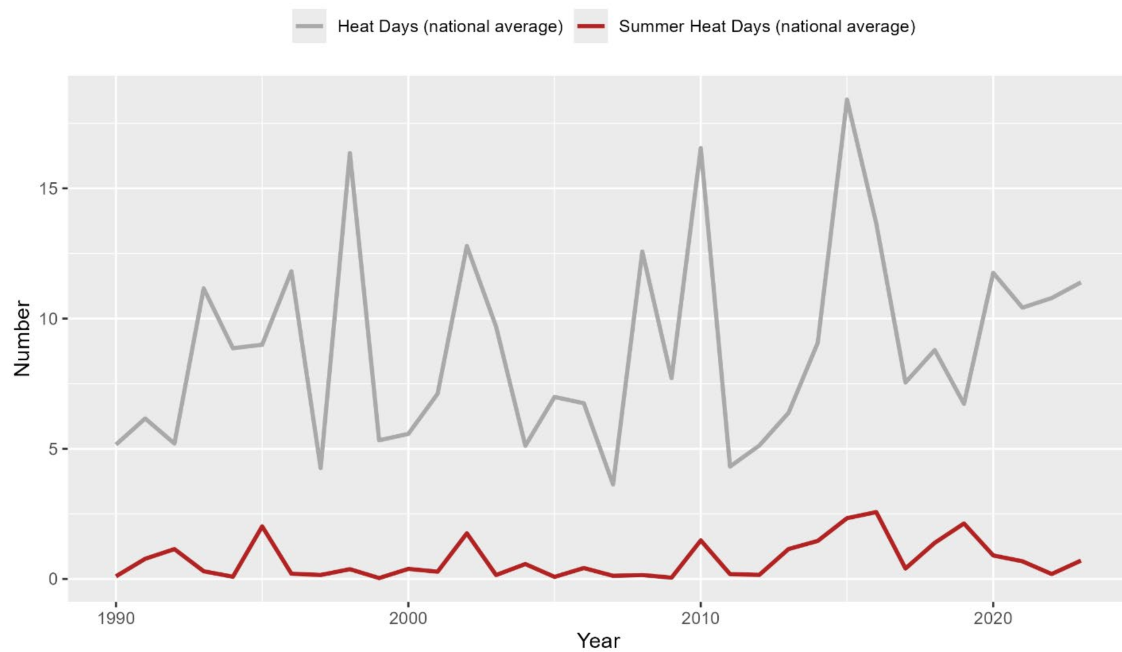
$$\Leftrightarrow \ \omega(T,l)L_1(T,l) + p(T,l)q(T,l) - \omega(T,l)L_0(T,L) \geq \frac{1}{2}[C(T) - C(T+1,l)\delta(1)] + \ c(T,l)a$$

$$\Leftrightarrow \ L_1(T,l) + \frac{p(T,l)}{\omega(T,l)}q(T,l) - L_0(T,L) \geq \frac{[C(T) - C(T+1,l)\delta(1)]}{2\omega(T,l)} + \ \frac{c(T,l)a}{\omega(T,l)}$$

Table 9. ISIC-4 economic activities considered in the AFS definition

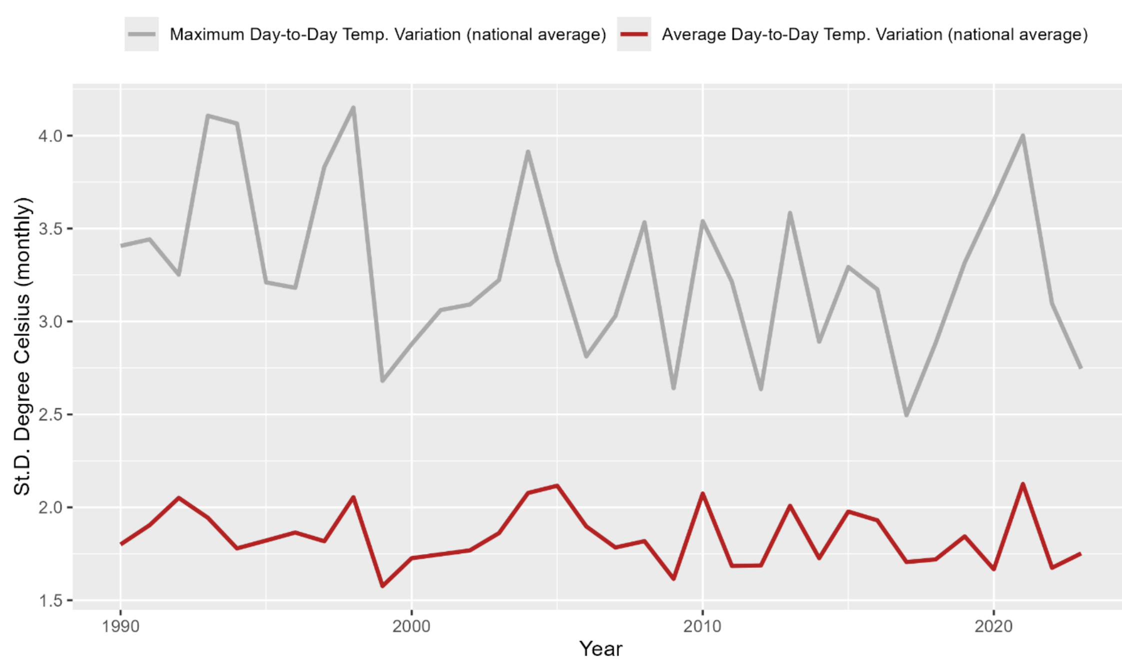
ISIC-4 (4 digit)	Description
111	Growing of cereals (except rice), leguminous crops and oil seeds
112	Growing of rice
113	Growing of vegetables and melons, roots and tubers
114	Growing of sugar cane
115	Growing of tobacco
116	Growing of fibre crops
119	Growing of other non-perennial crops
121	Growing of grapes
122	Growing of tropical and subtropical fruits
123	Growing of citrus fruits
124	Growing of pome fruits and stone fruits
125	Growing of other tree and bush fruits and nuts
126	Growing of oleaginous fruits
127	Growing of beverage crops
128	Growing of spices, aromatic, drug and pharmaceutical crops
129	Growing of other perennial crops
130	Plant propagation
141	Raising of cattle and buffaloes
142	Raising of horses and other equines
143	Raising of camels and camelids
144	Raising of sheep and goats
145	Raising of swine/pigs
146	Raising of poultry
149	Raising of other animals
150	Mixed farming
161	Support activities for crop production
162	Support activities for animal production
163	Post-harvest crop activities
164	Seed processing for propagation
170	Hunting, trapping and related service activities
210	Silviculture and other forestry activities
220	Logging
230	Gathering of non-wood forest products
240	Support services to forestry
311	Marine fishing
312	Freshwater fishing
321	Marine aquaculture
322	Freshwater aquaculture
1010	Processing and preserving of meat
1020	Processing and preserving of fish, crustaceans and mollusks
1030	Processing and preserving of fruit and vegetables
1040	Manufacture of vegetable and animal oils and fats
1050	Manufacture of dairy products
1061	Manufacture of grain mill products
1062	Manufacture of starches and starch products
1071	Manufacture of bakery products
1072	Manufacture of sugar
1073	Manufacture of cocoa, chocolate and sugar confectionery
1074	Manufacture of macaroni, noodles, couscous and similar farinaceous products
1075	Manufacture of prepared meals and dishes
1079	Manufacture of other food products n.e.c.
1080	Manufacture of prepared animal feeds
1101	Distilling, rectifying and blending of spirits
1102	Manufacture of wines
1103	Manufacture of malt liquors and malt
1104	Manufacture of soft drinks; production of mineral waters and other bottled waters
1200	Manufacture of tobacco products
1311	Preparation and spinning of textile fibres
1610	Sawmilling and planing of wood
1621	Manufacture of veneer sheets and wood-based panels
1622	Manufacture of builders' carpentry and joinery
1623	Manufacture of wooden containers
1629	Manufacture of other products of wood; manufacture of articles of cork, straw and plaiting materials
2012	Manufacture of fertilizers and nitrogen compounds
2021	Manufacture of pesticides and other agrochemical products
3600	Water collection, treatment and supply

3700	Sewerage
3811	Collection of non-hazardous waste
3812	Collection of hazardous waste
3821	Treatment and disposal of non-hazardous waste
3822	Treatment and disposal of hazardous waste
3830	Materials recovery
3900	Remediation activities and other waste management services
4510	Sale of motor vehicles
4520	Maintenance and repair of motor vehicles
4530	Sale of motor vehicle parts and accessories
4540	Sale, maintenance and repair of motorcycles and related parts and accessories
4610	Wholesale on a fee or contract basis
4620	Wholesale of agricultural raw materials and live animals
4630	Wholesale of food, beverages and tobacco
4641	Wholesale of textiles, clothing and footwear
4649	Wholesale of other household goods
4651	Wholesale of computers, computer peripheral equipment and software
4652	Wholesale of electronic and telecommunications equipment and parts
4653	Wholesale of agricultural machinery, equipment and supplies
4659	Wholesale of other machinery and equipment
4661	Wholesale of solid, liquid and gaseous fuels and related products
4662	Wholesale of metals and metal ores
4663	Wholesale of construction materials, hardware, plumbing and heating equipment and supplies
4669	Wholesale of waste and scrap and other products n.e.c.
4690	Non-specialized wholesale trade
4711	Retail sale in non-specialized stores with food, beverages or tobacco predominating
4719	Other retail sale in non-specialized stores
4721	Retail sale of food in specialized stores
4722	Retail sale of beverages in specialized stores
4723	Retail sale of tobacco products in specialized stores
4730	Retail sale of automotive fuel in specialized stores
4741	Retail sale of computers, peripheral units, software and telecommunications equipment in specialized stores
4742	Retail sale of audio and video equipment in specialized stores
4751	Retail sale of textiles in specialized stores
4752	Retail sale of hardware, paints and glass in specialized stores
4753	Retail sale of carpets, rugs, wall and floor coverings in specialized stores
4759	Retail sale of electrical household appliances, furniture, lighting equipment and other household articles in specialized stores
4761	Retail sale of books, newspapers and stationary in specialized stores
4762	Retail sale of music and video recordings in specialized stores
4763	Retail sale of sporting equipment in specialized stores
4764	Retail sale of games and toys in specialized stores
4771	Retail sale of clothing, footwear and leather articles in specialized stores
4772	Retail sale of pharmaceutical and medical goods, cosmetic and toilet articles in specialized stores
4773	Other retail sale of new goods in specialized stores
4774	Retail sale of second-hand goods
4781	Retail sale via stalls and markets of food, beverages and tobacco products
4782	Retail sale via stalls and markets of textiles, clothing and footwear
4789	Retail sale via stalls and markets of other goods
4791	Retail sale via mail order houses or via Internet
4799	Other retail sale not in stores, stalls or markets
5610	Restaurants and mobile food service activities
5621	Event catering
5629	Other food service activities
5630	Beverage serving activities



Source: ERA5 reanalysis data, authors' calculations.

Figure 6. Number of heat days between 1990 and 2023, yearly average across all villages



Source: ERA5 reanalysis data, authors' calculations.

Figure 7. Day-to-day temperature variation between 1990 and 2023, yearly average across all villages

Table 10. Comparison of different model specifications for the hazard ratios of temperature variables on startup rate of rural agrifood SMEs

	(1)	(2)	(3)	(4)	(5)	(6)
HD (# in year t)	1.005		0.999	0.984	1.049***	
	(1.00, 1.01)		(0.99, 1.01)	(0.94, 1.03)	(1.03, 1.07)	
HD (Average # in t_5)					1.017	
					(1.00, 1.04)	
Average TV. (t)		2.476***	2.542***	2.270***		0.799
		(1.61, 3.80)	(1.56, 4.15)	(1.26, 4.09)		(0.04, 15.33)
Average TV (t_5)						0.261
HD (t) × TV (t)				1.007		
				(0.99, 1.03)		
HD (t) × HD(t_5)					0.999***	
					(1.00, 1.00)	
TV (t) × TV (t_5)						1.813
						(0.41, 8.02)
AIC	6728.43	6712.09	6714.03	6715.56	6689.62	6715.04
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Governorate FE	No	No	No	No	No	No
N (households)	10,357					
N (enterprises)	607					

Note: 95% confidence intervals in parentheses (Std. errors clustered at village level); ***p < 0.01, **p < 0.05, *p < 0.1; HD = Heat days; TV = Day-to-day Temperature variation; t_5.= Yearly average over past five years.
Source: ELMPS 2023 and ERA5 reanalysis data, authors' estimations.

Table 11. Interaction effects (hazard ratios) of temperature variation and household farming activity on the startup rates of different types of rural SMEs

	(1) All SME	(2) AFS SME	(3) Registered SME
HD (# in *t*)	1.030***	1.041***	1.045**
	(1.02, 1.04)	(1.02, 1.06)	(1.01, 1.09)
HD (Average # in t_5)	1.004	1.013	1.036**
	(0.99, 1.02)	(0.99, 1.04)	(1.00, 1.07)
Heat Days (t) × Heat Days (t_5)	0.999***	0.999***	0.999***
	(1.00, 1.00)	(1.00, 1.00)	(1.00, 1.00)
Average TV (*t*)	1.756***	1.572*	1.653
	(1.24, 2.49)	(0.92, 2.68)	(0.75, 3.62)
Farm household (0/1)	0.335**	0.160**	0.11
	(0.13, 0.88)	(0.04, 0.72)	(0.01, 1.97)
Average TV (*t*) × Farm household	1.228	1.588	1.498
	(0.76, 1.99)	(0.76, 3.33)	(0.36, 6.16)
AIC	17849	6687.27	4239.99
Controls	Yes	Yes	Yes
Governorate FE	No	No	No
N (households)	10,357	10,357	10,357
N (enterprise)	1,912	607	347

Note: 95% confidence intervals in parentheses (Std. errors clustered at village level); ***p < 0.01, **p < 0.05, *p < 0.1; HD = Heat days; TV = Day-to-day Temperature variation; t_5.= Yearly average over past five years.
Source: ELMPS 2023 and ERA5 reanalysis data, authors' estimations.

Table 12. Interaction effects (hazard ratios) between heat stress and household distance to the Nile (remoteness) on the startup rates of different types of rural SMEs

	All SME	AFS SME	Registered SME
HD (# in *t*)	1.034***	1.042***	1.046**
	(1.02, 1.05)	(1.02, 1.07)	(1.01, 1.09)
HD (Average # in t_5)	1.008	1.011	1.043**
	(0.99, 1.02)	(0.99, 1.03)	(1.01, 1.08)
Heat Days (t) × Heat Days (t_5)	0.999***	0.999***	0.998***
	(1.00, 1.00)	(1.00, 1.00)	(1.00, 1.00)
Average TV (*t*)	1.815***	1.722**	1.69
	(1.28, 2.57)	(1.01, 2.93)	(0.78, 3.65)
Distance to Nile (km)	1.000	0.995	1.002
	(0.99, 1.01)	(0.98, 1.01)	(0.98, 1.02)
HD (*t*) × Distance to Nile	0.999*	1	1
	(1.00, 1.00)	(1.00, 1.00)	(1.00, 1.00)
HD (t_5) × Distance to Nile	0.999	1.001	0.999
	(1.00, 1.00)	(1.00, 1.00)	(1.00, 1.00)
HD (*t*) × HD (t_5) × Distance to Nile	1.000**	1	1.000**
	(1.00, 1.00)	(1.00, 1.00)	(1.00, 1.00)
AIC	17843.65	6691.9	4235.06
Controls	Yes	Yes	Yes
Governorate FE	No	No	No
N (households)	10,357	10,357	10,357
N (enterprise)	1,912	607	347

Note: 95% confidence intervals in parentheses (Std. errors clustered at village level); ***p < 0.01, **p < 0.05, *p < 0.1; HD = Heat days; TV = Day-to-day Temperature variation; t_5.= Yearly average over past five years.
Source: ELMPS 2023 and ERA5 reanalysis data, authors' estimations.

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