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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 study, we analyze the effects of household location and weather variability on the adoption of borewell technology in the rural-urban interface of Bangalore, India. Understanding these effects can help design policies that ensure smallholders' livelihoods and the functioning of ecosystems in drought-prone areas. Our analysis is based on a primary data set collected in 2016 and 2017 covering 574 farm households. With a semiparametric hazard rate model we analyze determinants of the borewell adoption rate. We incorporate different rainfall variables and a two-dimensional geo-spline to capture the effects of household location. Results show that more rain can lead to successful seasons that generate the capital needed for investment in borewell technology. However, we observe ad hoc adoption decisions to prevent harvest loss when rainfalls are low or missing. We also find that proximity to markets accelerates adoption rates. Further, we find that off-farm employment to decreases adoption rates.

Key words: Urbanization, climate change, borewell technology, India, semiparametric duration models

1 Introduction

The spread of borewell technology in India has surged since the *Green Revolution* in the 1970s, making India the largest groundwater user in the world (Shah, 2014). Initially, the uptake of groundwater lifting technology was supported by the Indian government. In recent years, the adoption of this technology has maintained momentum. Two possible drivers are economic development in India, and a shift in rain patterns due to climate change. Economic development leading to higher incomes and urbanization has improved access to markets and made it more profitable to intensify agriculture. However, this is only possible with a secure and perennial water source. Changing rain patterns have made traditional rainfed agriculture less predictable and more vulnerable, and borewell technology can be used to compensate for missing rains.

Nevertheless, this increased uptake of borewell technology comes at a cost. More wells and uncontrolled water extraction can lower aquifer water tables leading to over-exploited aquifers in the region (Srinivasan *et al.*, 2017). As a consequence, borewells fall dry, threatening the well-being of water users. It is thus essential to implement policies that strike a balance between the present well-being of smallholders and sustainable, long-term water resource management.

To do so, one has to understand what determines farmers' decisions to adopt borewell technology, particularly when they face rapidly changing conditions due to urban growth and changing weather patterns. However, this need for a better understanding has hardly been addressed in the literature in a way that considers temporal as well as spatial aspects of urbanization and climate change. Therefore, our analysis aims to understand how changing climate conditions and farmers' locations in the rural-urban interface of Bangalore affect decision-making to adopt borewell technology over time.

To achieve this objective, we first develop a microeconomic model that captures how weather and location can influence decision-making. Second, in our empirical analysis we apply a duration model that includes two-dimensional location effects (semiparametric hazard rate model). The duration model has been applied to evaluate technology adoption in a dynamic framework (Abdulai and Huffman, 2005; Dadi, Burton and Ozanne, 2004; Euler *et al.*, 2016). However, to our knowledge none of these studies includes an explicit location effect. If space is considered in previous studies, it is generally limited to one-dimensional proxies such as distance to markets (Chamberlin and Jayne, 2013). Our two-dimensional location effects have two significant advantages. First, they allow for more complex and systematic spatial patterns, e.g. if there are several market centers accessible for a household. Second, we are able to identify areas with especially high or low effects on adoption rates. Therefore, the results of our study can help policy makers to identify adoption clusters. This can be useful when implementing policies that address the sustainable use of immobile natural resources such as groundwater.

The remainder of this paper is structured as follows. In the second section, we give a short introduction to irrigation technologies in South India and the characteristics of our study area. In section 3 we present our survey design and data set. In section 4 we develop a conceptual framework and in section 5 we explain the econometric model we use for our empirical analysis. In section 6 we discuss our results and in section 7 we summarize our findings.

2 Background and study area

The adoption of borewells has been and will be crucial for the food security in large parts of South Asia. While the situation has been stable for the past few decades due to groundwater irrigation, the food security of future generations is at stake as many aquifers are over-exploited or degraded (Shah, 2007). To understand how and why farmers started to use borewell technology, we present a brief overview of irrigation systems in South India. The traditional irrigation system in South India was dominated by reservoirs and local water bodies, also called tanks. These local water bodies were used and managed at the communal level. Since the 1990s, however, many farmers have decided to invest in private well equipment to extract groundwater and exit the communal irrigation system. The reasons are manifold. First, because of coordination problems within the command area of the tanks, water availability was uncertain. Particularly during the critical stages of cultivation, farmers favor independent and secure water sources. Second, the maintenance of local water bodies requires high labor inputs. Third, pumping technology and drilling have become less expensive in absolute and relative terms. Domestic production of pumps and improved drilling technologies have lowered the prices for establishing a borewell, and decreased input prices through subsidized flat rate electricity prices and increased output prices for agricultural products have lowered the relative price of groundwater irrigation (Kajisa, Palanisami and Sakurai, 2007). All those reasons contribute to India being the biggest user of groundwater globally nowadays.

Nevertheless, India has still the largest area and production in rainfed agriculture indicating that adoption rates are still low (Srinivasa Rao *et al.*, 2015). To understand what drives the adoption process at individual farm level, several factors have been analyzed.

One of the main reasons for adopting irrigation 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 (Alcon, Miguel and Burton, 2011; Genius *et al.*, 2014). At farm level, unfavorable slopes and soil characteristics (Koundouri, Nauges and Tzouvelekas, 2006) as well as farm size and the degree of commercialization increases the probability to adopt (Feder, Just and Zilberman, 1985).

Another important factor which may explain the heterogeneity in adoption is the diffusion of technology. Diffusion is understood as the adoption process of a technology over time (Taylor and Zilberman, 2017). A key role in the diffusion of technology in agriculture is the distance to regional centers. The less remote a producer is, the higher the probability that he will adopt earlier than other producers. Since learning and implementation may require traveling, transportation and high opportunity costs can impede technology adoption (Sunding and Zilberman, 2001). More recently, the interconnectedness of market access and technology adoption has been studied. Damania *et al.* (2017) find that a reduction in transport costs to markets increases the likelihood of technology adoption. The distance to a regional center might also affect the diffusion of technology through the income composition of a household. The effect is, however, not clear cut. While off-farm income may have a positive effect on adoption due to income security, it might also have also a negative effect if it reduces the need to generate more farm income (Pannell *et al.*, 2006).

The goal of this study is to find out what determines the diffusion of the borewell technology in the rural-urban interface of Bangalore. We are particularly interested in the effect of farmers' perception of weather variability and changing conditions due to urban growth on their adoption behavior.

Bangalore is located on the southern Deccan Plateau in the South-Indian state of Karnataka. The city is quickly growing and expanding. Thus, it represents the global urbanization trend outlined by the report of the UN Population Division (United Nations, Department of Economic and Social Affairs, Population Division, 2015). Accordingly, larger cities will dominate the future urban development, particularly in Asia. The last official census for Bangalore district was conducted in 2011 and reports a population of 9.6 million inhabitants (Directorate of Census Operations Karnataka, 2011), roughly 3 million more than in the early 2000s. Extrapolations based on this growth rate estimate the current population to be about 12 million.

The climate of the region is classified as seasonal dry savanna (Directorate of Census Operations Karnataka, 2011). The seasons are defined by a south-west monsoon, normally bringing heavy rains from June to September. The agricultural seasons depend on monsoon rain as a perennial irrigation source. However, in recent years the monsoon rains have become less reliable, arriving late or failing completely (Kumar M, 2012; Qureshi, 2018). The area around Bangalore is famous for its fruit and vegetable production, which particularly rely on steady irrigation. The Bangalore Binny Mill market is the largest fruit and vegetable market in South India. However, also in several satellite towns within a 50 km radius around Bangalore, wholesale (APMC[1]) markets and other retail formats offer marketing possibilities to farmers.

The rural-urban interface of Bangalore is not completely homogenous in biophysical and topographical terms. The northern area is dominated by a level plateau, whereas the southern areas shows a more uneven, hilly landscape (Directorate of Census Operations Karnataka, 2011). In addition, while there are

[1] Government wholesale markets.

no larger water bodies, such as rivers, lakes, or reservoirs, located in the north, there are two reservoirs in the south (Directorate of Census Operations Karnataka, 2011) and some households report that waste water drainages from the industries in the south of Bangalore are also used for irrigation.

3 Survey design and data set

For our empirical analysis we use data collected in a survey of 1275 households in two transects following the rural-urban gradient of Bangalore (Figure 1) and thus capturing potential systematic spatial heterogeneity caused by urbanization dynamics. We applied a two-stage stratified sampling approach to identify the households to be interviewed. In the first stage we used a Survey Stratification Index (SSI) to classify all villages in the transects into three strata (rural, peri-urban, urban) (Hoffmann *et al.*, 2017) and then we randomly selected ten villages in each strata per transect. Afterwards on average 20 households[2] were randomly drawn from the household lists of the selected villages. All households were interviewed between December 2016 and May 2017.

[Figure 1]

Because we are interested in the adoption borewells for agricultural purpose, in the following analysis we only consider households that grew at least one crop in 2016 (farm households). Therefore, our sample comprises a total of 574[3] households of which 315 are located in the transect north of Bangalore (northern transect) and 259 in the transect south of Bangalore (southern transect).

All 574 farm households were asked whether they have a borewell and, if yes, when they installed it. This information was used to estimate adoption probabilities and the hazard rate, which is the dependent variable in the duration model framework. Figure 2 gives a first impression of the distribution of borewells among the households in our data set. It appears that the adoption level is substantially higher in the northern transect (Figure 2b), which is confirmed by the Kaplan-Meier estimates[4] of non-adoption probabilities (Figure 2a). Table 1 shows that 148 (26%) of the farm households in our sample had adopted the technology by 2016. Of these 148 households, 88 are located in the northern and 60 in the southern transect.

[Figure 2]

We further collected information on standard control variables such as age of household head, gender and caste, but also dummies representing income composition such as dairy production and off-farm employment (for descriptive statistics see Table 1). To capture the wealth or living standard of a household, we use a count of assets, which is also applied to classify households in the *New Socio-Economic Classification (SEC) system* (MRSI, Indian Market Research Society, 2011). The assets include transport equipment such as a car or two wheelers and other durable assets such as TVs, laundry machines or air conditioners. In addition, all households are geo-referenced.

[Table 1]

[2] We adjusted the number of households interviewed according to the total population of the respective village.

[3] This number already excludes all observation (only a few) which were excluded during the empirical analysis because of missing values in important covariates. Our inference strategy does not allow for missing values unfortunately.

[4] The Kaplan-Meier estimator is a standard method so we do not explain it in detail here. For detailed information see e.g. Moore (2016).

To address the two major points of interest of our study, we need variables capturing weather variability and spatial heterogeneity in the rural-urban interface. We use rainfall as proxy for weather variability. 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, we not only include the total yearly rainfall but also the pre-monsoon rainfalls and the southwest monsoon rainfalls in our dataset. Descriptive statistics are presented in Table 2. Further, we consider current and previous years' rainfalls. Yearly rainfall data for the *Bangalore urban* district was obtained from the website of the Agrometerology Department of the University of Agricultural Sciences, Bangalore.

[Table 2]

A common approach to model systematic spatial heterogeneity due to a city in the research area is to use measures such as distance or travel times to the city in the data analysis (Chamberlin and Jayne, 2013) as proxies for access to markets and other infrastructure. Particularly the access to in- and output markets has been identified as important channel by which cities influence smallholders' decision making (Damania *et al.*, 2017; Minten, Koru and Stifel, 2013). However, in section 3 we described the polycentric nature of the rural-urban interface of Bangalore, with several satellite towns offering additional marketing options to farmers. We therefore use a household's explicit location in two-dimensional space to capture market access. Location only proxies market access if other exogenous spatial (e.g. biophysical) heterogeneity among the observation points can be ruled out. We account for this issue in our empirical analysis by including village random effects[5], which correct for village-scale omitted variables (such as local variation in soil quality and other small-scale biophysical characteristics).

A final issue in constructing a data set for duration analysis is the notion of time. Some modeling frameworks allow for time-varying covariates, which also have some important methodological advantages (see section 5). However, for inference we have to augment the data set. This means that we need one observation per time observation period—in our case one year. Hence, our final data set for estimation includes 7601 observations for the northern and 6547 observations for the southern transect (our time spell starts in 1970, see section 5). We include all rainfall variables as well as age, experience, transportation equipment, durable assets, and off-farm employment as time-varying variables (Table 3).

[Table 3]

4 Conceptual framework

We conduct our empirical analysis in a duration model framework. This type of model has been applied to explain technology adoption before, and its ability to capture dynamics in time is highlighted as one of its biggest advantages (see for example Abdulai and Huffman, 2005; Dadi, Burton and Ozanne, 2004; Euler *et al.*, 2016). That means we cannot only identify determinants of farmers' decisions to adopt a technology but we can analyze a farmer's time preference—his hazard—to adopt a new technology. This ability to model time dynamics is especially interesting for settings such as the rural-urban interface of Bangalore, where conditions can change rapidly for smallholders and time is likely to play an important role for their decisions. Further, the notion of weather or climate change requires the observations of smallholders' responses over and not just at one point in time.

[5] In traditional (medical) duration model literature, those are also referred to as "frailties", which is however quite misleading in our context. Thus, we refer to the methodological concept of random effects.

Before starting with the empirical analysis, we provide some microeconomic intuition. This will help to better understand the mechanisms of decision making and to motivate the econometric model and its specifications. Genius *et al.* (2014) and Irwin and Bockstael (2004), for example, present some economic models in the context of duration analysis. However, they do not address the issue of household location in an urbanization setting or the effect of weather on household's decision making. We integrate these aspects in our conceptual framework as outlined in the following.

We assume smallholders to be profit maximizing agricultural producers. We simplify the possible production systems s to two, which are defined by the source of irrigation, i.e. s=1 if the household adopted the borewell technology, and s=0 if the technology has not been adopted. In that way, we can note down household i's expected profit $A_{s,i}$ generated by either system as function of time period t and household i's location l:

(1) $A_{s,i}(t,l) = p(t,l)q_s(t) - c(t,l)a_s, \;\; with\, s = 0{,}1$

where the expected profit, $A_{s,i}(t,l)$, is defined as the difference between the product of expected output prices $p(t,l)$ and expected output $q_s(t)$ and the product of expected used inputs a_s and expected input costs $c(t,l)$. Consequently, farmers' expectations are determined by three factors, namely time, location, and the chosen production system. Note that both prices $p(t,l)$ and $c(t,l)$ depend on time t. Prices depend on location l due to transportation costs and market access. In other words, a household's location will determine how readily it can access in- and output markets and thus determine the net prices it pays for inputs and receives for output. This has been repeatedly identified as a crucial factor for smallholders' management decisions (e.g. Minten, Koru and Stifel, 2013). The type of production system s influences the amount of input used and the amount of output produced. With reliable irrigation, farmers might apply additional and more sophisticated inputs. Further, a system with a borewell as water source (s=1) is likely to generate a higher output because more consistent irrigation is possible. Commonly, the output is modeled based on a time-constant production function only defined by a set of inputs (fertilizer, labor, land, etc.). Nevertheless, in regions subject to climate change farmers' expectations concerning their production and outputs (i.e. a production function) is very likely to vary with changing weather patterns, i.e. time. For example, if a farmer expects decreasing rainfall, his expectations for outputs from a rainfed production system will also decrease. Therefore, we capture the weather component of our research objective by allowing farmers' expectations regarding output quantities to vary over time.

Since we are interested in the decision to adopt a borewell, we also have to consider its one-time installation costs $C(t,l)$. 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.

Equation (1) is the basic building block that we use to formalize a rational farmers' decision whether or not to adopt borewell technology. The decision problem for household i is whether to adopt the technology in time period *T*, which leads to the expected net returns in equation (2a), or to wait another year to adopt it in T+1, which leads to the expected net returns in equation (2b):

$$(2a) \sum_{h=0}^{\infty} A_{1,i}(T+h,l)\delta(h) - C(T,l) - \sum_{h=0}^{\infty} A_{0,i}(T+h,l)\delta(h)$$

$$(2b)\ A_{0,i}(T,l) + \sum_{h=1}^{\infty} A_{1,i}(T+h,l)\delta(h) - C(T+1,l)\delta(1) - \sum_{h=0}^{\infty} A_{0,i}(T+h,l)\delta(h)$$

If the technology is adopted in *T* (equation 2a), the expected net returns are given by the net present value of a production system with borewell discounted to time T with discount factor $\delta(h)$, minus the installation costs in T, and minus the net present value of the production system without the technology. The net present value of the production system without the borewell represents the forgone profit from the original management system and the change to a system with the technology. Analogously, in equation (2b) the first two elements depict the profit from one more year in the management system without the borewell plus profits with 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.

Assuming that equations (2a) and (2b) are the basis on which household i makes its decision, we can define two decision criteria (3) and (4), which have to be fulfilled so that adoption will take place in year T.

First, the net returns of adopting the borewell technology in *T* have to be positive (equation 3).

$$(3)\ \sum_{h=0}^{\infty} A_{1,i}(T+h,l)\delta(h) - C(T,l) - \sum_{h=0}^{\infty} A_{0,i}(T+h,l)\delta(h)\ \geq 0$$

Second, given the first criterion in equation (3), the net returns of adopting in *T* have to exceed the net returns of waiting for another year *T*+1 (4).

$$(4)\ \sum_{h=0}^{\infty} A_{1,i}(T+h,l)\delta(h) - C(T,l) - \sum_{h=0}^{\infty} A_{0,i}(T+h,l)\delta(h)\ \geq$$

$$A_{0,i}(T,l) + \sum_{h=1}^{\infty} A_{1,i}(T+h,l)\delta(h) - C(T+1,l)\delta(1) - \sum_{h=0}^{\infty} A_{0,i}(T+h,l)\delta(h)$$

$$\Leftrightarrow A_{1,i}(T,l) - C(T,l)\ \geq\ A_{0,i}(T,l) - C(T+1,l)\delta(1)$$

If the first criterion is given, then plugging equations (1), (2a), and (2b) into equation (4) and rearranging (see Appendix 1) leads to:

$$(5)\ q_1(T) - q_0(T)\ \geq\ \frac{C(T,l) - C(T+1,l)}{p(T,l)} + \frac{c(T,l)(a_1 - a_0)}{p(T,l)}$$

The left-hand side 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 his production system, and to what extent available 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 rain or has alternative water sources.

The first term on the right-hand side of equation (5) shows the difference of expected installation cost in T and $T+1$ normalized by 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 on one side, and all variables that are affected by the household's location on the other side. Hence, the household will adopt the borewell technology if the output gain due to a management system with borewell is not less than the net installation costs and additional net variable input costs relative to the price that can be achieved for the output gain. Therefore, the more pessimistic a farmer is about weather prospects and the better the access to borewell technology and in- and output markets, the higher the likelihood that he/she will adopt the technology.

Following this idea of likelihood, we can write down the household's decision problem in probabilistic terms:

$$(6)\ P_i(t) = \Pr\big(p(T,l)(q_1(T) - q_0(T)\big) - c(T,l)(a_1 - a_0) - C(T,l) + C(T+1,l)\ )\ > 0)$$

Viewing the decision criterion as a probability has the advantage that it can be directly connected with the hazard rate, which is the dependent variable in the framework of duration models and is defined as a limiting probability.

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

The connection between equations (6) and (7) can be understood as follows. The farmer's true expectations on profits as defined in equation (5) are unobservable. However we can observe whether and at what time a household did adopt the borewell technology. Assuming that the decision to adopt is based on equation (5), we can estimate the adoption probability of household *i* for period *h*, if the technology has not been adopted so far, i.e. the hazard rate (6). Furthermore, we can estimate covariate effects on the hazard rate and, thus, identify determinants of the adoption probability and farmers' profit expectations.

5 Econometric model

To operationalize the conceptual framework above, we first summarize the assumptions underlying duration models. The idea is that the technology becomes available to a sample population of households at a time point $t_{0,}$ and households subsequently—some sooner, some later—adopt the technology at time points $t+h$, h=1,…n. In our analysis we assume that t_0 = 1970, when borewell technology started to become broadly available (*Green Revolution*). We assume that by t_n all households in the sample will have adopted the technology. Thus, it is possible to estimate the adoption rates for every interval on the time line t_0 to t_n and in addition how adoption rates are influenced by different covariates. Figure 2 shows that a large share of the households in our sample have not yet adopted the technology. Those observations are called right-censored and it is assumed that they will adopt the technology in the future (Moore, 2016).

One of the most popular duration models is the so-called Cox model (7) (Cox, 1972). The hazard rate 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 and Grambsch, 2000).

(7) $\lambda_i(t) = \lambda(t, x_i) = \lambda_0(t)\exp(x_i'\beta)$

By assuming that the hazard ratio of different subjects stays constant throughout the entire time spell (proportional hazard), the baseline hazard can be left unspecified for estimating the covariate effects β. This is a big advantage over other duration models, because it means that we do not have to make a priori assumptions about the functional form of the baseline hazard. However, it is unlikely that the hazard ratio is actually constant over longer periods. One possibility to counter the proportional hazard assumption is to include time-variant variables as covariates in $x_i'\beta$ (Therneau and Grambsch, 2000). We do so by considering the control variables age, experience, SEC assets, and off-farm employment as well as all three rainfall variables as time-variant (Table 1).

Because we want to model urbanization effect in a two-dimensional non-linear fashion, we extend the linear predictor $x_i'\beta$ in (7) by a geoadditive predictor η_i (Kneib and Fahrmeir, 2007). Further, by transforming $g_0(t) = \log(\lambda_0(t))$ we can specify a semiparametric hazard rate model (8).

(8) $\lambda_i(t) = \exp(\eta_i(t))$

with

$$\eta_i(t) = g_0(t) + x_i'\beta + u_i(t)'\gamma + f_{spat}(s_i) + b_{g_i}$$

Thus, the geoadditive predictor consists of the log-baseline hazard $g_0(t)$, standard linear effects β of time-invariant covariates x_i, linear effects γ of time-variant covariates $u_i(t)$, effects of households' location s_i, and the village frailties[6] b_{g_i}.

To estimate the effects in this additive regression model, we rely on a mixed model approach introduced by Kneib and Fahrmeir (2007). The estimation of smoothing parameters for non-linear effects is conducted via restricted maximum likelihood. Instead of requiring Markov chain Monte Carlo (MCMC) simulation techniques as in a fully Bayesian approach, this can be done by a Laplace approximation. In this way, the smoothing parameters can be estimated from the data in advance, given priors for the other regression parameters. The result is an empirical Bayes approach (Kneib and Fahrmeir, 2007)[7].

We initially also estimated non-linear penalized (P) spline effects for some of the continuous control variables but the splines pointed towards linear relationships. Therefore, for the sake of parsimony, we only consider a non-linear two-dimensional effect for the household location. This effect we specify as a two-dimensional P-spline with eight knots and a two-dimensional first order random walk penalty.

We estimate different model specifications including different sets of covariates. We start with a base model that only includes the control variables. Then we add the village fixed effects and the location effect. Afterwards the rainfall data is added in three different ways: i. both the current and past years' values together (Spatial Model I), ii. only the current year's values (Spatial Model II), and iii. only the past

[6] In order to accommodate time-variant variables the data set has to be augmented to yearly observations for every household. Therefore, we obtain several observations per households. To correct for omitted variable bias, we also tested household random effects. However, since the AIC did not improve they were not considered further in the later analysis.

[7] For detailed information about the model, inference strategies, and a comparison with results from a fully Bayesian approach, see Kneib and Fahrmeir (2007).

year's values (Spatial Model III). To compare the model fit, we use the Akaike information criterion (AIC).

6 Results and Discussion

In Tables 4 and 5 we present the estimation results for the three model specifications (Spatial Model I-III) described above. Village random effects do not improve the model fit; therefore they are not included in the model specifications presented. For both transects Spatial Model I yields the lowest AIC. Nevertheless, it appears that the lagged rainfall variables are particularly important in the southern transect as models I and III show very similar AICs. However, we want to emphasis that in general the difference among the different model specifications is rather small. In addition, estimated coefficients are quite robust throughout all model specifications (including the base model). Location effects of the model specification with the best model fit are plotted in Figures 3 and 4.

[Table 4 and 5]

[Figure 3 and 4]

Since the hazard rate is modelled as an exponential function of the geoadditive predictor $\eta_i(t)$, we do not report the coefficients but their exponentials, which can be interpreted as the effects of unit changes in the corresponding covariates on the adoption hazard rate (AHR). A value larger than one implies that the AHR accelerates and a value smaller than one that it decelerates. For example, in Table 4 the exponential of the coefficient estimated for the effect of farm size is 1.0402. This means that for each additional acre c.p. the AHR—the probability to adopt the technology now and not wait for another year—increases by 4.68 percent. The exponential 0.9555 for age means that as the household head ages, the AHR decreases c.p. by 4.45 percent per year.

The main interest of this analysis is the effects of the different rainfall variables and the location effect. Before we turn to those results, we first present the results of the control variables. Multiple significant coefficients signal that general household characteristics are important when it comes to adoption decisions. Furthermore, several differences between the two transects are relevant for the interpretation of location and weather effects.

Results show almost identical effects for age and farm size in both transects. Thus, there is a decelerating effect on the AHR with increasing age of the household head and an accelerating effect with increasing farm size. All other effects somewhat differ between the transects. Experience has a statistically significant positive effect in both transect but it is higher in the southern (9%) than in the northern (5%) transect. In addition, the p-values for education are low (though not statistically significant) in the southern transect but high in the northern transect. Hence, the human capital of households seems to play a stronger role in the southern than in the northern transect. The effect of gender also differs; it is significantly negative in the northern and not significant in the southern transect. However, since share of female households in our sample is extremely low (Table 1), the effect should not be over-interpreted.

Transport equipment and durable assets were included as measures of the living standard of a household. The count of transport equipment has a significant negative effect in the southern transect in two out of three model specifications, but no significant effect in the north. In contrast, the effects of durable assets are only significant and negative in the northern transect. If we generally associate a higher count of assets with a higher living standard and wealth, those results would imply that wealthier households are less likely to adopt borewell technology. This is somehow counterintuitive as one would assume that wealthier families have better access to financial resources needed to invest in borewell technology.

Income diversification might explain this surprising effect. Even though we only consider farm households in our sample, these households likely have additional off-farm income sources. Additionally, there might be diversification in the agricultural production itself. The borewell technology is important for crop production but many farms also keep dairy cattle or other livestock. In our analysis we include a dummy for dairy production, but it is insignificant in both transects (however almost significant in the north). Nevertheless, in terms of income diversification off-farm employment is probably even more important. A number of studies show that smallholders—if they have access to a labor market—will diversify their income sources (Deichmann, Shilpi and Vakis, 2009; Fafchamps and Shilpi, 2003; Imai, Gaiha and Thapa, 2015). With Bangalore and other satellite towns in or close to the transects, it is likely that off-farm employment is available to many of the households in our data set. In the northern transect we find off-farm employment significantly reduces the AHR. Also the high magnitude of more than 80% in all three model specifications is worth noting. Generally, off-farm income can have two effects on agricultural production. Either additional income is invested in agricultural production (e.g. in form of technology adoption) (Barrett, Bezuneh and Aboud, 2001; De Jaunvry, Sadoulet and Zhu, 2005), or the relevance of the agricultural production for the income of the household decreases (Huang, Wu and Rozelle, 2009). In our case, at least in the northern transect, the later seems to be the case. Further, if we assume that off-farm employment eventually yields equal income if not higher than agricultural production, this might also explain parts of the inverse wealth effect. This point is also supported by the literature, where the decrease in adoption can be explained by higher management demands of new technologies and the opportunity costs of skilled labor (Pannell *et al.*, 2006).

This result is also very interesting in the light of our conceptual framework presented in section 4. There we focus exclusively on the maximization of of profit from agricultural production. However households also consider other sources of income, which should be included in the maximization problem. Models developed by Ellis (1993) or Henning and Henningsen (2007) could be a good inspiration for expanding our framework in future studies.

Turning to the effects of the rainfall variables, we also observe some differences between the transects. First of all, we have accelerating as well as decelerating significant effects of rainfall. The decelerating effect is intuitive. When there is more rainfall, the farmer has less need for a second water source and he might decide to wait another year (the value of waiting increases). When there is less rain and the drought pressure increases, the farmer is more likely to adopt the borewell now than in the next year. This idea also fits our conceptual framework of section 4 (equation (5)). If there is less rain, the farmer will expect a larger output difference between the two production systems than if there is sufficient rain.

However, how do we understand the accelerating effect whereby more rain increases the likelihood that a farmer adopts the technology? We observe this effect in both transects for the southwest monsoon rainfalls in year t-1. A year with more monsoon rains should be more productive in terms of agricultural output as the monsoon season is the principal growing season. Thus, this accelerated AHR might result from extra agricultural income or the desire to keep up with a previous successful season. In addition, a positive experience with a production system without a borewell will decrease the expected output difference in equation (5). Since we observe this effect in both transects, it seems that 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 risk (Koundouri et al., 2006).

In the southern transect the effect of the southwest monsoon in *t*-1 is most important in terms of significance and robustness over all model specification. One way to interpret this is to assume that households in the southern transect focus on long-term strategies in their agricultural management, i.e. returns from previous years are invested in agricultural equipment (borewell) and current weather phenomena do not significantly influence adoption or management decisions. However, the low response to weather variables might also result from the relatively high availability of alternative water resources in the southern transect. When describing the study area, we highlighted that there are some reservoirs and waste water drainages in the south of Bangalore. Thus, the drought pressure might not be as high on households in the southern transect.

In contrast, the households in the northern transect are more responsive to rainfalls. The lowest AIC obtains when current as well as lagged rainfall values are included. Further, we observe decelerating effects. This might imply some ad hoc decision making probably focusing more on the reduction of crop loss risk than commercializing production. It thus appears that drought pressure is substantially higher in the northern than in the southern transect. This also would fit the observation of the higher relevance of off-farm employment as alternative income source.

[Figure 3 and 4]

Next to the weather effects, our second focus is on the effect of households' locations in the rural-urban interface. In the northern transect we find the highest coefficients close to Bangalore (Figure 3). If we interpret the effect as access to markets and infrastructure this result is quite intuitive. In terms of Equation (5) the right-hand side decreases for households located closer to the city. Interestingly this effect holds only for Bangalore but none of the secondary towns located in or close to the transect.

The effect in the south is less clear and more difficult to interpret as access to Bangalore only in terms of geographic distance. It appears there are two adoption clusters in the center of the transect (Figure 4). One explanation might be the highway that cuts through the east side of the transect in North-South direction, creating better access due to infrastructure. In addition, the area with the most negative effect on adoption rates is located close to the largest water reservoir[8] in the south. Here, alternative water sources might be competing with borewell technology.

7 Conclusions

Addressing our primary research focus, we find that the amount of rainfall affects decisions in two ways. First, higher amounts of rain can lead to more successful seasons generating extra capital, which can be invested in borewells. We understand this effect as a strategic and planned investment decision. Second, decreasing rainfalls lead to accelerated adoption. Since these effects are rather observed for rainfalls in year *t*, they point towards ad hoc adoption behavior to decrease the risk of harvest loss.

The effect of a household's location in the rural-urban interface is less clear. In the northern transect it seems that better market access accelerates adoption rates. In the southern transect roads might improve

[8] This reservoir is located close to several villages. Thus, the village random effects might not fully control for biophysical spatial heterogeneity.

access to new technology. In addition, alternative water sources—such as the wastewater outflows of Bangalore in the south—seem to decelerate adoption rates.

These results coincide with the mechanisms we derived from the model we developed in the conceptual framework to explain farmers' decision making regarding the optimal time to adopt borewell technology. However it seems there is room for improvement. Our 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. Consequently, the relevance of agriculture production for households and their decision making decreases. Since borewell water is primarily used for agricultural activities, this will reduce adoption rates. This aspect should be incorporated into theoretical models explaining technology adoption decisions. The exclusive focus on production theory may not adequately capture the complex interactions and indirect effects we find in our empirical analysis.

Despite this shortcoming, we can derive some policy implications from this study. Support for off-farm labor sector in areas of high drought pressure could help to improve the living standard of smallholders and reduce stress on aquifers at the same time.

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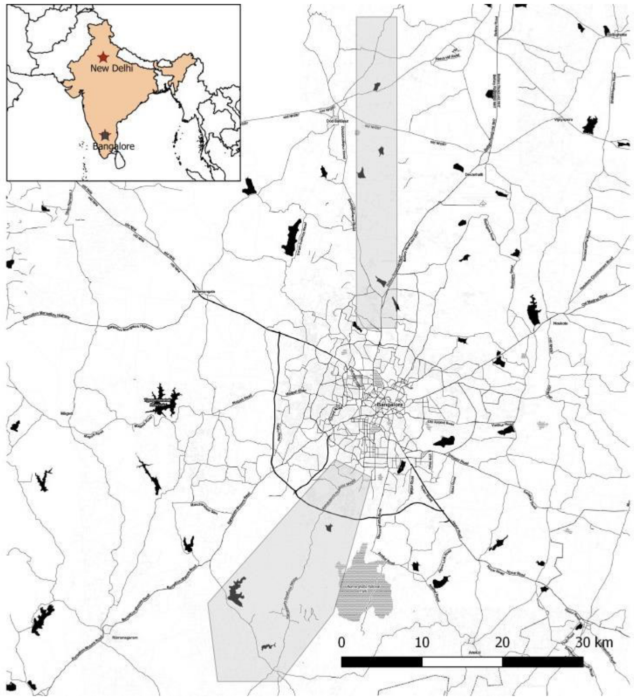

Figure 1. Research area. Grey polygons indicate northern and southern transect, respectively.

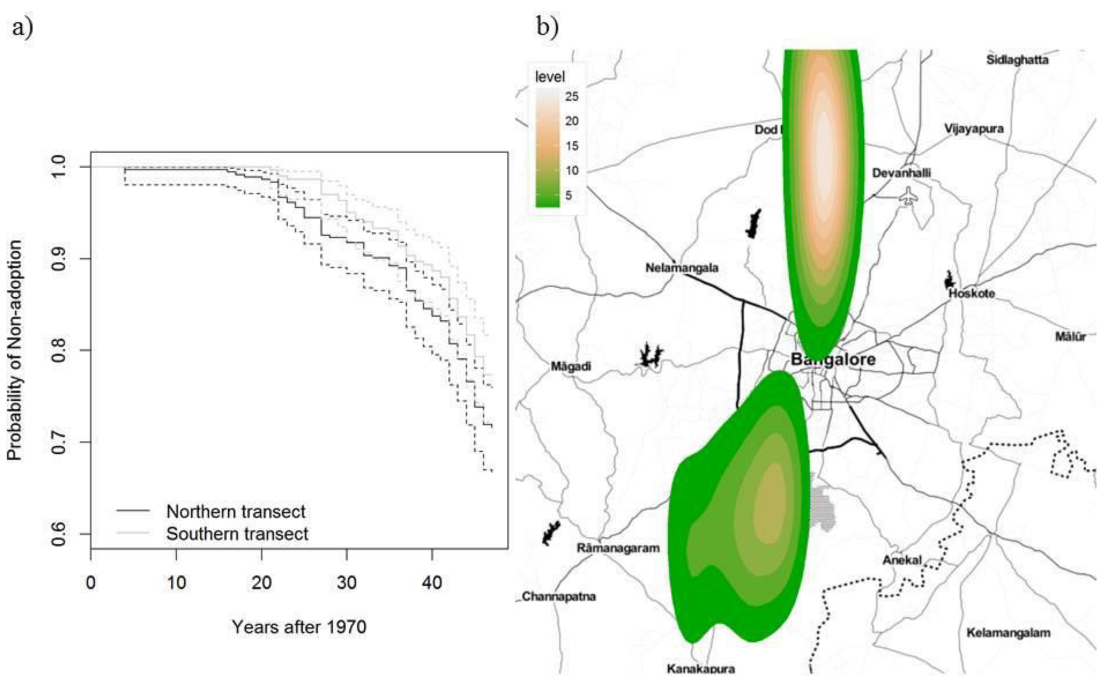

Figure 2. a) Kaplan-Meier plot of the probability of non-adoption over time since 1970 (in years) b) Heat map of borewell adoption based on our data set.

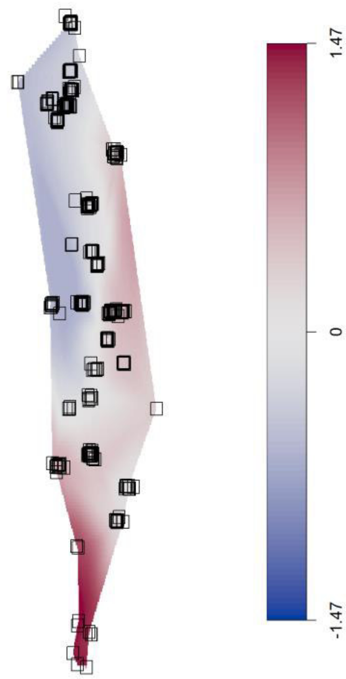

Figure 3. Location effect (two-dimensional P-spline) on the Adoption Hazard Rate in the northern transect (values are original coefficients, not exponentials)

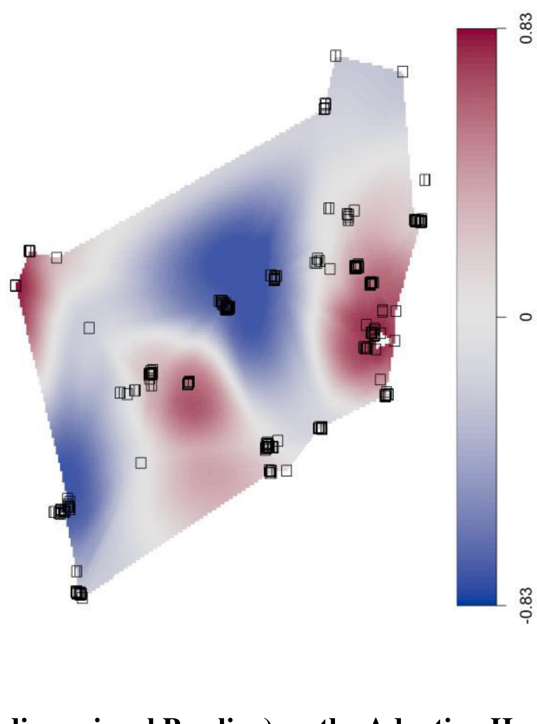

Figure 4. Location effect (two-dimensional P-spline) on the Adoption Hazard Rate in the southern transect (values are original coefficients, not exponentials)

Table 1. Descriptive statistics (Subsamples: Northern vs. Southern transect; Non-adopters vs. Adopters)

	All households			Northern transect			Southern transect		
	Non-adopt. (N=426)	**Adopters** (N=148)	**Total** (N=574)	**Non-adopt.** (N=227)	**Adopters** (N=88)	**Total** (N=315)	**Non-adopt.** (N=199)	**Adopters** (N=60)	**Total** (N=259)
Household characteristics									
Caste (Factor)									
General	0.4701	0.5605	0.4922	0.4314	0.4783	0.4438	0.5130	0.6769	0.5492
SC	0.1929	0.1083	0.1713	0.1686	0.1087	0.1527	0.2174	0.1077	0.1932
ST	0.0742	0.0382	0.0654	0.0824	0.0543	0.0749	0.0652	0.0154	0.0542
OBC	0.2227	0.2611	0.2321	0.2627	0.3370	0.2824	0.1783	0.1538	0.1729
Other	0.0413	0.0318	0.0389	0.0529	0.0217	0.0461	0.0261	0.0462	0.0305
Age (t)	50.1855	43.9257	48.5714	49.3877	43.9432	47.8667	51.0955	43.9000	49.4286
	(13.3048)	(13.6999)	(13.6732)	(13.4868)	(13.1301)	(13.5893)	(13.0684)	(14.6087)	(13.7522)
Gender (Dummy)	0.1878	0.1014	0.1655	0.2115	0.0682	0.1714	0.1608	0.1500	0.1583
Education	5.9718	6.5338	6.1167	6.5419	6.6250	6.5651	5.3216	6.4000	5.5714
	(4.8292)	(4.9079)	(4.8516)	(4.6906)	(4.6936)	(4.6841)	(4.9141)	(5.2439)	(5.0029)
Durable assets (t)	2.8122	1.4459	2.4599	2.8458	1.2386	2.3968	2.7739	1.7500	2.5367
	(1.2471)	(1.5354)	(1.4547)	(1.2366)	(1.4621)	(1.4882)	(1.2610)	(1.6011)	(1.4120)
Transport equipment (t)	0.7629	0.3649	0.6603	0.8282	0.4318	0.7175	0.6884	0.2667	0.5907
	(0.5761)	(0.5612)	(0.5978)	(0.5734)	(0.5832)	(0.6022)	(0.5716)	(0.5164)	(0.5861)
Off-farm employment (Dummy)	0.5892	0.2095	0.4913	0.6300	0.1136	0.4857	0.5427	0.3500	0.4981
Farm characteristics									
Farm size	2.3405	4.9180	3.0051	2.0782	5.3645	2.9963	2.6397	4.2630	3.0157
	(0.4926)	(7.6801)	(5.4134)	(3.3907)	(7.6112)	(5.1485)	(4.9030)	(7.7976)	(5.7292)
Experience (t)	27.6901	30.2838	28.3589	26.7753	30.2386	27.7429	28.7337	30.3500	29.1081
	(13.9063)	(14.3541)	(14.0565)	(13.6456)	(13.3967)	(13.6443)	(14.1601)	(15.7704)	(14.5334)
Dairy (Dummy)	0.7441	0.8649	0.7753	0.7313	0.8864	0.7746	0.7588	0.8333	0.7761

[a] Std. Deviation in brackets.
[b] For dummy and factor variables percentages are given.
[c] Statistics were derived based on variable values in 2016 for non-adopters, and variable values at the time of adoption for adopters.

Table2. Summary of rainfall variables

	Mean	Min	Max
Total Rainfall (mm)	777	475	1200
Pre-monsoon (mm)	158	60	313
Southwest monsoon (mm)	445	129	730

Table 3. Covariates included in geo-additive predictor

	Variable	Description
Time-invariant	Caste	1:General, 2:SC, 3:ST, 4:OBC, 5:Other
	Gender	0:Male household head, 1:Female household head
	Education	Years of education (household head)
	Farm size	Acres under management
	Dairy	0:No dairy production, 1:Dairy production
	Location	GPS coordinates of household
Time-variant	Age(t)	Age household head (years)
	Experience(t)	Years of farming experience (household head)
	Transport equipment(t)	Number of transport equipment available to household (according to new SEC index)
	Durable assets(t)	Number of durable assets available to household (according to new SEC index)
	Off-farm employment(t)	0: No household member involved in off-farm employment, 1: at least one member involved in off-farm employment
	Total Rainfall(t)	Millimeters of total rainfall in year t
	Pre-monsoon(t)	Millimeters of rain, January-May in t
	Southwest monsoon(t)	Millimeters of rain, June-September in t

Table 2. Estimation results, Northern transect [a)]

	Spatial Model I		Spatial Model II		Spatial Model III	
	exp(Coefficient)	p-Value	exp(Coefficient)	p-Value	exp(Coefficient)	p-Value
Intercept	0.0037	0.0255 *	0.0012	0.0014 **	0.0007	0.0013 **
Household characteristics						
Caste						
SC	0.5415	0.1273	0.4763	0.0662	0.4880	0.0762
ST	0.8270	0.7147	0.7969	0.6637	0.7851	0.6424
OBC	0.8497	0.5399	0.8140	0.4398	0.8309	0.4865
Other	0.5291	0.3907	0.5174	0.3774	0.5309	0.3951
Age (years)	0.9555	0.0002 ***	0.9489	<2e-16 ***	0.9491	<2e-16 ***
Gender						
Female	0.3559	0.0214 *	0.3334	0.0151 *	0.3406	0.0170 *
Education (years)	0.9827	0.5684	0.9708	0.3417	0.9737	0.3924
Durable assets (count)	0.6296	0.0001 ***	0.5694	<2e-16 ***	0.5773	<2e-16 ***
Transport equipment (count)	1.4948	0.1157	1.3894	0.2004	1.4005	0.1926
Off-farm employment						
Yes	0.1919	<2e-16 ***	0.1680	<2e-16 ***	0.1755	<2e-16 ***
Farm characteristics						
Farm size (ha)	1.0402	0.0039 **	1.0497	0.0003 ***	1.0451	0.0012 **
Experience (years)	1.0500	<2e-16 ***	1.0478	<2e-16 ***	1.0493	<2e-16 ***
Dairy						
Yes	1.9207	0.0706	1.8900	0.0771	1.8842	0.0783
Year t						
Total rainfall (mm)	0.9953	<2e-16 ***	0.9986	0.0423 *		
Pre-monsoon (mm)	1.0097	0.0048 **	1.0021	0.2757		
Southwest monsoon(mm)	1.0006	0.5510	0.9994	0.4712		
Year t-1						
Total rainfall (mm)	0.9975	0.0231 *			0.9994	0.4013
Pre-monsoon (mm)	0.9901	0.0002 ***			0.9933	0.0011 **
Southwest monsoon(mm)	1.0055	<2e-16 ***			1.0021	0.0052 **
AIC	1115.33		1148.58		1133.75	
N	7601		7601		7601	

[a)] Single, double, and triple asterisks (*, **, and ***) denote p = 0.05, p = 0.01, and p = 0.001, respectively.

Table 3. Estimation results, Southern transect

	Spatial Model I		Spatial Model II		Spatial Model III	
	exp(Coefficient)	p-Value	exp(Coefficient)	p-Value	exp(Coefficient)	p-Value
Intercept	0.0002	0.0117 *	0.0001	0.0005 ***	0.0002	0.0031 **
Household characteristics						
Caste						
SC	0.4105	0.0572	0.4184	0.0686	0.4060	0.0560
ST	0.1518	0.0707	0.1466	0.0669	0.1483	0.0677
OBC	0.5912	0.1849	0.5280	0.1143	0.5606	0.1475
Other	0.4045	0.2121	0.3689	0.1814	0.3999	0.2127
Age (years)	0.9405	<2e-16 ***	0.9318	<2e-16 ***	0.9363	<2e-16 ***
Gender						
Female	0.8761	0.7491	0.8132	0.6253	0.8256	0.6472
Education (years)	1.0594	0.0836	1.0509	0.1420	1.0561	0.1038
Durable assets (count)	1.0109	0.9268	0.9351	0.5515	0.9501	0.6474
Transport equipment (count)	0.5483	0.0874	0.4774	0.0349 *	0.5035	0.0482 *
Off-farm employment						
Yes	1.1624	0.6076	1.0406	0.8922	1.1148	0.7098
Farm characteristics						
Farm size (ha)	1.0601	0.0007 ***	1.0596	0.0007 ***	1.0611	0.0006 ***
Experience (years)	1.0863	<2e-16 ***	1.0875	<2e-16 ***	1.0867	<2e-16 ***
Dairy						
Yes	1.2380	0.5851	1.1721	0.6891	1.1985	0.6456
Year t						
Total rainfall (mm)	0.9971	0.0230 *	1.0003	0.7018		
Pre-monsoon (mm)	1.0090	0.0241 *	0.9998	0.9358		
Southwest monsoon(mm)	1.0006	0.5891	0.9996	0.6578		
Year t-1						
Total rainfall (mm)	0.9969	0.0196 *			0.9987	0.1572
Pre-monsoon (mm)	0.9935	0.0313 *			0.9950	0.0358 *
Southwest monsoon(mm)	1.0057	<2e-16 ***			1.0029	0.0018 **
AIC	819.876		836.508		822.746	
N	6547		6547		6547	

[a] Single, double, and triple asterisks (*, **, and ***) denote p = 0.05, p = 0.01, and p = 0.001, respectively.

Appendix

Appendix 1

Derivation of equation (5):

$$A_{1,i}(T,l) - C(T,l) \;\geq\; A_{0,i}(T,l) - C(T+1,l)\delta(1)$$

$$\Leftrightarrow A_{1,i}(T,l) - A_{0,i}(T,l) \;\geq\; C(T,l) - C(T+1,l)\delta(1)$$

$$\Leftrightarrow p(T,l)q_1(T) - a_1c(T,l) - p(T,l)q_0(T) - a_0c(T,l) \geq C(T,l) - C(T+1,l)$$

$$\Leftrightarrow p(T,l)(q_1(T) - q_0(T)) - c(T,l)(a_1 - a_0) \geq C(T,l) - C(T+1,l)$$

$$\Leftrightarrow p(T,l)(q_1(T) - q_0(T)) \geq C(T,l) - C(T+1,l)\,) + c(T,l)(a_1 - a_0)$$

$$\Leftrightarrow q_1(T) - \; q_0(T) \;\geq\; \frac{C(T,l) - C(T+1,l)}{p(T,l)} + \frac{c(T,l)(a_1 - a_0)}{p(T,l)}$$