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Digging deep and running dry—the adoption of borewell technology in the face of climate change and urbanization

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Abstract

In this article, we analyze the effects of household location and weather variability on the adoption of borewell technology along the rural–urban interface of Bangalore, India. Understanding these effects can help to design policies that ensure smallholders' livelihoods and the functioning of ecosystems in drought-prone areas. First, a theoretical framework was developed that conceptualizes how household location and weather can influence farmers' adoption decisions. Then, an empirical analysis based on a primary data set collected in 2016 and 2017, covering 576 farm households, was conducted. With a semiparametric hazard rate model, determinants of the borewell adoption rate were analyzed. Different rainfall variables were included to capture the effect of changing climate conditions as well as a two-dimensional penalized spline (P-spline) to estimate the effects of household location. Results show that proximity to Bangalore, but also secondary towns accelerate adoption rates. In terms of weather variability, the study finds that a higher amount of total annual rainfall decelerates adoption rates, whereas higher amounts of rainfall during the southwest monsoon (the most important cropping season) accelerate adoption.

KEYWORDS

borewell technology, climate change, India, semiparametric duration models, urbanization

JEL CLASSIFICATION

C41, C14, O33, Q25

1 | INTRODUCTION

Borewell technology has surged in India since the *Green Revolution* of the 1970s, making India the largest groundwater user in the world today (Shah, 2014). The Indian government supported the uptake of groundwater lifting technology from the start and the adoption of this technology has maintained momentum to the present day. Changing rainfall patterns have made traditional rainfed agriculture less predictable and more vulnerable (Alcon, Miguel, & Burton, 2011), thereby making borewell technology an attractive option to compensate for unreliable or insufficient rainfall. Furthermore, economic development, improved infrastructure, and urbanization have improved access to input and output markets and have made it more profitable to modernize and intensify agriculture

(Vandercasteelen, Beyene, Minten, & Swinnen, 2018). Though agricultural intensification can considerably improve smallholders' livelihood, increased uptake of borewell technology comes at a cost. More wells and uncontrolled water extraction have already led to overexploited aquifers in several regions of India, particularly in the western and southern states including the Bangalore area (Blakeslee, Fishman, & Srinivasan, 2020; Srinivasan, Penny, Lele, Thomas, & Thompson, 2017). As a consequence, borewells dry up, threatening the well-being of water users. Thus, it is essential to implement policies that strike a balance between the present well-being of smallholders and sustainable, long-term availability of water resources.

To do so, an understanding of what determines farmers' decisions to adopt borewell technology, particularly when facing weather changes and urbanization, is necessary. Recent literature primarily analyzes the adoption of irrigation technologies with a focus on water use efficiency (Alcon et al., 2011; Caswell & Zilberman, 1985; Caswell & Zilberman, 1986). However, these studies—generally examining case studies in the Global North—assume that farmers already have access to groundwater and the question is how they use it. The case is different in developing countries, where many farmers still rely on rainwater as a primary irrigation water source. Thus, adoption decisions in this part of the world focus more on the access to groundwater itself than on technologies for efficient water use. To enhance agricultural productivity the Indian government subsidizes borewell implementation and electricity for pumping water despite concerns of overexploited aquifers; water extraction is hardly regulated and generally free of cost once a borewell is installed (Srinivasan et al., 2017). This is in clear contrast to the water management policies in the Global North, where groundwater access is strictly regulated and studies show that water prices, for example, have a statistically significant effect on adoption decisions (Alcon et al., 2011; Caswell & Zilberman, 1985). It follows that results from adoption studies based on data from the Global North cannot be generalized and applied in a developing country context without respective empirical analysis. However, to the best of our knowledge such evidence is scarce in the literature so far.

By analyzing farmers' decisions to adopt borewell technology in the rural–urban interface of Bangalore, this study aims at providing such empirical evidence. Bangalore is a rapidly growing city and the area has experienced drastic weather changes (reduced or absent monsoon rains) in recent years. Such developments are prevalent in many developing countries and have been repeatedly identified as drivers of smallholders' decisions to adopt new technologies (Dadi, Burton, & Ozanne, 2004; Damania et al., 2017; Euler, Schwarze, Siregar, & Qaim, 2016). Thus, the area presents an excellent showcase to analyze farmers' decision making regarding groundwater extraction in a developing country context.

For the analysis, a microeconomic model was developed to conceptualize the influence of weather and household location on farmers' borewell adoption behavior. Household location is used as a spatially explicit proxy for market access, that is, the transaction costs necessary to reach potential market centers. In the literature, market access is generally modeled with one-dimensional (1D) measures such as distance to a market (Chamberlin & Jayne, 2013; Key, Sadoulet, & de Janvry, 2000). However, when households have access to more than one market center, such proxies are of limited use because they require one single point of reference to be calculated. For example, if a household is located between two accessible markets in different directions, which market should be chosen as the reference point? Such a scenario is particularly likely in the periphery of large urban centers. These have been shown to often grow in polycentric patterns with a whole network of well-connected smaller towns around the main city channeling urbanization effects into the hinterland (Marull, Font, & Boix, 2015; Taylor, Evans, & Pain, 2008). This is also the case for the Bangalore area. There are several satellite towns with functioning agricultural market infrastructure within a 40-km radius around Bangalore and in direct proximity to our research area. Therefore, by modeling market access spatially explicit as household location in two-dimensional (2D) space, we propose a more flexible approach to represent market access in a polycentric urbanization pattern.

In the empirical analysis, a duration model framework was applied. This model class is particularly suitable for analyzing the adoption of durable technologies such as a borewell (Abdulai & Huffman, 2005; Dadi et al., 2004). Several nonparametric elements were included in the model, among others a 2D Penalized Spline (P-spline) based on household GPS coordinates to directly estimate the effect of household location derived in the microeconomic model. The coordinates were treated as a bivariate variable (latitude, longitude) and used to estimate nonlinear effect surfaces (2D spline). Because these surfaces are spatially explicit (coordinates), they can be mapped and areas with high or low effects on borewell adoption rates can be identified.

The remainder of this article is structured as follows: First, a short overview of irrigation in South India and technology adoption is given. Then a conceptual framework (Section 3) is developed and the empirical strategy (Section 4) is described. Finally, results (Section 5) are discussed and the findings (Section 6) are summarized.

2 | BACKGROUND ON IRRIGATION IN SOUTH INDIA AND TECHNOLOGY ADOPTION

The adoption of borewells has become crucial for food security in large parts of South Asia; however, nowadays it is threatened by increasing overexploitation and degradation of aquifers (Shah, 2007). A borewell describes a deep and narrow well that is cased into the ground using a tube. This type of well is often equipped with an electric pump and is the most frequently used technology for groundwater extraction in the study area (Srinivasan et al., 2015). Water pumped from the ground can be combined with other irrigation techniques; most commonly in the region are flood, sprinkler, or drip irrigation.

The traditional irrigation system in South India was dominated by reservoirs and local water bodies, also called tanks. These tanks were used and managed at the communal level. Since the 1990s, however, many farmers have decided to exit the communal irrigation system by investing in private well equipment to extract groundwater (Srinivasan et al., 2017). The reasons for this are manifold. First, coordination problems within the command area of the tanks led to uncertainty in water availability. Particularly during the critical stages of cultivation, farmers favor independent and secure water sources (Kajisa, Palanisami, & Sakurai, 2007). Second, the maintenance of local water bodies requires high labor inputs (Shah, 2003). Third, pumping technology and drilling have become cheaper in absolute and relative terms. Domestic production of pumps and improved drilling technologies have lowered the cost of establishing a borewell, and input prices have decreased through subsidized flat rate electricity prices (Srinivasan et al., 2017). Moreover, increased output prices for agricultural products have also contributed to lowering the relative price of groundwater irrigation (Kajisa et al., 2007). Due to the aforementioned reasons, India is now the biggest user of groundwater globally (Siebert et al., 2010).

Nevertheless, this development is spatially concentrated and large areas remain under rainfed agriculture (Srinivasa Rao et al., 2015), indicating that there are local differences in adoption rates. To understand what drives the adoption process at the individual farm level, several factors were analyzed.

One of the main reasons for adopting groundwater lifting technology is to hedge against production risks. One major production risk in agriculture is adverse climate and its consequences, such as drought and water scarcity as well as increased volatility in weather events (Alcon et al., 2011; Genius, Koundouri, Nauges, & Tzouvelekas, 2014). At the farm level, unfavorable slopes and soil characteristics (Genius et al., 2014; Koundouri, Nauges, & Tzouvelekas, 2006), as well as farm size and the degree of commercialization, additionally increase the probability to adopt (Feder, Just, & Zilberman, 1985).

Another important factor, which may explain the differences in adoption rates, is the diffusion of technology. Diffusion is understood as the adoption process of technology over time (Taylor & Zilberman, 2017). A key role in the diffusion of technology in agriculture is the distance to regional centers. The closer producers are, the higher the probability that they will adopt earlier than other producers. Since learning and implementation may require traveling for more remote farmers, opportunity costs can be high and impede technology adoption (Sunding & Zilberman, 2001). More recently, the interconnectedness of market access and technology adoption has been studied. Damania et al. (2017) or Vandercasteelen et al. (2018), for example, find that lower transportation costs due to the proximity to cities and/or markets increase the likelihood of technology adoption. Another factor related to technology diffusion is learning due to social interaction (Abdulai & Huffman, 2005; Sampson & Perry, 2019). Even though our research focuses on exogenous spatial heterogeneity induced by urbanization dynamics, potential spatial interdependence in the decision making of neighboring farmers has to be mentioned and will be controlled for in the empirical analysis of this study.

3 | CONCEPTUAL FRAMEWORK

To identify mechanisms of technology adoption in the context of weather variability and urbanization, some microeconomic intuition is provided in this section following models such as by Abdulai and Huffman (2005), Irwin and Bockstael (2004), and Genius et al. (2014). Note that for the conceptual model it is assumed that spatial heterogeneity exclusively results from urbanization dynamics, to be more precise it results from households' access to markets in a town. This is a standard concept in the literature based on the idea of transportation costs, which decrease with proximity to markets (Damania et al., 2017; Ebata, Velasco Pacheco, & Cramon-Taubadel, 2017; Minten, Koru, & Stifel, 2013; Vandercasteelen et al., 2018).

It is assumed that smallholders are profit-maximizing agricultural producers and they choose one out of two possible production systems s. The possible production systems are defined by the source of irrigation, that is, $s = 1$ if the household adopted the borewell technology, and $s = 0$ if the technology has not been adopted. In that way, it can be noted that household i's expected operational cash flows $A_{s,i}$ are generated by either system, s, as a function of time period t and household i's location l:[1]

$$A_s(t,\ l) = p(t,\ l)\, q_s(t) - c(t,l)\, a_s, \quad \text{with } s = 0, 1. \qquad (1)$$

$A_s(t,\ l)$, is described by the difference between the product of expected output prices $p(t, l)$ and expected output $q_s(t)$ and the product of expected input prices $c(t,\ l)$ and expected used inputs a_s. Prices $p(t,\ l)$ represent the difference between the price received for farm produce at the market at time t and transportation costs $\mu(l)$ defined by the household location, l; whereas $c(t, l)$ is defined as the sum of the price paid for inputs a at the market in time, t, and transportation costs $\varphi(l)$ also defined by the household location, l, along the rural–urban interface[2]:

$$p(t,\ l) = p_{market}(t) - \mu(l), \text{ with } \mu(l) > 0 \qquad (2)$$

$$c(t,\ l) = c_{market}(t) + \varphi(l), \text{ with } \varphi(l) > 0. \qquad (3)$$

The amount of used inputs a only depends on s. With reliable irrigation ($s = 1$), farmers might apply additional and more sophisticated inputs. Such a system is also likely to generate a higher output, q_s, as more consistent irrigation is possible. Additionally, in regions highly vulnerable to altering weather patterns in the course of climate change, farmers' expectations concerning their production and outputs (i.e., a production function) are likely to vary with changing weather patterns, that is, time. For example, if a farmer expects decreasing rainfall, the expected outputs from a rainfed production system will decrease. Therefore, the weather component of the research objective is captured by allowing farmers' expectations regarding output quantities to vary over time, $q_s(t)$.[3]

In the decision to adopt a borewell, also one-time installation costs $C(t,\ l)$ have to be considered. These costs depend on when a household decides to adopt the borewell technology and, as in the case of other input costs, the household's location (inherent transportation costs).

Equation (1) and the one-time installation costs, $C(t,\ l)$, are the basic building blocks that are used to formalize the decision of a profit-maximizing farmer. Furthermore, for durable technologies such as a borewell, the timing of adoption is often more important to understand the drivers of decision making (*optimal timing problem)* (Abdulai & Huffman, 2005; Dadi et al., 2004; Irwin & Bockstael, 2004). Therefore, it can be assumed that the farmer optimizes the time of adoption based on the comparison of the present value of expected net returns, $V(T, l)$, of adopting a borewell in time period T (Equation 4a), and the present value of expected net returns, $V(T+1,\ l)$, of adopting a borewell in time period $T+1$ (Equation 4b) as:

$$V(T,l) = \sum_{h=0}^{\infty} A_1(T+h,l)\,\delta(h) - C(T,l) - \sum_{h=0}^{\infty} A_0(T+h,l)\,\delta(h) \qquad (4a)$$

$$V(T+1,\ l) = A_0(T,l) + \sum_{h=1}^{\infty} A_1(T+h,l)\,\delta(h) - C(T+1,l)\,\delta(1) - A_1(T,l) - \sum_{h=1}^{\infty} A_0(T+h,l)\,\delta(h). \qquad (4b)$$

For simplicity, the time horizon of the decision is limited to $T+1$, that is, until the technology is adopted, the farmer decides every year whether to adopt a borewell at that moment or wait another year.[4]

If the technology is adopted in T (Equation 4a), the present value of the expected net returns is given by the present value of the expected operating cash flows of a production system with borewell discounted to time T with discount factor $\delta(h)$, minus the installation costs in T, and minus the expected operating cash flows of the production system without the technology discounted to time T. The net present value of a production system with a borewell ($s = 1$) represents the farmer's expectation of all potential profits, which they make after the installation of a well; the net present value of a production system without a borewell ($s = 0$) represents the forgone profit that is not earned because of the change to the system with a well. Analogously, in Equation (4b) the first two elements depict the profits from one more year in the management system without the borewell plus all profits after the installa-

[1] For better clarity we drop the subscript i in Equations (1)–(6).

[2] In our model $\mu(l)$ and $\varphi(l)$ allow for transportation costs to differ between input and output markets.

[3] Thus, when talking about weather variability in this study, we generally refer to changing weather patterns over time. One could argue that q_s also depends on location, that is, rainfall might also show spatial patterns. However, the research area is rather small and farmers mainly refer to Bangalore weather forecasts. Furthermore, possible alternative water sources in the research area are limited to one larger water reservoir in the southern transect, which is also completely rainfed. That means farmers' expectations concerning reliability also depend on their expectations about weather, rather than the location as such.

[4] We are aware that a full strand of literature on optimal stopping problems and stochastic dynamic optimization exists (Dixit & Pindyck, 1994). However, we believe that our simplification represents the time horizon of decision making in our research area appropriately. For example, many farmers make cropping decisions from season to season, which underscores farmers' short-term decision making.

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tion of the technology for all the following years. Since the adoption decision is delayed by one year ($T+1$), also the installation costs of the year $T+1$ are considered. The last two elements represent the forgone profits from waiting until year $T+1$.

Assuming that Equations (4a) and (4b) are the basis on which household i makes its decision, two decision criteria were defined, which have to be fulfilled so that the adoption of the borewell technology takes place in year T. First, the net returns of adopting the borewell technology in T have to be positive:

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

Second, given the first criterion in Equation (5), the technology is adopted in T, if the net returns in time T exceed the net returns of waiting (*value of waiting*) for another year $T+1$ (see Derivation of Equation (6) in the Appendix):

$$V(T,l) \geq V(T+1,l) \Leftrightarrow q_1(T) - q_0(T) \geq \frac{C(T,l) - C(T+1,l)\,\delta(1)}{2p(T,l)} + \frac{c(T,l)(a_1 - a_0)}{p(T,l)}. \tag{6}$$

The left-hand side of Equation (6) describes the expected output difference of both production systems in T. It, therefore, quantifies how relevant a farmer thinks water is for the success of their production system, and to what extent available rain-dependent water sources (e.g., reservoirs, rain) are as reliable as a borewell. Thus, a farmer who thinks that weather is becoming less predictable will expect a larger output difference than a farmer who assumes sufficient and timely rain or has alternative water sources.

The first term on the right-hand side of Equation (6) shows the difference of expected installation cost in T and $T+1$ normalized by two times the price of one output unit q_s. Similarly, the second term describes the difference between the variable inputs of both production systems normalized by the unit output price. Note that this representation places all variables that are influenced by farmers' expectations concerning weather and water availability in general to one side, and all variables that are affected by the household's location—market access—to the other side. Thus, the household will adopt borewell technology if the output gain due to a management system with borewell is larger than or equal to the net installation costs and additional net variable input costs relative to the price achieved for the output gain. Therefore, the more pessimistic farmers are about weather prospects, and the greater the access to borewell technology and input and output markets, the higher the likelihood that they adopt the technology in T.

4 | EMPIRICAL STRATEGY

The theoretical model of optimal timing of the adoption decision presented in the previous section can be empirically represented in the duration model framework. Thus, it can be assumed that the borewell technology became available to the sample population with the *Green Revolution*, $t_0 = 1970$, after which households subsequently—some sooner, some later—adopt the technology at time points $t+h$, $h = 1, \dots n$ until time t_n when all households adopted the technology. Based on the observed adoption times it is possible to estimate the probability that a household will adopt a borewell in the next time interval h if they have not adopted the borewell by t. This probability is referred to as hazard rate $\lambda_i(t)$ with T being a nonnegative random number and the nonadoption period ending if $T = t$:

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

One of the most popular duration models to estimate covariate effects is the so-called Cox model (Cox, 1972):

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

In this model the hazard rate, $\lambda_i(t)$, consists of two parts: the baseline hazard $\lambda_0(t)$ and the effects of covariates x_i. The baseline hazard can be understood as the pure time effect on the hazard rate and, by construction, must be nonnegative as adoption rates cannot be negative (Therneau & Grambsch, 2000). The overall framework of the Cox model in the empirical analysis was followed but extended by a semiparametric predictor to accommodate more flexible effects. Since duration models require a certain type and preparation of data, the next sections describe the survey and variables included in the empirical analysis; afterwards the specifications of the semiparametric predictor are presented.

4.1 | Survey design and data set

The empirical analysis is based on data collected in a survey from 1,275 households in two transects following the rural–urban gradient of Bangalore (Figure 1). To capture the systematic spatial heterogeneity caused by urbanization dynamics, a two-stage stratified sampling approach was applied to identify the households to be interviewed. In the first stage, a Survey Stratification Index was used to classify all villages in the transects into three strata (rural, peri-urban, and urban) (Hoffmann, Jose, Nölke, & Möckel, 2017). Then, 10 villages in each stratum per transect were

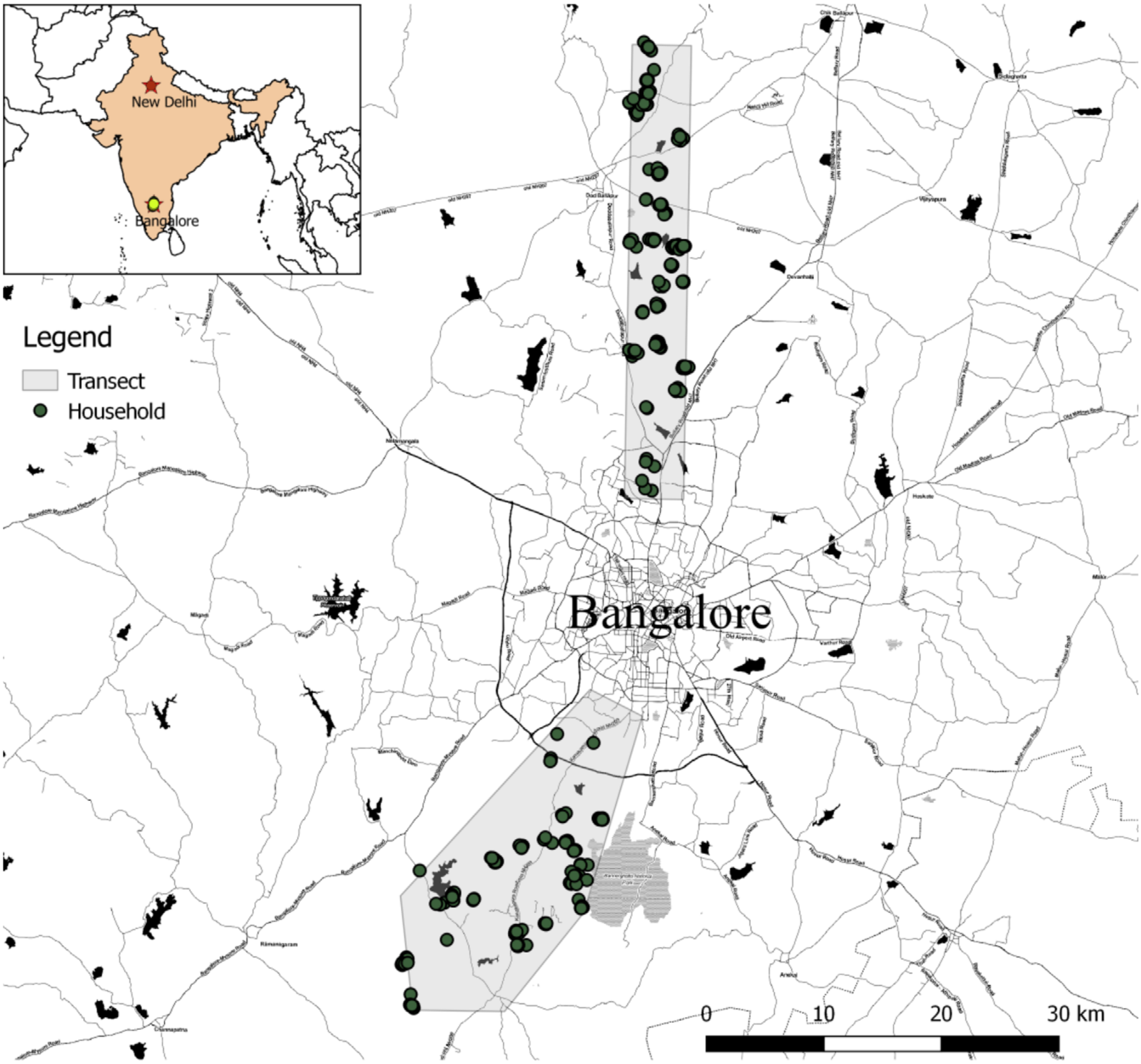

FIGURE 1 Research area, gray polygons indicate northern and southern transect, respectively [Color figure can be viewed at wileyonlinelibrary.com]
Source: Own survey data.

randomly selected. This equates to about one-third of all villages located in the transects. Afterward, an average of 20 households (adjusted by the village population) was randomly drawn from the household lists of the selected villages. All households were interviewed between December 2016 and May 2017. Thus, the maximum observed time period in the duration model is 47 years (1970–2016). Household information prior to 2016 is based on recall data (e.g., year an asset was purchased) and calculation (e.g., age or years of experience).

Because the focus is on the adoption of borewells for agricultural purposes, in the following analysis only households that grew at least one crop in 2016 were considered (farm households). Therefore, the sample comprises a total of 576 households of which 316 are located in the transect north of Bangalore (northern transect) and 260 in the transect south of Bangalore (southern transect).[5]

To accommodate time-variant covariates, the data set had to be augmented in a way that there is one observation per year and per household, that is, a maximum number of 47 observations per household. An indicator variable

[5] This number of households excludes 66 observations that were excluded during the empirical analysis because of missing values in important covariates. The inference strategy does not allow for missing values unfortunately. The dropped observations are evenly distributed over both transects and include two households, which already had adopted the borewell technology.

(1/0) for each year observation signals whether the household adopted the borewell technology in the respective year. Once the household adopted the technology ($t = T$) all subsequent year observations were dropped; the adoption period of the respective household ended. Comparably, year observations were omitted, if households entered the adoption period later due to migration or age (left-truncation). If the technology had not been adopted, the indicator variable remained zero in the last year observation (year 47). These observations are called right-censored and it is assumed that they will adopt the technology in the future (Moore, 2016). As a consequence, our final data set for estimation included 7,641 observations for the northern and 6,563 observations for the southern transect.

The consideration of time-variant covariates has some important methodological advantages (Dadi et al., 2004; Euler et al., 2016). First, one general assumption of the Cox model is that the hazard ratio of different subjects stays constant throughout the entire time period (proportional hazard). Therefore, the baseline hazard can be left unspecified for estimating the covariate effects β and no a priori assumptions about the functional form of the baseline hazard are necessary. However, it is unlikely that the hazard ratio is constant over longer periods such as the 47 years in our case. Time-variant covariates in $x_i'\beta$ can counter the proportional hazard assumption (Therneau & Grambsch, 2000). Second, some covariates might cause problems of reverse causality or endogeneity if they are included in a cross-sectional fashion. If these covariates are included as time-varying, a temporal causality is established and, thus, these issues (see Section 4.2. for respective variables) are avoided.

4.2 | Variable description

To estimate adoption probabilities and the hazard rate, all 576 farm households were asked whether they have a borewell and, if yes, when they installed it. To prevent recall bias and heaping effects[6], (i.e., a farmer is more likely to give responses such as five or ten years than seven years,) farmers were asked to give the year of adoption instead of the number of years that they have had a borewell. In the sample, 149 (26%) of the farm households had adopted the technology by 2016. Of these 149 households, 88 are in the northern and 61 in the southern transect. Thus, the adoption level appears to be higher in the northern transect.

To model the effect of urbanization, that is, market access, on borewell adoption rates, explicit household locations were used. The GPS coordinates of every household are a bivariate and continuous variable consisting of the latitude and longitude information of the respective location. Therefore, they can be used to estimate smooth surfaces of location effects (see Section 4.3 for details). Previous studies quantify market access by proxies such as distance to the city based on the assumption that distance and transportation costs are proportional (Chamberlin & Jayne, 2013). However, urbanization dynamics in the rural–urban interface of Bangalore are polycentric, with several satellite towns offering additional marketing options to farmers. As a consequence, it is impossible to determine only one market or town of reference to establish a 1D proxy such as distance.

The amount of rainfall was used to measure weather variability over time. Rainfall has become more and more volatile in recent years in the Bangalore area (Figure A1 in the Appendix), substantially increasing the drought pressure. Rain patterns define the agricultural seasons in Bangalore, of which the southwest monsoon determines the main cropping season. Therefore, to obtain a more nuanced understanding of the effect of weather, not only the amount of total yearly rainfall but also the amount of premonsoon rainfall and rainfall during the southwest monsoon was included in the dataset. A summary of the rainfall variables is presented in Table 1. Furthermore, the current and previous years' rainfall is considered. Rainfall data were used for the *Bangalore urban* district published on the website of the Agrometeorology Department of the University of Agricultural Sciences, Bangalore (UASB). The department provides disaggregated measures such as premonsoon or southwest monsoons on a yearly basis. The rainfall variables are time-variant but can be assumed to be consistent for the entire research area, that is, they vary over time t but not among the households. This assumption is reasonable as the research area is rather small and farmers in the transects generally build their expectations about weather based on the weather forecast for Bangalore.

Tables 2 and 3 present a description and descriptive statistics for all other time-invariant and time-variant covariates, respectively. These tables also show the variation between the two transects and between adopters and nonadopters of the borewell technology.

As for time-invariant variables, the following are considered: household caste, a dummy for dairy production, years of education of the household head, farm size, and the gender of the household head (Table 2). Caste is still

[6] The problem is that estimates of adoption probability will approximate zero at time points with no observed positive adoption decisions (Kneib, 2006). This would lead to highly fluctuating estimates of the baseline hazard in the duration analysis. This does not seem to be a problem either (see Figure A3 in the Appendix). In addition, the histogram in Figure A2 in the Appendix shows that there is no obvious heaping. Therefore, we are confident that recall bias in the dependent variable is no issue in the empirical analysis and hence strategies such as interval censoring to correct it were not applied.

TABLE 1 Summary of rainfall variables, 1970–2016

Variable	Mean	SD	Min	Max
Total rainfall (mm/year)	777.24	211.31	475	1,200
Premonsoon (mm/year)	157.89	59.38	60	313
Southwest monsoon (mm/year)	444.7	129.46	129	730

Source: Rainfall data (Department of Agrometeorology, University of Agricultural Sciences, Bangalore (UASB)).

an important social factor in India often defining access to resources and income level. A share of 77% of households in the sample pursues dairy production; the share appears to be even higher among borewell adopters (83–89%). Household heads received an average of 6 years of formal education, without any large differences between the two transects or adopters and nonadopters. In contrast, adopters hold on average double the area of land than nonadopters. Only 17% of interviewed household heads were female. Furthermore, the share is even lower when looking exclusively on adopters (7–15%).

Time-variant variables included in the model are the age of the household head, years of experience as a farmer, the number of durable assets available to the farmer, the amount of transport equipment available, a dummy for off-farm employment and the number of adopted borewells in the village at $t-1$. Table 3 shows that adopters are on average 5– 10 years younger than nonadopters. However, adopters seem to have slightly more farming experience than nonadopters. Living standard and purchasing power can also affect farmers' decisions to adopt technologies (Cameron, 1999). In India the *New Socio-Economic Classification (SEC) System* is a common tool to classify households according to their socioeconomic status, particularly when comparing rural and urban households (MRSI, Market Research Society of India, 2011). The SEC is based on two variables, namely the education of the household head and a count of durables out of a list of 11 items. The items include transport equipment, such as a car or two-wheelers, and other durable assets like TVs, washing machines, or air conditioners. The education variable is time-invariant, the number of assets can, however, change during the years. Hence, the SEC components are considered separately (durable assets and transport equipment).[7] In addition, considering transport equipment and durable assets in a time-variant way allows us to establish temporal causality and, thus, to prevent potential endogeneity between the asset variable and farmers' adoption decisions. The same holds for the dummy of off-farm employment. Abdulai and Huffman (2005) show that the number of technology adopters in a village at $t-1$ is a useful way to capture social learning and interaction among farmers. Farmers observe their neighbors' experiences with the borewell technology and include them in their own optimization decision. This can include production-related information (e.g., yields) but also technical

[7] There are some concerns that asset indices do overestimate the wealth of a household. These indices only count assets without taking the depreciated value of older assets (Harttgen, Klasen, & Vollmer, 2013). Nonetheless, depreciation is often hard to measure or to estimate (Booysen, van der Berg, Burger, Maltitz, & Du Rand, 2008), especially in a developing country context and for long time periods as in our case. Therefore, the asset count only provides an upper bound estimate.

TABLE 2 Descriptive statistics of time-invariant variables (Subsamples: northern vs. southern transect; nonadopters vs. adopters)

Variable	Variable description	Both transects Nonadopters ($N = 427$)	Adopters ($N = 149$)	Total ($N = 576$)	Northern transect Nonadopters ($N = 228$)	Adopters ($N = 88$)	Total ($N = 316$)	Southern transect Nonadopters ($N = 199$)	Adopters ($N = 61$)	Total ($N = 260$)
Caste	Factor variable									
General		0.48	0.56	0.50	0.45	0.48	0.46	0.52	0.67	0.56
Scheduled castes		0.18	0.11	0.17	0.17	0.11	0.15	0.20	0.12	0.18
Scheduled tribes		0.07	0.04	0.06	0.08	0.06	0.07	0.07	0.02	0.05
Other backward class		0.22	0.26	0.23	0.26	0.33	0.28	0.18	0.15	0.17
Other		0.04	0.03	0.04	0.05	0.02	0.04	0.03	0.05	0.04
Dairy	Dummy variable (1: Dairy production)	0.74	0.87	0.77	0.73	0.89	0.77	0.76	0.83	0.78
Education	Education of household head (years)	5.96 (4.83)	6.5 (4.91)	6.1 (4.85)	6.51 (4.7)	6.63 (4.69)	6.54 (4.69)	5.32 (4.91)	6.33 (5.23)	5.56 (5.0)
Farm size	Acres under management	2.5 (5.33)	5.77 (12.92)	3.35 (8.13)	2.38 (5.68)	5.37 (7.61)	3.21 (6.41)	2.64 (4.9)	6.36 (18.09)	3.51 (9.83)
Gender	Dummy variables (1: Female household head)	0.19	0.10	0.17	0.21	0.07	0.17	0.16	0.15	0.16

Note: SD in parentheses. For dummy and factor variables shares are given. Statistics were derived based on variable values in 2016 for nonadopters, and variable values at the time of adoption for adopters.
Source: Survey data.

TABLE 3 Descriptive statistics of time-variant variables (Subsamples: northern vs. southern transect; nonadopters vs. adopters)

		Both transects			Northern transect			Southern transect		
Variable	Variable description	Nonadopters ($N = 427$)	Adopters ($N = 149$)	Total ($N = 576$)	Nonadopters ($N = 228$)	Adopters ($N = 88$)	Total ($N = 316$)	Nonadopters ($N = 199$)	Adopters ($N = 61$)	Total ($N = 260$)
Age (t)	Age household head (years)	50.2 (13.3)	43.85 (13.68)	48.56 (13.67)	49.42 (13.47)	43.94 (13.13)	47.9 (13.58)	51.1 (13.07)	43.7 (14.55)	49.37 (13.76)
Experience (t)	Farming experience of household head (years)	27.72 (13.9)	30.2 (14.35)	28.36 (14.05)	26.83 (13.64)	30.24 (13.4)	27.78 (13.64)	28.73 (14.16)	30.13 (15.73)	29.06 (14.53)
Durable assets (t)	Durable assets available to household (count)	2.81 (1.25)	1.44 (1.53)	2.46 (1.45)	2.85 (1.23)	1.24 (1.46)	2.4 (1.49)	2.77 (1.26)	1.74 (1.6)	2.53 (1.41)
Transport equipment (t)	Transport equipment available to household (count)	0.76 (0.58)	0.36 (0.56)	0.66 (0.6)	0.83 (0.57)	0.43 (0.58)	0.72 (0.6)	0.69 (0.57)	0.26 (0.51)	0.59 (0.59)
Off-farm employment (t)	Dummy variable (1: at least one member involved in off-farm employment)	0.59	0.21	0.49	0.63	0.11	0.49	0.54	0.35	0.50
Peer effect (t)	Number of adopted borewells on village level in t − 1	3.83 (3.24)	2.49 (2.69)	3.48 (3.16)	4.04 (3.55)	2.51 (2.64)	3.48 (3.16)	3.6 (2.83)	2.46 (2.78)	3.33 (2.86)

Note: SD in parentheses. For dummy and factor variables shares are given. Statistics were derived based on variable values in 2016 for nonadopters, and variable values at the time of adoption for adopters.
Source: Survey data.

information, for example the depth of water tables which is generally unknown in the area. Next to quantifying the effect of social interaction, the variable also ensures that the location effect based on household coordinates is not biased by endogenous or small-scale local spatial patterns.

4.3 | Model specification and the use of P-splines

To accommodate more flexible, nonlinear effects in the duration model, the linear predictor $x_i'\beta$ in Equation (8) is extended to an additive predictor η_i (Kneib & Fahrmeir, 2007). By transforming $g_0(t) = \log(\lambda_0(t))$, the following semiparametric hazard rate model was specified:

$$\lambda_i(t) = \exp(\eta_i(t)) \tag{9}$$

with

$$\begin{aligned}\eta_i(t) = \; & g_0(t) + x_i'\beta + u_i(t)'\gamma + f_{1D}(u_i(t)) \\ & + f_{2D}(s_i) + b_{v_i}.\end{aligned} \tag{10}$$

Thus, the additive predictor consisted of the log-baseline hazard $g_0(t)$, linear effects β of time-invariant covariates x_i, linear effects γ of time-variant covariates $u_i(t)$, potential nonlinear effects of continuous and time-variant covariates $f_{1D}(u_i(t))$, effects of household location $s_i = (latitude_i, longitude_i)$, and the household and village random effects b_{v_i}.

The baseline hazard, $g_0(t)$, and $f_{1D}(u_i(t))$ are estimated as 1D P-splines, that is, nonlinear effect functions. However, explorative data analysis implied that most of the explanatory variables show simple linear relationships with the hazard rate $\lambda_i(t)$ and a nonlinear estimate is unnecessary. The only exception is the number of borewell adopters in a village at $t-1$, which is considered in $f_{1D}(u_i(t))$ in the subsequent analysis.

The characteristic and advantage of P-splines can be described as an optimized tradeoff between the flexibility of an estimated function $f(z)$ and the smoothness of the function due to a penalty term (Fahrmeir, Kneib, Lang, & Marx, 2013). Function $f(z)$ is estimated as a polynomial spline of degree $l \geq 0$. Such a spline is a piecewise construct of polynomials of degree l in intervals $[\kappa_j, \kappa_{j+1})$ defined by a number of knots $a = \kappa_1 < \ldots < \kappa_m$. Finally, to ensure that these interval polynomials result into one smooth function $f(z)$, the condition that $f(z)$ is $(l-1)$-times continuously differentiable must hold. With higher degrees and more knots, function $f(z)$ can become quite rough and is likely overfitted and difficult to interpret. Therefore, when estimating a P-spline, simultaneous to the polynomial spline a penalty term based on differences of neighboring coefficients is considered. This ensures that the spline is smooth but still presents enough detail. For a detailed introduction to P-splines and smoothing approaches see, for example, Eilers & Marx (2010), Fahrmeir et al. (2013), Kneib (2006).

The concept of P-splines can be transferred to spatial effects. Considering the GPS coordinates s_i as bivariate (latitude, longitude) and continuous variable, a 2D nonlinear effect of household location ($f_{2D}(s_i)$) on the borewell adoption rate can be estimated. Such 2D effects are referred to as smooth surfaces. Comparable to the 1D P-splines, smoothness is achieved by a penalty term based on differences in coefficients of neighboring observations. Because smooth surfaces are spatially explicit, they can be mapped and areas with particularly large or small effects of household location on adoption rates can be identified. The 1D P-splines are estimated with three degrees of freedom and 20 knots. The 2D P-splines are specified with ten knots and a 2D first-order random walk penalty.

Traditionally, random effects (sometimes also referred to as frailties) are used in the duration model framework to correct for omitted variables such as small-scale local patterns (e.g., soil quality, biophysical characteristics) or time-variant variables that are very difficult to collect, especially over the time of 47 years (Therneau & Grambsch, 2000). Examples would be crops, which have been grown in the past years, or other information concerning the agricultural management system. Therefore, random effects on household (i) and village (v) level (b_{v_i}) are included.[8]

A mixed model approach introduced by Kneib and Fahrmeir (2007) was used for the inferences of the additive regression model in Equation (9). The model was implemented using the software *BayesX* and the respective R-package *R2BayesX* (Umlauf, Adler, Kneib, Lang, & Zeileis, 2015). The estimation of smoothing parameters for nonlinear effects was conducted via restricted maximum likelihood (REML). This estimation approach relies on a Laplace approximation and, thus, no Markov chain Monte Carlo (MCMC) simulation techniques as in a fully Bayesian approach were necessary. In this way, the smoothing parameters could be estimated from the data in advance, given priors for the other regression parameters. The result was an empirical Bayesian approach (Kneib & Fahrmeir, 2007). The REML approach became fairly standard in recent years and studies show that results are very similar to the ones of the fully Bayesian inference (Kneib,

[8] The model displayed in Equation (9) is large and its estimation is computationally intense. Consequently, estimations of household random effects did not converge. However, estimations of reduced model specifications imply that household random effects do not improve model fit or contribute to coefficient estimates (Table A2 in the Appendix). Therefore, household random effects were excluded in all subsequent estimations.

2006). Furthermore, one can avoid mixing and convergence problems in the MCMC simulation step.

Three model specifications were estimated as a robustness check to differentiate between the effects of current and past rainfall. The first model (I) includes all variables in Equation (10), that is, both the current and past years' rainfall values. The second model (II) only contains the current year's rainfall variables and the third model (III) only the past year's values. To compare the model fit, the Akaike information criterion (AIC) and the log-likelihood of estimates are presented.[9]

5 | RESULTS AND DISCUSSION

Tables 4 and 5 show the estimated linear effects of models I–III for the northern and the southern transect. The linear effects are presented as percentage changes of the adoption hazard rate (AHR), a convenient transformation of estimated coefficients since the hazard rate is modeled as an exponential function of the additive predictor $\eta_i(t)$. Estimated nonlinear effects of household location (2D P-spline) and borewell adopters in the village (1D P-spline) are displayed in Figures 2 and 3, respectively. These figures show results for the northern transect based on model specification I and for the southern transect based on model specification III. These are the model specifications that yield the lowest AIC values (Tables 4 and 5) and are supported by likelihood ratio tests (10% significance level). However, estimated effects—linear as well as nonlinear—are robust through all model specifications and, thus, we can regard the effects presented in Figures 2 and 3 as statistically significant patterns. This is also supported by rather small differences among the AIC and log-likelihood values of the three model specifications for the respective transect.

Figure 2 shows the estimated 2D effect (smooth surface) of household location on the AHR. The scale at the bottom of Figure 2 represents direct coefficient estimates and, thus, is an exponential scale. Transforming them comparably with the linear effects in Tables 3 and 4 (e.g., $(e^{\hat{\beta}} - 1) \times 100$)), an absolute coefficient magnitude of 2 (the margins of the scale) implies a 639% change in the adoption rate, whereas a coefficient of 1 results in a change of 122%.

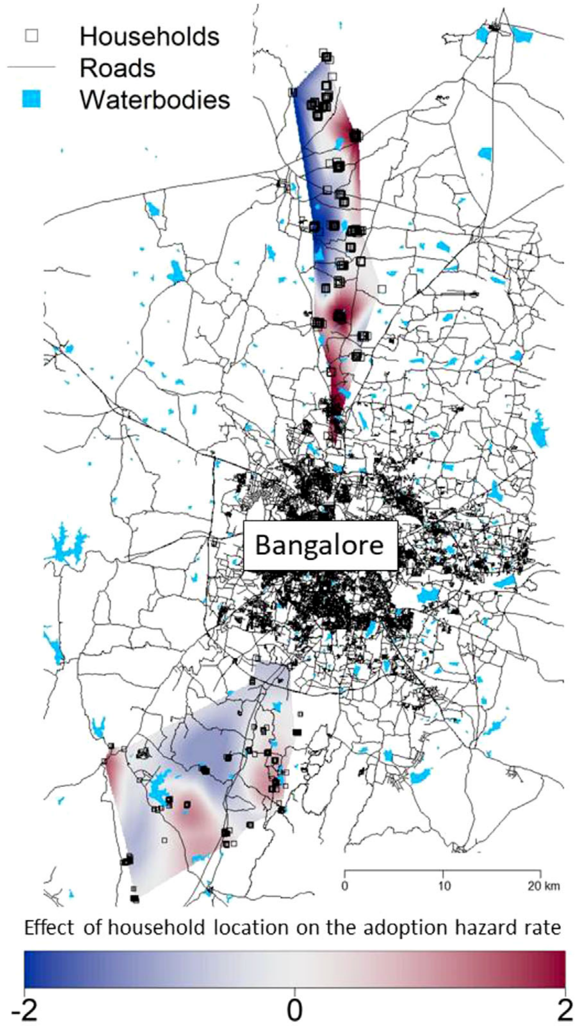

FIGURE 2 Estimated smooth effect surfaces of household location (values are original coefficients; Northern transect: $N = 7{,}641$, Model I; Southern transect: $N = 6{,}563$, Model III) [Color figure can be viewed at wileyonlinelibrary.com]

Note: Red areas imply an acceleration of the adoption hazard rate, whereas blue areas signal decelerating effects. The scale represents direct coefficient estimates and is an exponential scale. For percentage changes transform by $(e^{coefficient} - 1) \times 100$, for example, an absolute coefficient magnitude of 2 implies a 639% change in the adoption rate.

Source: Own survey data.

Furthermore, red areas imply an acceleration of the AHR, whereas blue areas signal decelerating effects. Since the color shades in the northern transect are generally darker than in the southern transect, the urban influence appears to be more heterogeneous in the north. Households located in the southern part of the northern transect are likely to adopt borewells up to 6.39 times faster, ceteris paribus, than the average household in the transect. This is in line with the conceptual framework. In terms of Equation (6), the right-hand side decreases for households located closer

[9] As a robustness check we also estimated the same model specification only replacing the 2D P-Splines by a 1D urbanization proxy, namely the geographic distance between households and the city center of Bangalore. Results are reported in Table A3 in the Appendix. Coefficient estimates of control variables hardly vary between specifications with 1D and 2D proxies and we can assume that the estimated effects are robust. However, estimations with 2D P-Splines yield significantly better AIC values. Hence, the 2D P-Splines appear to show and capture the urbanization effect more appropriately.

TABLE 4 Estimation results for linear effects on adoption hazard rate, northern transect

	Percentage change $((e^{coefficient} - 1) \times 100)$		
	Model I	**Model II**	**Model III**
Intercept	−99.981 (0.001)	−99.997 (< 0.001)	−99.997 (< 0.001)
Time-invariant variables			
Caste (Ref.: General)			
Scheduled castes	−39.86 (0.264)	−42.161 (0.25)	−40.566 (0.272)
Scheduled tribes	−0.995 (0.986)	15.639 (0.798)	−0.19 (0.997)
Other backward class	−12.733 (0.622)	−15.541 (0.549)	−14.717 (0.569)
Other	−57.975 (0.262)	−61.349 (0.232)	−58.355 (0.264)
Dairy			
Yes	135.773 (0.026)	140.873 (0.025)	133.474 (0.028)
Education (years)	0.19 (0.95)	0.05 (0.987)	−0.27 (0.931)
Farm size (ha)	2.01 (0.145)	2.624 (0.069)	2.204 (0.122)
Gender			
Female	−75.877 (0.03)	−79.336 (0.002)	−78.437 (0.002)
Time-variant variables			
Age (years)	−3.382 (0.004)	−3.488 (0.004)	−3.642 (0.002)
Experience (years)	5.201 (< 0.001)	4.917 (< 0.001)	5.096 (< 0.001)
Durable assets (count)	−34.111 (< 0.001)	−36.479 (< 0.001)	−37.412 (< 0.001)
Transport equipment (count)	52.791 (0.103)	39.612 (0.201)	45.659 (0.154)
Off-farm employment			
Yes	−82.464 (< 0.001)	−83.815 (< 0.001)	−83.778 (< 0.001)
Year t			
Total rainfall (mm)	−0.389 (< 0.001)	0.11 (0.086)	
Premonsoon (mm)	0.823 (0.012)	0.21 (0.276)	
Southwest monsoon(mm)	0.05 (0.5612)	−0.06 (0.462)	
Year $t - 1$			
Total rainfall (mm)	−0.21 (0.043)		−0.05 (0.512)
Premonsoon (mm)	−0.886 (< 0.001)		−0.638 (0.002)
Southwest monsoon(mm)	0.491 (< 0.001)		0.2 (0.011)
Akaike information criterion	1,073.16	1,086.18	1,078.5
Log-likelihood	−493.128	−499.096	−496.663
N	7,641	7,641	7,641

Note: Exact p-values are given in parentheses. N refers to the number of observations of the augmented data set, not to the number of households.
Source: Own Survey data and rainfall data from Department of Agrometeorology, University of Agricultural Sciences, Bangalore (UASB).

TABLE 5 Estimation results for linear effects on adoption hazard rate, southern transect

	Percentage change $((e^{coefficient} - 1) \times 100)$		
	Model I	**Model II**	**Model III**
Intercept	−99.991 (0.004)	−99.996 (< 0.001)	−99.993 (< 0.001)
Time-invariant variables			
Caste (Ref.: General)			
Scheduled castes	−66.915 (0.026)	−67.044 (0.029)	−67.851 (0.023)
Scheduled tribes	−89.816 (0.031)	−91.084 (0.023)	−90.672 (0.025)
Other backward class	−43.17 (0.159)	−48.149 (0.109)	−45.382 (0.135)
Other	−55.974 (0.243)	−58.996 (0.206)	−56.308 (0.239)
Dairy			
Yes	49.616 (0.293)	53.71 (0.264)	51.907 (0.276)
Education (years)	4.645 (0.176)	3.884 (0.264)	4.362 (0.206)
Farm size (ha)	2.881 (< 0.001)	2.747 (< 0.001)	2.819 (< 0.001)
Gender			
Female	−10.031 (0.798)	−12.392 (0.753)	−12.383 (0.751)
Time-variant variables			
Age (years)	−6.471 (< 0.001)	−7.42 (< 0.001)	−6.919 (< 0.001)
Experience (years)	8.937 (< 0.001)	9.221 (< 0.001)	9.09 (< 0.001)
Durable assets (count)	1.725 (0.887)	−3.806 (0.741)	−2.244 (0.846)
Transport equipment (count)	−48.737 (0.056)	−54.674 (0.023)	−52.365 (0.032)
Off-farm employment			
Yes	17.257 (0.594)	6.396 (0.837)	14.176 (0.658)
Year t			
Total rainfall (mm)	−0.21 (0.084)	0.05 (0.581)	
Premonsoon (mm)	0.713 (0.061)	−0.05 (0.826)	
Southwest monsoon(mm)	0.06 (0.593)	−0.03 (0.75)	
Year $t - 1$			
Total rainfall (mm)	−0.28 (0.026)		−0.14 (0.13)
Premonsoon (mm)	−0.509 (0.076)		−0.419 (0.071)
Southwest monsoon(mm)	0.491 (< 0.001)		0.260 (0.006)
Akaike information criterion	824.33	832.684	823.005
Log-likelihood	−376.895	−382.16	−378.444
N	6,563	6,563	6,563

Note: Exact p-values are given in parentheses. N refers to the number of observations of the augmented data set, not to the number of households.
Source: Own survey data and rainfall data from Department of Agrometeorology, University of Agricultural Sciences, Bangalore (UASB).

to the city as market access increases and transport costs decrease. However, there is also an area in the northeast of the transect, where the household location has strong accelerating effects on the AHR. Though rather far away from Bangalore, this area is located close to a road, which connects households to the secondary town of Chikballapur (road intersection in the northeast corner of the map) and thus provides these households with access to markets. In the southern transect, there is one red area in the east of the transect, close to Bangalore and right next to a large highway (road in north-south orientation in Figure 2). Furthermore, there are two red areas located in the southern part of the transect. Comparable with the northern transect, there are three secondary towns located close to these areas (Bidadi, Ramanagara, and Kanakapura) and connected by highways. Interestingly, there is a break between these two red areas just next to a large water reservoir. This might suggest that water demand is covered by sources that are cheaper to establish in this area. Pumping water from the reservoir saves the installation costs needed for drilling a borewell and, thus, could explain negative effects on the AHR. Finally, differences in the effect patterns and magnitude between the two transects as well as their fragmentation support the assumption that effects of market access in a complex rural–urban interface are nonlinear and polycentric and, thus, require a 2D representation. In contrast, the 1D measure of market access (e.g., distance) will be of limited use because they assume that urban influences spread in uniform and concentric rings around an urban center (see Table A3 in the Appendix for estimation results with the 1D measure).

Concerning the effects of the rainfall variables on the AHR, the effects are very similar in both transects (Tables 4 and 5). Adoption rates decelerate with an increasing amount of total rainfall in the current (t) or preceding time period ($t-1$) as well as with the premonsoon rainfall in period $t-1$. The effects range from -0.2% to -0.9% per additional millimeter of rain. According to the conceptual framework in Section 3 (in particular Equation 6), the value of waiting increases when the amount of rainfall increases. The farmer then has less need for a second water source and sticks to the old production system for another year. When there is less rain, the farmer expects a larger output difference between the two production systems and is more likely to adopt the borewell now rather than in the next year. However, we also observed an accelerating effect of increasing premonsoon rainfall in both transects in year t as well as with the southwest monsoon in year $t-1$, effect sizes between 0.2 and 0.8 per additional millimeter of rain. A year with more monsoon rain usually generates higher agricultural output as the monsoon season is the principal growing season. Thus, the accelerated AHR might result from extra agricultural income and capital available for the next season or the desire to keep up with a previous successful season. This explains the positive lagged effect of monsoon rainfalls, but an explanation of the contemporaneous effect of premonsoon rainfalls is less clear. First of all, the effect is only statistically significant in model I and, thus, not robust (compare to model II in Tables 4 and 5). Additionally, we observe borewell adoption on a yearly basis and since the premonsoon occurs early in the year (March to May) a time-lag in the adoption decision making might be lost due to the level of aggregation. After observing this effect in both transects, it seems that the households observe and take some time for their decision to adopt a borewell. This is consistent with the literature, which states that farmers try to hedge against production risks (Koundouri et al., 2006).

Differences between the transects become more evident when looking at the effects of the control variables in Tables 4 and 5 and Figure 3. Only the effects of age and experience are similar. Increasing age reduces the AHR, in the northern transect by about 3.5% and in the southern transect around 7%. In contrast, farming experience increases the AHR by 5% in the northern and 9% in the southern transect.

Turning to variables describing agricultural management and income composition of the household, dairy production has a large accelerating effect and off-farm employment a large decelerating effect on the AHR in the northern transect. Dairy production requires a lot of water for the animals to drink and wash them but also to grow fodder crops. In addition, dairy production is profitable and might lead to extra income that can be invested into borewell adoption.[10] Off-farm employment can generally have two effects on agricultural production. Either additional income is invested in agricultural production (e.g., in the form of technology adoption) (Barrett, Bezuneh, & Aboud, 2001; de Janvry, Sadoulet, & Zhu, 2005), or the relevance of agricultural production for the income of the household decreases (Huang, Wu, & Rozelle, 2009). Several studies show that smallholders—if they have access to a labor market—will diversify their income sources (Deichmann, Shilpi, & Vakis, 2009; Fafchamps & Shilpi, 2003; Imai, Gaiha, & Thapa, 2015). Moreover, the literature shows that higher management demands of new technologies and the opportunity costs of skilled labor further decreases technology adoption (Pannell et al., 2006). At least in the northern transect, it appears that the latter negative effect (82—84%, Table 4) of off-farm employment is the case. Neither dairy production nor off-farm employment shows significant coefficients in the southern

[10] Unfortunately, no time-variant information on dairy production is available. Hence, results might suffer from potential endogeneity, thus we observe correlation rather than causality.

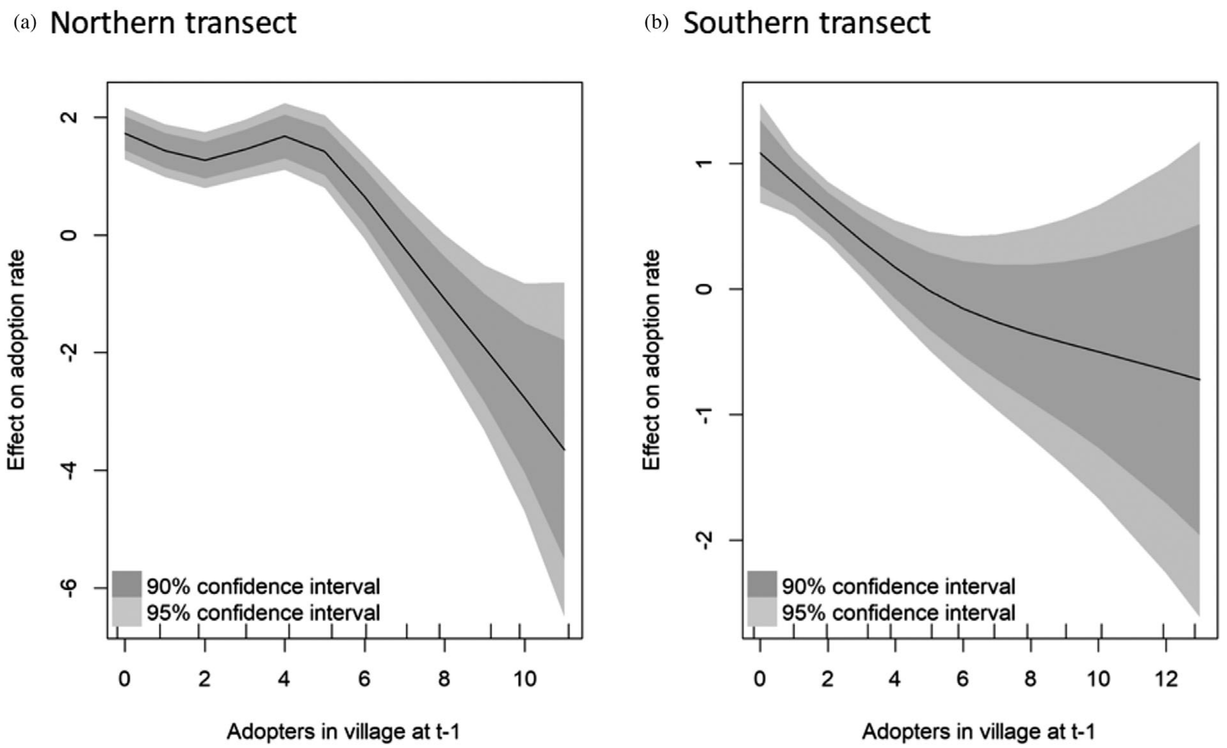

FIGURE 3 Estimated nonlinear effect of the number of adopters in a village at $t-1$ on borewell adoption rate (values are original coefficients; northern transect: $N = 7{,}641$, model I; southern transect: $N = 6{,}563$, model III)
Note: The scale represents direct coefficient estimates and is an exponential scale. For percentage changes transform by $(e^{coefficient} - 1) \times 100$, for example, an absolute coefficient magnitude of 2 implies a 639% change in the adoption rate.
Source: Own survey data.

transect. However, farm size is a highly statistically significant factor for borewell adoption (in the northern transect only significant in model II). With every additional acre, the AHR increases by 3% everything else being equal.

Furthermore, transport equipment and durable assets were included as measures of the living standard of a household. In the northern transect only durable assets show significant effects, whereas in the southern transect only transport equipment yields significant effects. However, both show negative signs and comparable magnitudes. Since both are measures of living standard, they are likely to signal the same effect (see correlation Table A1 in the Appendix). Accordingly, these results imply that wealthier households are less likely to adopt borewell technology. This is somehow counterintuitive as it could be assumed that wealthier families have better access to financial resources needed to invest in borewell technology. One explanation of this effect could be that wealthier families are less dependent on agricultural production. Similar to the effect of off-farm employment, income diversification decreases the borewell adoption rate. Table 3 shows that about 50% of the sample has at least one household member in the off-farm sector and off-farm employment is positively correlated with both wealth indicators (Table A1 in the Appendix). If farming is no longer the main income source, the need to modernize production systems and adopt groundwater lifting technology might decrease.

Furthermore, measures of social status and interaction produce different effects as well. For caste, significant negative effects of *scheduled castes* and *scheduled tribes* in the southern transect were found. These represent the castes that generally hold the lowest social status. Thus, belonging to these groups in the southern transect reduces a household's adoption rate by 67% and 90%, respectively. While no significant effects for caste were found in the northern transect, gender has a statistically significant negative effect on the AHR (not significant in the southern transect). If the household head is female, the adoption rate of the household is 75–79% lower in the northern transect. These results imply different social structures between the two transects. Since the shares of households in the different castes are very similar in both transects (Table 1), caste boundaries are more relevant in the southern transect. Lower caste households have less and later access to groundwater lifting technology. However, the same holds for female-headed households in the northern transect. As a consequence, already disadvantaged households will be more vulnerable to water shortage.

The number of borewell adopters in a village shows statistically significant effects in both transects (Figure 3). Up to a number of six adopters per village in $t-1$ (sample population), strong accelerating effects on the AHR (about 700%, the y-axis in Figure 3 represents coefficient estimates) are observed in the northern transect (Figure 3a). In the southern transect, the effect is lower (by about 100%) and is observable for up to four adopters in the sample per village. Hence, there is a positive effect of social interaction on technology diffusion. Interestingly, effects change at higher numbers of adopters. In the northern transect, effects even become significantly negative, that is, if there are more than nine adopters, the adoption probability of remaining nonadopters decreases. A reason might be that wells are shared among neighbors. Since water extraction is unregulated, water prices are close to zero once the well is drilled. Consequently, even if farmers have to pay their neighbors a fee to use their well, it might still be cheaper than drilling one for themselves. However, no household in the sample reported such agreements. Another explanation could be that with more wells and unregulated water extraction, groundwater tables are likely to fall (Blakeslee et al., 2020). Observing the drop in water availability in already existing wells might prevent further adoption as farmers are less optimistic that their own drilling will be successful.

6 | CONCLUSIONS

This analysis aims at understanding both the effect of households' location as a measure of urban influence and market access, and the effect of changing climate conditions on borewell adoption behavior along the rural–urban interface of Bangalore. Duration models were applied with semiparametric predictors to accommodate for complex and polycentric urbanization patterns (e.g., secondary towns) and three rainfall variables were used to obtain nuanced insights into the effect of weather changes.

The results show that household location matters. Both proximity to Bangalore and proximity to secondary towns increase the borewell adoption rate. This supports the assumption that urbanization effects are polycentric and that empirical strategies using 2D splines are a useful instrument to quantify them. Moreover, adoption rates are further accelerated by social interaction within villages. The study finds that the number of adopters in a village increases the adoption probability of remaining nonadopters. Only if adoption shares are already high, the effects will decrease and even turn negative in the northern transect. Considering changing climate conditions, the study finds that the amount of rainfall affects decisions in two ways. First, a decelerating effect with the amount of total rainfall in year t as well as in the lagged time period $t-1$ was observed. Hence, dry periods accelerate the adoption of borewell technology. Second, an accelerating effect with the amount of rainfall during the southwest monsoon in period $t-1$ was observed. As the monsoon season is the most important growing period, the adoption rate also depends on households' additional income.

Based on these results, we propose the following policy implications distinguishing between two issue areas policy makers might be interested in: sustainable resource use and the accessibility and equal distribution of borewell technology as a development tool. For policy makers concerned with overexploitation of groundwater, our results hint at possible increasing effects of social learning on adoption rates. Such dynamics might amplify already increasing adoption rates due to proximity to urban centers and better market access. Borewell adoption is not an evenly distributed phenomenon and there might be geographic clusters of high borewell density. Hence, a close monitoring of drilling activities is necessary to ensure a sustainable use of the resource. If such clusters coincide with falling groundwater tables, the implementation of regulatory policies might be necessary. For policy makers more concerned with accessibility and an equal distribution of the access to a resource, our results suggest focusing on vulnerable and already disadvantaged groups. The study finds that for example female-headed or lower caste households have statistically significantly lower adoption rates.

There is also room for further research. The estimation results show that a household's income composition affects decision making in the context of urban growth and drought pressure. Urban centers provide opportunities for off-farm employment and increasing water insecurity might encourage farm households to pursue off-farm opportunities. This means, farmers' decision making might not rely on the maximization of agricultural production but rather on the maximization of overall household utility. This aspect could be an interesting addition to models explaining technology adoption decisions.

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SUPPORTING INFORMATION

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

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APPENDIX
DERIVATION OF EQUATION (6)

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

$$\Leftrightarrow \sum_{h=0}^{\infty} A_1(T+h,l)\,\delta(h) - C(T,l)$$

$$- \sum_{h=0}^{\infty} A_0(T+h,l)\,\delta(h) \;\geq\; A_0(T,l)$$

$$+ \sum_{h=1}^{\infty} A_1(T+h,l)\,\delta(h) - C(T+1,l)\,\delta(1) - A_1(T,l)$$

$$- \sum_{h=1}^{\infty} A_0(T+h,l)\,\delta(h)$$

$$\Leftrightarrow A_1(T,l) - A_0(T,l) - C(T,l) \;\geq\; A_0(T,l)$$

$$-A_1(T,l) - \; C(T+1,l)\,\delta(1)$$

$$\Leftrightarrow A_1(T,l) - A_0(T,l) \;\geq\; \frac{1}{2}\left[C(T,l) - C(T+1,l)\,\delta(1)\right]$$

$$\Leftrightarrow p(T,l)\,q_1(T) - a_1 c(T,l) - p(T,l)\,q_0(T)$$

$$-a_0 c(T,l) \geq \frac{1}{2}\left[C(T,l) - C(T+1,l)\,\delta(1)\right]$$

$$\Leftrightarrow p(T,l)\,(q_1(T) - q_0(T)) - c(T,l)\,(a_1 - a_0)$$

$$\geq \frac{1}{2}\left[C(T,l) - C(T+1,l)\,\delta(1)\right]$$

$$\Leftrightarrow p(T,l)\,(q_1(T) - q_0(T)) \geq \frac{1}{2}\left[C(T,l) - C(T+1,l)\,\delta(1)\right]$$

$$+c(T,l)\,(a_1 - a_0)$$

$$\Leftrightarrow q_1(T) - \; q_0(T) \;\geq\; \frac{C(T,l) - C(T+1,l)\,\delta(1)}{2p(T,l)}$$

$$+ \frac{c(T,l)\,(a_1 - a_0)}{p(T,l)}.$$

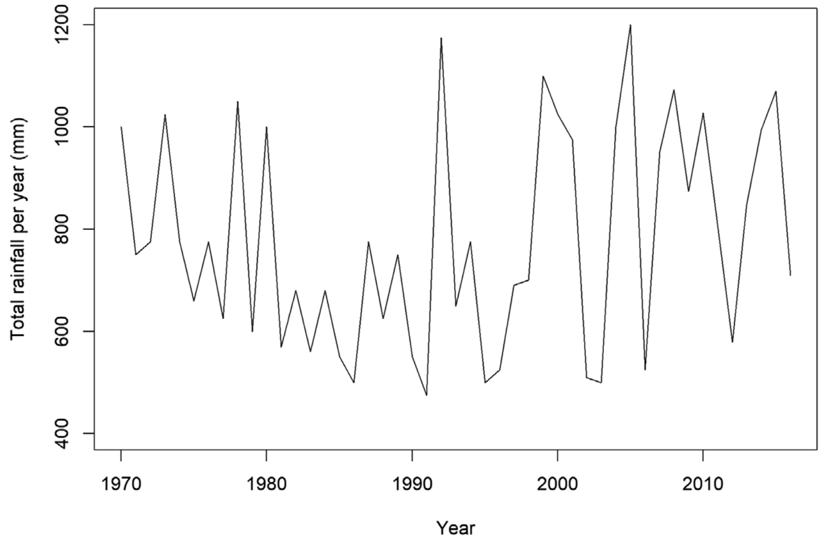

FIGURE A1 Total rainfall in the Bengaluru urban district, 1970–2016
Source: Rainfall data (Department of Agrometeorology, University of Agricultural Sciences, Bangalore (UASB)).

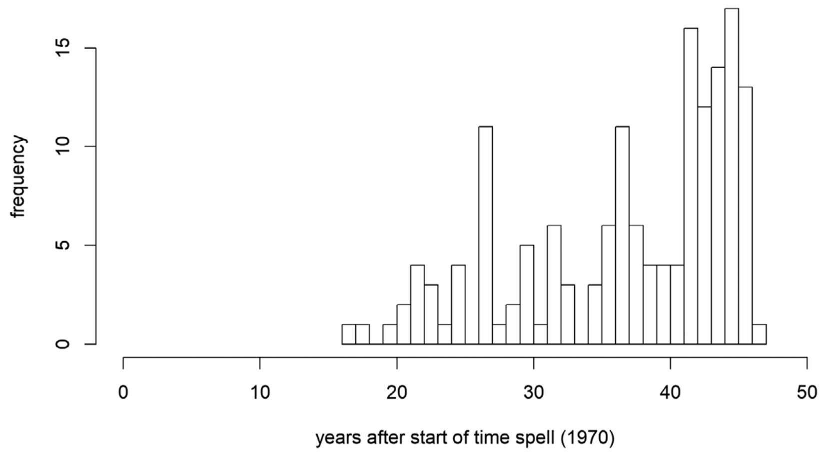

FIGURE A2 Response frequency of when borewell was adopted ($N = 149$, households)
Source: Survey data.

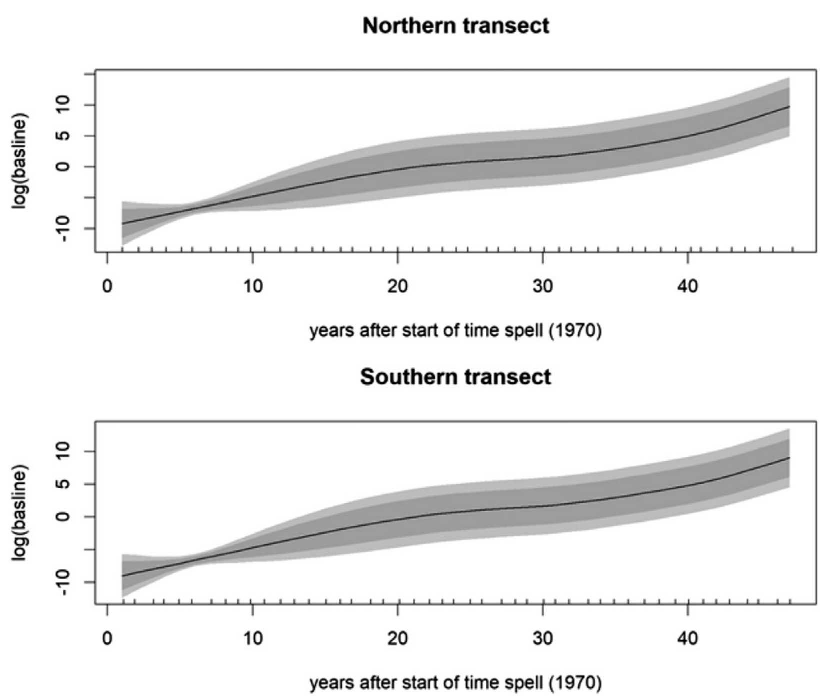

FIGURE A3 Estimated log-baseline of spatial model I (P-spline), northern and southern transect (northern transect: $N = 7{,}641$; southern transect: $N = 6{,}563$)
Note: Dark gray bandwidth indicates the 90% confidence interval, light gray bandwidth indicates the 95% confidence interval.
Source: Own survey data and rainfall data from Department of Agrometeorology, University of Agricultural Sciences, Bangalore (UASB).

TABLE A1 Correlation among off-farm employment and assets owned by households

	Off-farm employment (dummy)	Durable assets (count)	Transport equipment (count)
Off-farm employment (dummy)	1.00		
Durable assets (count)	0.219 (< 0.001)	1.00	
Transport equipment (count)	0.14 (< 0.001)	0.552 (< 0.001)	1.00

Source: Own survey data.

TABLE A2 Akaike information criterion (AIC) and log-likelihood values of estimations[a] with different random effects included

Random effects included	AIC	Log-likelihood
Northern transect		
None	1,147.69	−547.74
Household	1,147.69	−547.74
Village	1,141.8	−542.23
Southern transect		
None	830.843	−388.866
Household	830.843	−388.866
Village	835.726	−393.958

Note: Estimated coefficients and standard errors of models without and with household random effects are equal up to the third decimal place, [a]A reduced model was estimated, that is, the model in Equation (9) without 1D P-splines and weather variables.
Source: Own survey data.

TABLE A3 Estimation results for models with 1D urbanization proxy, robustness check

	Percentage change ($(e^{coefficient} - 1) \times 100$)	
	Northern transect	**Southern transect**
Intercept	−99.960 (0.051)	−99.976 (0.004)
Time-invariant variables		
Caste (Ref.: General)		
Scheduled castes	−40.076 (0.177)	−62.446 (0.022)
Scheduled tribes	−3.921 (0.871)	−42.328 (0.149)
Other backward class	−11.980 (0.796)	−90.294 (0.025)
Other	−45.741 (0.407)	−22.879 (0.697)
Dairy		
Yes	118.518 (0.034)	50.306 (0.275)
Education (years)	−0.797 (0.791)	3.904 (0.231)
Farm size (ha)	2.480 (0.026)	2.665 (< 0.001)
Gender		
Female	−68.670 (0.009)	−12.041 (0.74)
Time-variant variables		
Age (years)	−3.777 (0.001)	−5.692 (< 0.001)
Experience (years)	5.982 (< 0.001)	7.326 (< 0.001)
Durable assets (count)	−38.165 (< 0.001)	−3.729 (0.73)
Transport equipment (count)	41.964 (0.172)	−54.801 (0.021)
Off-farm employment		
Yes	−83.569 (< 0.001)	−3.014 (0.916)
Year *t*		
Total rainfall (mm)	−0.439 (< 0.001)	
Premonsoon (mm)	0.944 (0.006)	
Southwest monsoon(mm)	0.040 (0.657)	
Year *t* – 1		
Total rainfall (mm)	−0.240 (0.027)	−0.140 (0.114)
Premonsoon (mm)	−0.955 (< 0.001)	−0.449 (0.057)
Southwest monsoon(mm)	0.531 (< 0.001)	0.270 (0.004)
Distance to Bangalore city center (km)	−4.734 (< 0.001)	−2.098 (0.38)
Akaike information criterion (AIC)	1,109.98	847.32
Log-likelihood	−525.435	−400.554
N	7,641	6,563

Note: For the northern transect Model Specification I and for the southern transect Model Specification III is presented. These are the model specifications yielding the best AICs in Tables 4 and 5. Results for the other model specifications hardly differ and are available on request.
Source: Own survey data.