Groundwater Use and Management along the Rural-Urban Interface:

Attitudes, Preferences and Decision Making Behavior

Dissertation

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I. Introduction

On a global scale freshwater consumption has increased by about one percent per year since the 1980s (WWAP, 2019). The increased consumption imposes stress on water resources and has led to or aggravated water scarcity in many regions all over the world. Water scarcity describes a situation when the demand for freshwater cannot be met. According to Mekonnen and Hoekstra (2016) over 4 billion people worldwide experience a lack of freshwater for at least one month of the year. These people face inadequate access to safe drinking water, sanitation and hygiene (WASH), but also diminished yields in agriculture. Moreover, water scarcity in the environment is related to its degradation and diminished water-related ecosystem services (Yeh and Huang, 2012; Mekonnen and Hoekstra, 2016; FAO, 2012).

Four main causes have been identified as the driving forces behind the increased stress on freshwater resources: population growth, socio-economic development, changing consumption patterns, and expansion of irrigated agriculture (WWAP, 2019; Yeh and Huang, 2012). Many of these changes happen in urban centers or are driven by urbanization. It is projected that urban water consumption will increase by 50-80 percent until 2050 to meet the increased demand for domestic and industrial purposes (Flörke et al., 2018). This imposes further water stress and scarcity mainly within the rural-urban interface where most of the cities' water supply is sourced from (Garrick et al., 2019; Decker et al., 2000; Kroll et al., 2012). Together with the expansion of irrigated agriculture in these areas, competition over water is spurred between the domestic, industrial and agricultural sectors but also between supply for cities, food security and rural livelihoods (Rozzoli and Maheshwari, 2016; Molle and Berkoff, 2009).

As rapid urbanization and the expansion of cities is mainly taking place in arid or semi-arid areas of Asia, the problem of water insecurity and related allocation problems between the domestic, industrial and agricultural sectors is most prevalent there. In particular, South Asia is one of the world's fastest urbanizing but also most water insecure regions (WWAP, 2019). In India alone some 600 million people lack water for at least one month per year (Mekonnen and Hoekstra, 2016). The problem is especially prevalent in and around rapidly increasing cities and megacities such as Delhi or Chennai (Punjabi and Johnson, 2019; Ray and Shaw, 2019). Within the next decade, more than 40 percent of India's urban population will live in cities, amounting to 600 million people (United Nations, Department of Economic and Social Affairs, Population Division, 2015). By 1960, only 16 percent of India's population lived in cities. Besides population growth, many of these urban areas have experienced an increase in real income per capita and show economic growth rates above the country's average (Bloom et al., 2008). Along with the increase in wealth, dietary patterns have diversified with increased intakes of meat, egg, and diary as well as vegetables and fruits, fats and oils (Pingali, 2007). As these products are more water-intense than products used for staple based diets such as rice and wheat but also to meet the demand of the growing population, the area under irrigation has increased from 29.5 percent in 1993 to 41.5 percent in 2013 (FAO, 2016). While traditional surface irrigation from communally managed tanks or channels was not sufficient to satisfy the needs, groundwater irrigated agriculture has become an important cornerstone to sustain food security (Kajisa et al., 2007). With 39 million hectares of groundwater irrigated area, India is the world's largest user of groundwater (Siebert et al., 2010; FAO, 2016). Along with the adoption of new variety seeds, chemical fertilizers, and pesticides, groundwater lifting technologies are one of the most important innovations which were introduced during the "green revolution" in the 1960s to improve agricultural productivity (Roy and Shah, 2002). With an increased variability in precipitation, soil moisture, and surface water due to climate change, the importance of groundwater will probably increase to sustain food security in India (Taylor et al., 2013). Nevertheless, the expansion of groundwater irrigated agriculture also led to a considerable drawdown in water tables showing the vulnerability of the resource.

With the growing tension between increased consumption and declining resources, the question arises how groundwater resources can be managed sustainably. Of particular interest is the question at the rural-urban interface where most of the competition over water takes place. In order to answer this question, this dissertation introduces three papers which use the rural-urban interface of Bengaluru in India as research area. The city exemplifies the development of many cities in the global south as it is rapidly growing in terms of physical extent and in population. By now the city has more than 11 million inhabitants which make it a megacity (United Nations, 2018). Moreover, Bengaluru has experienced a relatively large increase in per capita income along with a growing middle class. While the inner city itself is mainly supplied with water from the Kaveri River, the rural-urban interface mainly dependents on groundwater extraction for water supply. As in large parts of India, many small private borewells are used to extract groundwater. This development is favored by institutional and geohydrological circumstances. Access to groundwater is not limited and every land owner has the right to extract groundwater below their property. Moreover, the low storage capacity of hard-rock aquifers can sustain a large number of borewells. As land is often fragmented and plot sizes are rather small, many small wells have been established resulting in a high density of wells (Shah, 2009; Shah, 2014). As a consequence, many aquifers in the area are overexploited. Due to the small and individually used borewells, sustainable groundwater management is challenging as many individuals need to be addressed. Therefore, the three papers seek to understand how individual extraction decisions of groundwater users are made and understand what drives their decisions. These insights can be useful to achieve sustainable groundwater management. As urbanization transforms societies, the papers further aim to analyze the effects of urbanization on attitudes, preferences or social norms, and groundwater related decision making processes.

The first paper focuses on how inter-temporal decisions over risky outcomes are made and how urbanization affects the attitudes and preferences underlying these decisions. In the context of groundwater use, many decisions have uncertain outcomes and their consequences become visible only in the future. This includes the investment into groundwater lifting technology such as borewells as well as the quantity of extracted groundwater. For example, the profitability of an investment into groundwater lifting technology often depends on future prices for agricultural products, changing political framework or altering climate conditions which are not foreseeable at the time of the investment (Coble and Lusk, 2010). Having a good understanding about individual risk attitudes and time preferences can contribute to improve models which deal with intergenerational distribution of, for instance, groundwater resources or help to improve cost-benefit analysis for policy evaluation. Furthermore, the paper explores one of the most fundamental hypotheses of development economics. It is assumed that poorer people exposed to adverse risks and weak institutions are highly risk averse and reveal high discount rates, i.e. they are more impatient. As the adoption of new technologies implies uncertain or varying returns in the future, adoption is less likely to occur. However, without the adoption of new technologies, a substantial improvement in profits is less likely to achieve. Eventually the likelihood to remain poor increases for those households which do not adopt new technologies. Therefore, sub-optimal investment decisions are closely linked to risk attitudes and time preferences and even described as poverty trap

(Brick and Visser, 2015; Dercon and Christiaensen, 2011; Haushofer and Fehr, 2014). With the agglomeration of economies in cities and increased economic growth, spillover can enhance economic growth also in adjacent regions. Especially for low skilled workers, income opportunities increase (Christiaensen and Todo, 2014). Hence, urbanization provides opportunities to break out of this poverty trap and may thereby reshape preferences. Rural-urban comparisons in the past have presented contradictory results, regarding the risk attitudes and time preferences. In Tanzania, researchers found that urban dwellers are more impatient, i.e. reveal higher discount rates, than the rural population they studied (D'Exelle et al., 2012), while researchers in Vietnam found that urban dwellers are more patient than the rural population (Anderson et al., 2004). Considering risk attitudes, migrants to urban areas are more risk loving than their rural counterparts or assimilate to the more risk loving urban environment (Akgüç et al., 2016; Shi and Yan, 2018). Given these contradicting results for time preferences, further research is needed. Moreover, none of these studies considered how these risk attitudes and time preferences constitute in peri-urban areas. Another weakness of these studies is that time preferences have only been separately analyzed in rural urban comparisons (D'Exelle et al., 2012; Anderson et al., 2004). Yet, it has been shown that time preferences measured without taking into account risk attitudes are biased. Therefore, this paper aims to answer the following research questions: How do jointly measured risk and time preferences evolve along the rural-urban gradient? Which other individual and household characteristics shape these preferences? Two well established incentivized experiments, namely the Holt and Laury task (Holt and Laury, 2002) and the Coller and Williams (Coller and Williams, 1999) task were carried out to elicit risk attitudes and time preferences, respectively. In order to estimate these two jointly the estimation method of Andersen et al. (2008) was used.

The second paper explores how location and rainfall variability affect technology adoption decisions of groundwater lifting technology. As mentioned above, one of the most important pillars of India’s agricultural sector is groundwater irrigation. Even though India is the largest user of groundwater worldwide, there are still many farmers who have not adopted groundwater lifting technology yet and large areas still remain under rainfed agriculture (Srinivasa Rao et al., 2015). As urbanization provides additional income opportunities and market access, they might adopt deep wells, providing a perennial source of water. Moreover, changing rain patterns might lead to even higher adoption rates as outcomes of traditional rainfed agriculture might be even less predictable and more vulnerable to longer dry spells and more intense rainfall. However, the adoption of deep wells does not come without cost: more wells and uncontrolled water extraction can increase the water stress in the region. As a consequence, borewells fall dry, threatening the livelihood of other groundwater users. It is thus essential to implement policies that strike a balance between the present livelihood of smallholders and sustainable, long-term water resource management. For this purpose, a better understanding how and where farmers adopt borewell technology is necessary. Therefore, the second paper aims to analyze the determinants of farmers' borewell technology adoption decision, particularly when they face rapidly changing conditions due to urban growth and changing weather patterns. In order to achieve the objective a semiparametric hazard model was used to estimate the effect of location and precipitation on the adoption of borewell technology. While rainfall and distance to market places have been analyzed before in irrigation technology adoption studies, the explicit use of location has not.

The third paper analyzes how groundwater extraction decisions are made in groups and which institutional designs are able to prolong the life of the resource. As mentioned above, the access to aquifers is hard to restrict but groundwater is subtractable, i.e. rivalry in consumption is present. Hence, groundwater is a common pool resource (CPR) and decision making is interlinked. This also means that each user's decision could result in externalities experienced by other users. Therefore, users face a social dilemma situation in which short-term profit maximization leads to a fast depletion of the resource. In order to prolong the life of the resource, users would need to relinquish some of their immediate profits. While there is a rich literature how to design management institutions of CPRs and solve social dilemmas (Ostrom, 2010; Anderies et al., 2013; Cardenas et al., 2000; Cardenas and Carpenter, 2008), only a few have considered groundwater (Meinzen-Dick et al., 2016; Meinzen-Dick et al., 2018; Salcedo, 2014). The CPR management literature has identified two important types of institutions to overcome the social dilemma and manage CPRs sustainably. One strand states that external regulators are able to overcome the coordination problem in extraction by sanctioning and monitoring users (Schlager, 2007; Ross and Martinez-Santos, 2010; Cox et al., 2010). A second strand finds that collective action and internal coordination of users is more effective as crowding-out effects can be avoided which often result from the lack of local knowledge of the resource (Ostrom, 1990; Poteete and Ostrom, 2004). An important determinant of the success of a management institution depends on the attitudes of the users. In a theoretical model approach, researchers found that the user type who takes into account externalities and long-term effects of their action would extract less water without any intervention but increase water extraction if a costly intervention is applied (Madani and Dinar, 2012a; Madani and Dinar, 2012b; Madani and Dinar, 2013). Furthermore, the literature also states that the compliance of social norms is key for the success of CPR management institutions (Anderies et al., 2011). As urbanization affects social norms, the same institutional designs might affect decision making behavior differently at different stages of urbanization (Ostrom, 2000). Taking these three aspects together, the objectives of the paper are as follows: Firstly, three different designs of management institutions with regard to their effectiveness to prolong the use of groundwater are evaluated. These three designs embrace an externally imposed reward-based and an externally imposed punishment rule as well as cheap-talk communication to enable internal arrangements. Secondly, it is analyzed how different user types affect the outcome of these institutional designs. Thirdly, the performance of these institutional designs is assessed along the rural-urban interface which resembles different stages of urbanization. To do so, we conducted a dynamic resource extraction group experiment along the rural-urban gradient of Bengaluru.

In order to answer the research objectives, primary data was collected from 1200 agricultural and non-agricultural households along the rural-urban interface of Bengaluru. The sampling was done using a multistage approach. The first step was to define two transects in the north and south of the city. These two transects run along two major roads connecting Bangalore to two smaller cities, namely Doddballapur and Kanakapura. The two transects represent the rural-urban interface as they expand from the outskirts of Bengaluru, to rural areas up to 47.7 km away from the city center and about 39 km away from the most urban point in the transect. To be able to analyze different stages of urbanization, all villages or urban wards of the two transects were assigned a sample stratification index (SSI) developed by Hoffmann et al. (2017). The SSI consists of the product of the inverse of the built-up area and the distance to the city center of the village/ward. Afterwards, the villages/wards were stratified into six groups each. Out of these six strata, a total of 31 villages/wards were randomly selected from the northern transect and 30 villages/wards from the southern transects. As the main focus of the survey was agricultural households, more villages from the fifth and sixth strata were selected than from the first two strata. After the selection of the villages, the angandwadi officers (kindergarten teachers) were approached in these wards/villages in order to retrieve household lists. These lists are updated regularly by the officers and include all households in the village/wards even those who do not have children. In order to mitigate possible biases households were randomly selected from these lists.

Data was collected between December 2016 and early May 2017. The timing was chosen as the work-load of agricultural households is lower during the dry season. For the interview a computer assisted personalized interview (CAPI) technique was used. The questionnaire embraced socio-economic information, agricultural production, psychometric scales, assets and experiments to elicit risk and time preferences but also social generalized trust. The economic experiment was conducted between March and April 2017 and consisted of a sub-sample of 600 households.

The remainder of the dissertation is as follows. Chapter 2 discusses the first paper which explores the evolution of risk attitudes and time preferences along the rural-urban interface. Chapter 3 presents the second paper in which the adoption of groundwater lifting technologies in the two transects is analyzed. In chapter 4, the third paper is presented which analyses groundwater use and discusses potential designs for groundwater management institutions. Chapter 5 concludes, discusses the limitation of the studies and provides an outlook for further research.

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II. The evolution of risk attitudes and time preferences along the rural-urban interface – results from Bengaluru, India

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Abstract

One fundamental hypothesis in development economics is that poor households are and remain poor because of unfavorable economic behavior such as impatience and high risk aversion which hinder the adoption of new technologies and long-term investment decisions. However, these preferences may be reshaped when transformational processes such as urbanization take place. In this paper, we analyze how risk attitudes and time preferences evolve along the rural-urban interface providing thereby insights from rural and urban areas, as well as for the transitional area in between. Moreover, we want to find out which other individual and household characteristics shape these preferences. As risk attitudes and time preferences can explain household investment decisions, understanding how these preferences are influenced by urbanization can help to design policies which foster economic growth and reduce poverty. For our analysis, we jointly estimate risk attitudes and time preferences of 1,105 households along the rural-urban interface of Bengaluru, India. Our study shows that discount rates decline with decreasing urbanization while we find no considerable effect of urbanization on risk preferences. This result holds when we include other individual and household characteristics. From the literature we expected that risk aversion and impatience would decrease with increasing urbanization as urban areas are considered to be wealthier than rural areas. Controlling for different wealth measurement, risk aversion decreases as the number of assets possessed increases but discount rates increase. At the same time, risk aversion and discount rates decrease with the ownership of land. Hence, wealth only cannot explain differences in discount rates. Our results provide also important information for policy makers. Policies which aim to support investments such as investment incentives should take the differences between rural and urban areas into account.

Keywords: Discount Rates; Risk Aversion; Experiments; Urbanization; South Asia; India

1. Introduction

One fundamental hypothesis in development economics is that poor households are and remain poor because of unfavorable economic behavior such as impatience and high risk aversion which hinder the adoption of new technologies and long-term investment decisions (Haushofer and Fehr, 2014; Liebenehm and Waibel, 2014). However, these preferences may be reshaped when transformational processes such as urbanization take place. As the urban population is rapidly growing, in particular in low and medium income countries, understanding how risk attitudes and time preferences are reshaped by this process can help to craft policies which foster growth and reduce poverty.

In the past, researchers have compared preferences between rural and urban dwellers, however, results for time preferences have been mixed. Anderson et al. (2004) reveal high discount rates in rural areas and low rates in urban areas in Vietnam. They argue that urban areas are wealthier than rural ones, which explains the difference in discount rates. D'Exelle et al. (2012) find the opposite to be true in Tanzania and claim that modernization in urban areas and the persistence of the traditional concept of time (i.e. time has no economic value) in rural areas explain the difference in discount rates.

As for the comparison of risk preferences, many studies focus on migrants and how they differ from their rural counterparts. In China, researchers found that rural-urban migrants are more risk loving than their rural counterparts (Akgüç et al., 2016; Shi and Yan, 2018). This result is consistent with studies which look at migration in general (Dohmen et al., 2011; Jaeger et al., 2010).

However, none of these studies have taken into account that urbanization generates spillover effects which enable economic growth in adjacent rural areas and eventually reduce poverty (Christiaensen and Todo, 2014). As a reduction of poverty is associated with a decrease in risk aversion and impatience (Haushofer and Fehr, 2014; Tanaka et al., 2010), one would also expect that risk attitudes and time preferences differ in rural, peri-urban and urban sites. Moreover, the studies which reveal discount rates in rural and urban areas do not take into account the risk attitude of the respondents. As risk attitudes may differ in rural and urban sites, joint estimation of risk attitudes and time preferences is needed in order to estimate the true discount rates (Andersen et al., 2008; Liebenehm and Waibel, 2014; Nguyen, 2011).

To close the above mentioned research gaps, this study pursues two different objectives. Firstly, we want to assess how risk attitudes and time preferences evolve along the rural-urban interface. Secondly, we want to find out which other individual and household characteristics shape these preferences. As we expect that urbanization will change the structure of farms fundamentally in terms of production and employment, we put a particular emphasis on the agricultural sector. To achieve our objectives, we jointly estimate risk attitudes and time preferences using a structural model. We have conducted two well established elicitation methods for risk attitudes and time preferences – the Holt and Laury Lottery task (HL task, Holt and Laury (2002)) and the Coller and Willams task (CW task, Coller and Williams (1999)), respectively. For our study we use data of 1,105 households from the metropolitan area of Bengaluru and its surrounding areas. The city of Bengaluru was chosen as it is one of the fastest growing cities in the world (United Nations, Department of Economic and Social Affairs, Population Division, 2015) and has also shown an increase in wealth with the agglomeration of international information technology companies in the city.

To the best of our knowledge this study is one of the first which (i) jointly estimates risk attitudes and time preferences along the rural-urban interface and thereby provides insights from rural and urban areas, as well as for the transitional area in between. While there are few examples of joint estimations of risk attitudes and time preferences mainly from Vietnam, (ii) this study focuses on India.

The structure of the paper is as follows: section 2 reviews the literature and derives the hypotheses. Section 3 introduces the experimental design and study region while section 4 describes the joint estimation of risk attitudes and time preferences. Section 5 discusses the results while section 6 concludes.

2. Literature review and hypotheses generation

The literature to date has shown mixed results concerning differences between rural and urban economic preferences. For discount rates, Anderson et al. (2004) find that the rural population in Vietnam is more impatient than the urban population. They argue that this difference is rooted in the varying wealth levels in these two areas. This argument was taken up by Tanaka et al. (2010) who show that poverty makes people more impatient. However, the opposite is shown by D'Exelle et al. (2012) from a case study in Tanzania. They argue that urbanization induces a process of modernization which makes people more impatient, as opposed to the rural population that values time differently than people in more industrialized societies (time has no economic value). As for risk aversion, there is evidence that rural-urban migrants are more risk-loving than their rural counterparts (Akgüç et al., 2016; Shi and Yan, 2018). Therefore, one would assume that risk aversion is lower in urban areas. Assuming that income opportunities increase with urbanization, and taking into account that there is a negative relationship between income and risk aversion (Dohmen et al., 2011) as well as income and discount rates (Pender, 1996), hypothesis 1 can be formulated as follows:

H1a) There is a decline in risk aversion from rural to urban areas

H1b) Discount rates decline from rural to urban areas

It is assumed that poverty increases risk aversion and makes people more impatient in their economic decisions (Haushofer and Fehr, 2014). Recently, the effect of urbanization on poverty in rural areas has received more attention (Calì and Menon, 2013; Christiaensen and Todo, 2014). The agglomeration of industries in urban areas produces economies of scale and induces structural change. This process can generate economic growth which sprawls to surrounding areas. In this context, the expansion of secondary towns and villages can thus provide additional nonfarm income for unskilled or semiskilled laborers. As the rural population has been employed mainly in the agricultural sector before, we expect the most notable changes here. The additional income can have a consumption smoothening and poverty reducing effect which leads to less risk aversion and more patience. Therefore, hypothesis 2 is as follows:

H2a) Households with additional nonfarm income are less risk averse than those who have farm income only

H2b) Households with additional nonfarm income reveal lower discount rates than those who have farm income only

Besides labor markets, urbanization can also stimulate agricultural production due to an increased demand for more and higher quality agricultural products that also enables marketing and income opportunities for farmers. In a recent study, Vandercasteelen et al. (2018) show that agricultural intensification is affected positively by the proximity of major cities. Moreover, we would expect that commercial farmers are less risk averse than subsistence farmers. This leads to hypothesis 3:

H3a) Farmers that have intensified their agricultural production are less risk averse

H3b) Farmers that have intensified their agricultural production reveal lower discount rates

Finally, one important source of income in rural areas, which also increases the purchasing power of rural households, is remittances transferred from urban to rural areas. Those who receive remittances are more likely to have higher household incomes than those who do not. Therefore, hypothesis 4 is as follows:

H4a) Households who receive remittances are less risk-averse

H4b) Households who receive remittances reveal lower discount rates

3. Experimental design and estimation strategy

3.1. Eliciting individual time preferences

We used a multiple price list introduced by Coller and Williams (1999) and Harrison et al. (2002) to elicit time preferences. This methodology is commonly used to elicit risk attitudes and time preferences jointly (Andersen et al., 2008; Hermann and Musshoff, 2016; Liebenehm and Waibel, 2014).

In order to explain the method to participants with low educational backgrounds, the choice sets were illustrated with pictures of coins and dice on a choice card (see table A1 of the appendix for the choice card of the CW task). On each card there were ten rows, each of which consisted of two options the participants could choose from. Each option represented payoffs with different due dates. The first option was a payment of 120 INR[1] delayed by one week. The second option was a payment delayed by 3 months and one week that varied based on an ascending annual (effective) interest rate. The annual interest rates ascended in symmetric intervals of ten percent ranging from 10 to 100 percent. The individual time preference of a risk-neutral participant was revealed at the switching point from option A to B. If, for instance, a respondent chose option A twice and then switched to option B, the elicited annual effective discount rate for that person would range between 22 and 34 percent.

[1] Exchange rate during the survey was 75 INR ≈ 1 EUR; daily wages were between 100 and 300 INR for unskilled workers.

We incentivized the experiment by giving each participant cell phone credit according to their choices. To determine the payoff amount, the participants rolled a 10-sided die. The number on the die determined the row and the participants received the amount of either option A or B according to their choice in that row. The amount was transferred directly to the participant's account on the due date.

3.2 Eliciting risk attitudes

The HL task is a measure used to determine risk attitudes (Holt and Laury, 2002). The method has been carried out successfully in different developing country contexts (Brauw and Eozenou, 2014; Moser and Mußhoff, 2016).

We visualized the HL task with a decision card to make it more easily understandable (see table A2 of the appendix for an excerpt of the choice card). The cards contained two blocks named lottery A and lottery B. Each block contained a high and a low payoff. In lottery A, the high payoff is 100 INR and the low 80 INR while in Lottery B, payoffs are 192 INR and 5 INR for the high and low payoffs, respectively. As the variation between the two payoffs is lower in lottery A, it is the safer alternative. The subjects had to choose between the two blocks in 10 lines. With each line, the chance to win the high payoff was increased by 10%. In line one, the chance to win the high payoff is 10% and the low 90% percent, respectively. As probabilities are often not understood, a 10-sided die was used to illustrate them.

The HL task was also incentivized and participants could again win cell phone credit. After choosing lottery A or B in the 10 rows, the participant rolled a 10-sided die which determined the row. According to the participant's choice, lottery A or B was considered. Rolling the die a second time determined whether the high or the low payoff was paid out.

3.3 Study region and sampling

In order to evaluate how risk attitudes and time preferences evolve over the rural-urban interface in our study, the sampling design and the study area are presented here. The city of Bengaluru was chosen because it exemplifies the characteristics of rapidly urbanizing areas such as rapid expansion as well as ecological and infrastructural overloads.

In order to capture the effect of urbanization, we used three steps to identify our sampling households. Firstly, two transects in the northern and in the southern part of the city along two major roads were defined. The transects reach from the outskirts of the city to rural areas 40 km away from the city center. The villages and urban wards within the two transects were stratified into six groups such that each group represented a distinct stage in urbanization. For this purpose, the survey stratification index (SSI) was developed, consisting of the distance to the city center and the built-up density (Hoffmann et al., 2017). Secondly, 61 villages/wards were randomly selected so that the urban wards (stratum one and two) account for 20% of the sample, while peri-urban (stratum three and four) and rural villages (stratum five and six) make up respectively 40% of the sample (for the location of villages/wards see figure A3 in the appendix). Thirdly, household lists from the angandwadis (kindergartens) were acquired and households randomly selected. These household lists are updated regularly by the angandwadi-officers and include all households including those without children. In total, 1,275 households were sampled out of which 1,160 participants completed the survey. Out of these, 1,105 observations are used in this analysis as these are the households for which full information sets are available. The survey was carried out between December 2016 and May 2017 which is the dry season. The interviews were conducted one-on-one in the homes of the participants. Along with the experiments, a wide range of socio-economic characteristics, preferences and agricultural production information was asked for.

4. Joint estimation of risk attitude and discount rate

In order to derive a likelihood function which allows a joint estimation of the risk aversion parameter and the discount rate, some assumptions about the underlying utility function have to be made. Following Holt and Laury (2002) and Andersen et al. (2008), the utility function takes the form of the power utility function[2]

$$U(M) = \frac{M^{1-r}}{1-r} \tag{1}$$

where M denotes an income option and r a constant relative risk aversion (CRRA) (Holt and Laury, 2002; Andersen et al., 2008). As described before in section 3.2, for each row of the HL task, there is a choice between two lotteries with two possible payouts each. For

[2] We assume that the background consumption is 0 and that the payments are integrated in the consumption within one day Andersen et al. (2008).

every lottery i, the payout j is defined as M_{ij} and the probability of the payout as $p(M_{ij})$. Similar to Andersen et al. (2008), the expected utility (EU) for lottery i is expressed as

$$EU_i = \sum_{j=1,2} p\left(M_{ij}\right) \times \frac{M_{ij}^{1-r}}{1-r}. \tag{2}$$

Using equation (2), the probabilistic choice function $Pr_i^{HL}(A)$ which is the probability of a participant choosing lottery A instead of lottery B in choice situation i of the HL task is defined as

$$Pr_i^{HL}(A) = \frac{EU_A^{1/\mu}}{EU_A^{1/\mu} + EU_B^{1/\mu}}. \tag{3}$$

In order to allow noise in the deterministic Expected Utility Theory (EUT) model, the structural noise parameter μ (Luce, 1959)[3] is implemented. Using the probabilistic choice function in equation (3), the conditional log-likelihood can be derived as

$$\ln L^{HL}(r, \mu; y, \boldsymbol{X}) = \sum_i \Big((\ln(Pr_i^{HL}(A) \big| y_i = A) + (\ln(1 - Pr_i^{HL} \big| y_i = B) \Big), \tag{4}$$

where $y_i = j$ describes selection of lottery j in observation i, and $\boldsymbol{X}$ is a vector of individual and household characteristics (Andersen et al., 2008).

The derivation of the likelihood function for the discount rate measured with the CW task is comparable to the procedure for the HL task. The participants had the choice between the payout M_A in time t and the equal or larger payout M_B at time $t + \tau$ in each row i.[4] Assuming the power utility function of equation (1), the following present values (PV) of the two options can be derived:

[3] We applied the common error specification following Luce (1959). For an overview of modeling approaches for the stochastic components of behavior in experiments, we referred to Loomes (2005).

[4] We use M_A and M_B instead of M_t and $M_{t+\tau}$ as the discounting choices are labeled with A and B.

$$PV_A = \left(\frac{1}{1+\delta}\right)^t \times \frac{M_A^{1-r}}{1-r} \tag{5}$$

and

$$PV_B = \left(\frac{1}{1+\delta}\right)^{t+\tau} \times \frac{M_B^{1-r}}{1-r}. \tag{6}$$

Analogously to equation (3), the probability that a participant prefers payout A over payout B in row i of the CW task is defined as

$$Pr_i^{CW}(A) = \frac{PV_A^{1/\nu}}{PV_A^{1/\nu} + PV_B^{1/\nu}}. \tag{7}$$

Here, ν is a structural error term, comparable to μ from equation (3) (Andersen et al., 2008). However, it is not a condition that the values of μ and ν are identical.[5] The conditional log-likelihood takes the form of

$$\begin{aligned} \ln L\,(r,\delta,\mu,\nu;y,\boldsymbol{X}) \\ &= \sum_i \Big(\big(\ln(Pr_i^{CW}(A)\big|y_i = A\big) \\ &+ \big(\ln(1 - Pr_i^{CW}(A)\big|y_i = B\big)\Big), \end{aligned} \tag{8}$$

where $y_i = j$ describes selection of lottery j in row i (Andersen et al., 2008). For the joint estimation, the conditional log likelihoods of equation (4) and (8) are summarized to

$$\ln L\,(r,\delta,\mu,\nu;y,\boldsymbol{X}) = \ln L^{\mathrm{HL}} + \ln L^{CW}. \tag{9}$$

5. Results and discussion

5.1. Descriptive statistics

The descriptive statistics are presented in Table 1. The SSI variable is an index based on the inverse of the distance to the city center and the built-up density. We rescaled this

[5] Based on the higher complexity of the HL task, it is to be expected that $\mu > \nu$ (Andersen et al. (2008).

variable by a factor of 100 in order to make interpretation easier. Hence, a value of zero indicates a densely built area close to the city center whereas 100 indicates a rural area with the longest distance to the city center in our sample. According to the sample design, most households are located in more rural areas, therefore the SSI value is on average 59.77. Moreover, our sample consists of roughly 70 percent male and 30 percent female participants. The participants have completed on average six years of schooling and are mid-aged. The households own on average four durable or transportation assets according to the socio-economic classification (SEC[6]) and belong hence to the middle segment of the consuming class (MRSI, 2011). Roughly 56% of the households work in agriculture but the majority of these households generates additional income in non-agricultural sectors.

5.2. Results of the joint estimation without individual and household characteristics

Table 2 shows the results of the joint estimation of risk attitudes and time preferences without taking into account individual or household characteristics. The risk aversion coefficient r is 0.19 and its 95% confidence interval ranges from 0.12 to 0.25. This means that participants in our sample are on average slightly risk averse. Even though our sample comprises urban and rural populations, most studies find that the rural population in low income countries is extremely risk averse (Binswanger, 1980; Liebenehm and Waibel, 2014; Yesuf and Bluffstone, 2009), hence our results are different to these results. However, Nguyen (2011) also finds less risk averse participants in rural Vietnam.

Furthermore, Table 2 shows the estimated yearly effective discount rates. The estimate is 2.01, i.e. the elicited discount rate is 201%. Hence, the participants in the sample are extremely impatient on average. However, this result is consistent with previous studies in low income countries (e.g. Tanaka et al. (2010) find a monthly discount rate of about 168% in Vietnam). The two estimates μ and ν for the structural noise terms are statistically significantly different from zero. Consistent with the work of Andersen et al. (2008), we find that there are deviations from the deterministic EUT assumptions for both processes. Moreover, the estimate for the error term μ of the risk aversion task is considerably higher than for the time discount task ν. It has been argued that the HL task is more difficult than the CW task and therefore has a higher estimate. Our results are consistent with previous findings in this regard (Andersen et al., 2008; Hermann and Musshoff, 2016).

[6] The asset list comprises ceiling fans, LPG stoves, TVs, refrigerators, washing machines, PC/laptops, air conditioners, two wheelers, cars/jeeps/vans.

Table 1. Descriptive Statistics

Variable		Mean	Standard Deviation
Location			
SSI (urban = 0/ rural = 100)		59.77	24.67
Transect (south in %)		49.23	
Individual Characteristics			
Age (years)		44.42	13.79
Education (years)		6.46	5.26
Gender (male in %)		70.58	
Household Characteristics			
Assets (amount)		4.79	2.69
Caste (%)			
	General	46.06	
	Scheduled castes (SC)	19.73	
	Scheduled tribes (ST)	8.51	
	Other backwards castes (OBC)	24.16	
	Other	1.54	
Household size (number of persons)		4.65	2.22
Intensive agriculture (%)		47.51	
Land holdings (acres)		1.76	4.38
Remittances received (%)		3.07	
Time living in area (%)			
	>30 years	83.35	
	10 – 30 years	11.13	
	2 – 10 years	4.43	
	0.5 – 2 years	0.81	
	<0.5 year	0.27	
Employment			
Agricultural income only (%)		25.16	
Additional nonfarm income (%)		30.41	
Nonfarm income (%)		40.63	
Retired/unable to work (%)		3.80	
Number of observations		1,105	

Number of observation 22,080 (Number of clusters = 1,105)

Table 2. Maximum likelihood estimates of risk attitudes and time preferences without individual and household characteristics

	Estimate	Standard error	Lower 95% confidence interval	Upper 95% confidence interval
r	.1888	.0334	.1233	.2544
δ	2.0138	.1862	1.648	2.3789
μ	.4142	.0158	.3831	.4452
ν	.1400	.0101	.1201	.1598

5.3. Testing hypotheses

In order to test our hypotheses, we have estimated four different models. The results of the joint estimation are shown in table 3 for risk aversion and in table 4 for discount rates. Firstly, Model (1) simply includes the SSI variable. Secondly, model (2) controls for urbanization and the effect of wealth on economic preferences, while model (3) captures the spill-over effects of urbanization on surrounding areas. Finally, model (4) includes all For the joint estimation, the conditional log likelihoods of equation (4) and (8) are summarized tovariables of model (2) and (3) and adds individual and household characteristics.

In the first hypothesis, we were interested in how urbanization affects risk attitudes and time preferences. We do not find a statistically significant effect of the SSI on risk preferences in any of the different model specifications in table 3. However, all four models in table 4 show that this estimate has a statistically significant effect, at least at the five percent level, on the discount rates and has a negative sign. Our sample reveal a reduction in discount rates of 187 percent when there is a change from a completely urbanized area (SSI = 0) to a least urbanized area (SSI = 100). This outcome indicates that discount rates are lower in rural than in the urban areas and that there is a decline towards rural areas. Therefore, we cannot support hypotheses 1. This result is somewhat unexpected as we have seen in the literature that discount rates in rural areas in Asia are higher than in urban areas (Anderson et al., 2004). However, the result is in line with D'Exelle et al. (2012).

Table 3. Maximum likelihood estimates of risk attitudes with individual and household characteristics

Dependent Variable: risk aversion (*r*)				
Model	(1)	(2)	(3)	(4)
Location				
SSI (urban = 0/ rural = 100)	.0001	-.0004	.0001	-.0014
	(.0011)	(.0011)	(.0013)	(.0014)
Transect (north = 0/ south =1)				-.1007
				(.0626)
Individual Characteristics				
Age (years)				.0032*
				(.0019)
Education (years)				.0022
				(.0061)
Gender (female = 0 /male = 1)				-.0236
				(.0652)
Household Characteristics				
Assets (amount)		-.0201**		-.0263**
		(.0094)		(.0114)
Caste (ref. group: general castes)				
Scheduled castes (SC)				-.1423*
				(.0777)
Scheduled tribes (ST)				-.1095
				(.0164)
Other backward classes (OBC)				-.1495**
				(.0692)
Other				-.1802
				(.1973)
Intensive agriculture (0/1)			.0093	.0008
			(.0710)	(.0750)
Land holdings (acres)		-.0049		-.0075*
		(.0042)		(.0042)
Remittances (0/1)			-.3415**	-.2684
			(.1718)	(.1829)
Time living in area (ref. group: > 30 years)				
10 – 30 years			-.0233	-.0157
			(.1047)	(.1035)
2 – 10 years			.0666	.0506
			(.1441)	(.1486)
0.5 – 2 years			.4477	.2064
			(.4821)	(.4236)
<0.5 year			.4656***	.2486
			(.1232)	(.1563)
Employment				
Income group (ref. group: nonfarm income)				
Agricultural income only			.0321	.0067
			(.0779)	(.0806)
Additional nonfarm income			-.0066	.0141
			(.0781)	(.0759)
Retired/unable to work			-.1001	-.2226
			(.1729)	(.1694)
Constant	.1791***	.3174***	.1792**	.3789**
	(.0772)	(.0928)	(.0827)	(.1688)

Note: Number of observation 22,080 (Number of clusters = 1,105). Standard errors in parentheses. Single, double, and triple asterisks (*, **, and ***) denote $p < 0.10$, 0.05, and 0.01, respectively.

Table 4. Maximum likelihood estimates of time preferences with individual and household characteristics

Dependent Variable: discount rate (δ) Model	(1)	(2)	(3)	(4)
Location				
SSI (urban = 0/ rural = 100)	-.0251***	-.0177***	-.0236***	-.0187**
	(.0074)	(.0061)	(.0073)	(.0078)
Transect (north = 0/ south =1)				-.8143***
				(.2830)
Individual Characteristics				
Age (years)				-.0044
				(.0085)
Education (years)				.0045
				(.0277)
Gender (female = 0 /male = 1)				.1604
				(.2748)
Household Characteristics				
Assets (amount)		.1354***		.0985*
		(.0400)		(.0531)
Caste (ref. group: general castes)				
Scheduled castes (SC)				-.2918
				(.3051)
Scheduled tribes (ST)				.3297
				(.4487)
Other backward classes (OBC)				.4164
				(.3525)
Other				.5763
				(1.2388)
Intensive agriculture (0/1)			.1353	.1604
			(.2855)	(.2871)
Land holdings (acres)		-.0378***		-.0325**
		(.0080)		(.0123)
Remittances (0/1)			.2695	.1351
			(.7449)	(.7002)
Time living in area (ref. group: > 30 years)				
10 – 30 years			.2819	.1974
			(.4700)	(.4569)
2 – 10 years			-.5556	-.4134
			(.5692)	(.5174)
0.5 – 2 years			-1.0183	-.3503
			(1.1880)	(1.459)
<0.5 year			4.3260	4.603
			(4.3599)	(4.8018)
Employment				
Income group (ref. group: nonfarm income)				
Agricultural income only			-.5598*	-.3982
			(.3152)	(.3248)
Additional nonfarm income			-.2042	-.2871
			(.3269)	(.3337)
Retired/unable to work			-.6209	-.1645
			(.6948)	(.6330)
Constant	3.6384***	2.5906***	3.708***	3.301***
	(.6209)	(.5249)	(.6363)	(.8623)

Note: Number of observation 22,080 (Number of clusters = 1,105). Standard errors in parentheses. Single, double, and triple asterisks (*, **, and ***) denote $p < 0.10$, 0.05, and 0.01, respectively.

One explanation could be that wealth and income opportunities do not evolve gradually along the rural-urban interface. Another explanation could be that rural households are wealthier than urban households. If we control for the number of assets owned by a household according to the SEC in India (MRSI, 2011), we see that households who own more durable and transportation assets are less risk averse and more impatient. This result holds for model (2), where only measurements for wealth are included, and for the full model (4)[7]. In model (2), the results are statistically significant at the five percent level for risk aversion and at the one percent level for discount rates.

For the full model (4), the effect is statistically significant at the 10% level for discount rates and remains at the five percent level for risk aversion. In terms of risk aversion, this result is not surprising and is consistent with the literature. However, the results concerning the discount rate are not what one would have expected given the existing literature, which associates additional income with reduced discount rates (Haushofer and Fehr, 2014; Tanaka et al., 2010). If we compare the mean value of assets possessed by a household along the rural-urban interface, it shows that there are no differences between urban and peri-urban areas (stratum one to four) but between urban and rural areas (stratum one and two). In rural areas, households possess on average 1.14 assets less than those in the urban or peri-urban areas. Therefore, we cannot support the general assumption that poverty increases the discount rate.

Land holdings are also often used to measure wealth in particular in low-income countries (Vieider et al., 2018). Owning land is also used for the SEC in India. The results indicate a reduction in risk aversion behavior at the 10 percent significance level in model (4) but no statistically significant effect in model (2). The results in model (4) are again consistent with the literature. If we look at the discount rates, we see a negative effect at the one percent significance level in model (2) and at the five percent level in model (4). This result seems consistent with the fact that urbanization increases land prices. Waiting pays off as the value of land is likely to increase in the future.

The second hypothesis was derived from the literature that deals with the spillover effects of urbanization on adjacent areas. We wanted to control for whether additional nonfarm income would lead to a change in economic behavior. None of the variables specified in

[7] All values of the VIF are below two, hence, there is no multicollinearity issue.

model (3) or (4) are statistically significant in table 3 or 4. Therefore, we cannot support hypothesis 2a and b as well.

If we control for intensification (measured as whether farmers use modern variety seeds or inorganic fertilizers), there is no statistically significant effect in model (3) or in model (4) on risk attitudes or discount rates. Our hypothesis was that the city creates spillover effects which lead to more intensive agriculture in the surrounding areas, and that those who have intensified their agriculture have better marketing opportunities and would be less risk averse and more patient. However, we cannot support hypothesis 3a and b.

When we look at the payment of remittances, we see in model (3) that those who receive remittances are less risk averse than those who do not, as we predicted in hypothesis 5a. The effect is negative and significant at the five percent level. However, the effect vanishes if we control for other individual and household characteristics in model (4). Moreover, we do not find a statistically significant effect on discount rates in any of the two models. Therefore, we cannot support hypothesis 4a and b.

Finally, we have included several other controls in model (4). One concern is that migration into the city or even rural-rural migration could drive the difference in time preferences and risk attitudes between rural and urban populations. In previous studies it has been shown that migrants are risk-takers (Dohmen et al., 2011; Jaeger et al., 2010). If we include a categorical variable asking for the time living in the area, we find a statistically significant effect at the one percent level for those who have lived in the area for less than six months in model (3) and at the 10 percent level in model (4). However, the sign is positive. This result suggests that those who recently arrived are more risk-averse than those who have lived longer in the area. However, this result should not be overstressed as there are only three households in the sample who are in this group.

We also control for differences between the two transects. We see that the samples in the northern and southern transects differ in time preferences. Participants in the southern transect are more patient than participants in the northern transect. Table 5 shows the outcome of the regression of the SSI for both transects separately. While the constants are different, the SSI is not statistically significant for risk aversion but statistically significant with the same sign and a comparable magnitude for the discount rates in both regressions.

Table 5. Maximum likelihood estimates of risk attitudes and time preferences for Northern and Southern Transect separately

	Northern transect	Southern transect
Risk aversion (r)		
SSI (urban = 0/ rural = 100)	-.0023	.0026
	(.0015)	(.0016)
Constant	.4195***	-.0773
	(.0959)	(.1010)
Discount rate (δ)		
SSI (urban = 0/ rural = 100)	-.0313**	-.0320***
	(.0131)	(.0100)
Constant	4.353***	3.897***
	(1.1868)	(.8146)
Number of observations	11,220	10,880
Number of clusters	561	544

Note. - Standard errors in parentheses. Single, double, and triple asterisks (* , ** , and ***) denote p < 0.10, 0.05, and 0.01, respectively.

Another concern is how socio-demographic characteristics affect decision making. We find a positive and statistically significant effect of age on risk attitudes at the 10 percent level. This result is consistent with other findings in the literature (Tanaka et al., 2010). For education, results are quite mixed in the literature. Some find that higher education favors patient and more risk averse behavior (Bauer and Chytilová, 2010; Tanaka et al., 2010). Others do not find any relationship between these variables (Cassar et al., 2017). In our case, the outcome for education is also statistically insignificant. However, we find that the more economically and socially disadvantaged castes show a slightly higher risk taking behavior. For the scheduled caste (SC) the effect is significant at the 10 percent level and for the other backward classes (OBC) at the five percent level. However, we do not find this difference for the discount rates.

6. Conclusion

The elicitation of risk attitudes and time preferences can help to understand production and investment decision behavior. In particular the effect of urbanization on these preferences in low and middle income countries can help to craft policies which foster growth and reduce poverty.

In this paper we have analyzed how risk attitudes and time preferences evolve along the rural-urban interface using a structural model to estimate these preferences. Moreover, we wanted to analyze which individual and household characteristics shape these preferences. To do so, we use 1,105 observations in the rural-urban interface in Bengaluru, India.

We find that our sample is on average slightly risk averse and highly impatient which is consistent with the literature. We had expected a decline in risk aversion and discount rates from rural to urban areas. Instead we do not find any statistically significant differences for risk aversion along the interface and contrary to our expectations an increase in discount rates from rural to urban areas. In order to understand why urbanization has such puzzling effect on time preferences, we included different measurements of wealth to evaluate the influence of different income levels on these preferences. When we control for durable and transportation assets, the results show that people with more assets are less risk averse and more impatient. This result is puzzling as we had expected less risk aversion and lower discount rates. As expected, households in peri-urban and urban areas hold more assets than households in rural areas. Therefore, we cannot directly link poverty to impatience. This raises the question of how consumption and consumption opportunities might affect decision making and how economic development and poverty is affected by this. The results show that people are less risk averse and more patient, the more land they own when controlling for land holdings. This makes sense as land prices increase when the city expands and will hence increase the value of properties in the future.

As most fundamental changes induced by urbanization will probably occur in the agricultural sector, we control for influences on rural areas that are enabled by nearby urbanization such as income diversification or intensification of the agricultural production. However, we do not find any statistically significant effect of these variables on risk or time preferences. The same holds for remittances which are another important source of income diversification in particular in rural areas. Therefore, our hypotheses that income diversification or intensification of agricultural production decreases risk aversion and impatience cannot be supported.

Our results provide important information for policy makers. Policies which aim to support investments such as investment incentives should take the high discount rates into account. Adequate timing of the provision seems to matter for a successful implementation of such policies. Moreover, the differences between rural and urban areas should be taken into account.

Future research could focus on why impatience increases with the number of assets. One explanation might be that consumption opportunities is a stimuli for impatience. However, this question cannot be answered within the scope of this article. Our study is limited to

Bengaluru, India. Whether or not our results are generalizable to other low and medium income countries is left for future research. Moreover, the results of the study could be validated by using different methods to elicit risk attitudes and time preferences.

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Appendix

Table A1. Excerpt Choice card of Coller and William task

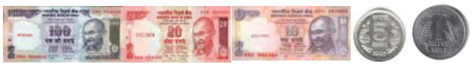
	Plan A	Plan B	Annual Interest Rate (in %)	Annual effective Interest Rate (in %)
	in 1 Week	in 3 Month + 1 Week		
1			10	10,471
2			20	21,939
3			30	34,489
4			40	48,213
5			50	63,209
6			60	79,586
7			70	97,456
…	…	…	…	…

Table A2. Holt and Laury lottery decision table (excerpt)

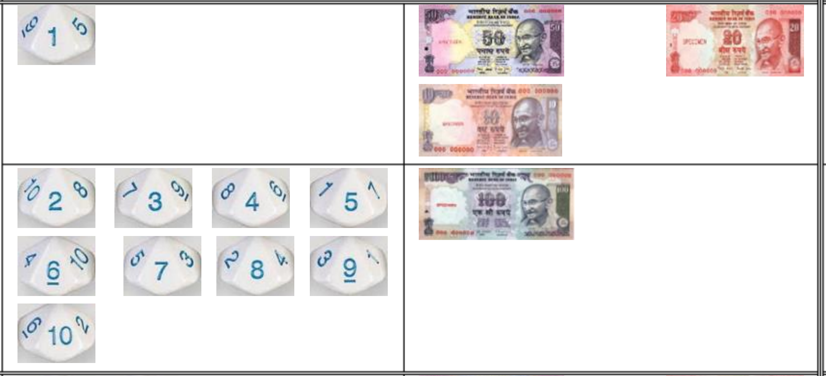
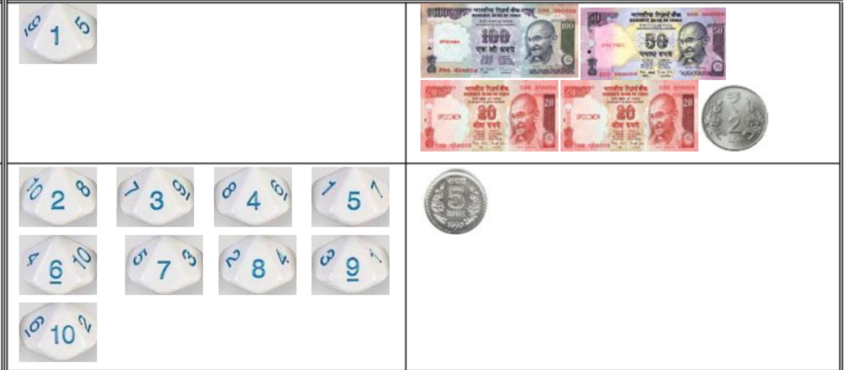
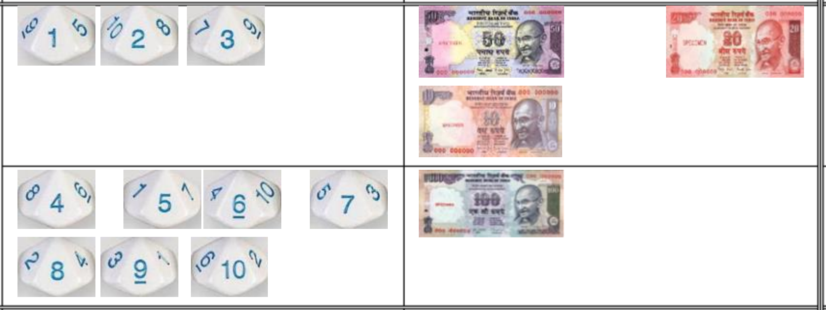
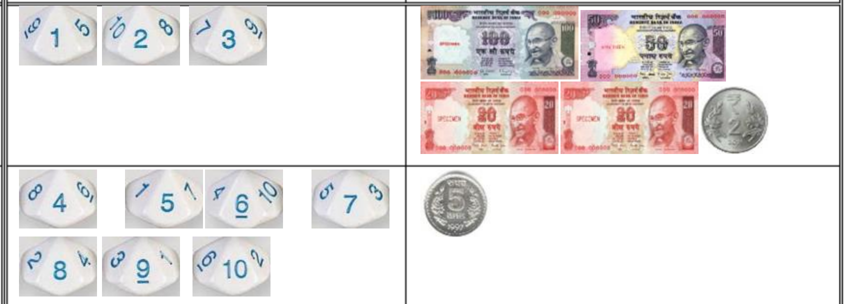
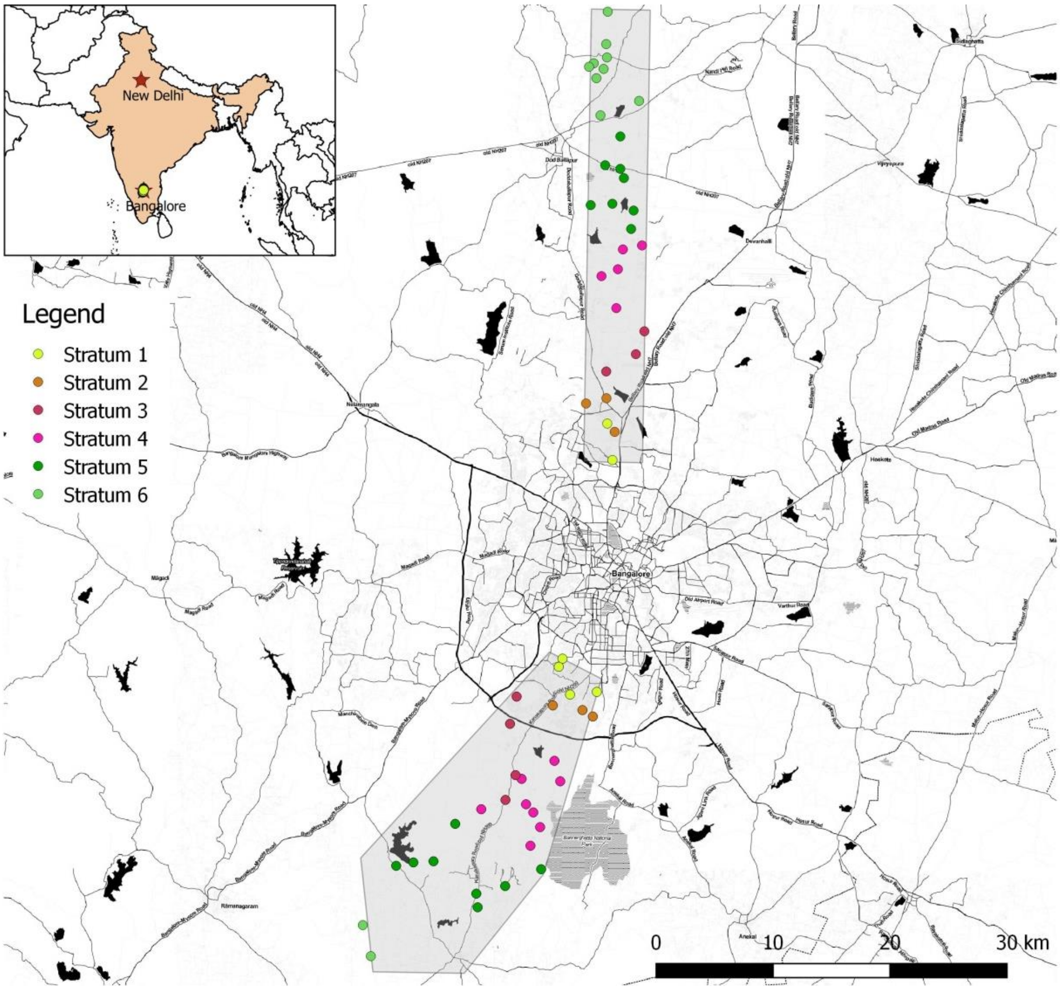
	Plan A	Plan B
1		
2		
3		
...		

Figure A3. Map of research area[a)]



[a)]Note: Shaded areas depict the two transects. Colored points depict selected villages.

III. Digging deep and running dry – the adoption of borewell technology in the face of climate change and urbanization

Authors: Linda Steinhübel, Johannes Wegmann, Oliver Mußhoff

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. We first developed a theoretical framework that conceptualizes how household location and weather affect farmers' adoption decisions. Afterwards, we conducted an empirical analysis based on a primary data set collected in 2016 and 2017, covering 574 farm households. With a semiparametric hazard rate model, we analyzed determinants of the borewell adoption rate. We incorporated different rainfall variables and a two-dimensional penalized spline (P-spline) to capture the effects of household location. Results show that proximity to the city center of Bangalore and to roads accelerates adoption rates. In terms of weather variability, we find that a higher amount of total annual rainfall decelerates adoption rates whereas higher amounts of rainfalls during the southwest monsoon, the most important cropping season, accelerate adoption rates. Furthermore, we find that off-farm employment decreases adoption rates.

Keywords*:* borewell technology, climate change, India, semiparametric duration models, urbanization

1. Introduction

The spread of borewell technology in India has surged 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. Two possible drivers of this phenomenon are the economic development in India and a shift in rain patterns due to climate change. Economic development has led to higher incomes and urbanization has improved access to markets and has made it more profitable to modernize and 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 (Alcon et al., 2011), thereby making borewell technology an attractive option to compensate for unreliable or lack of sufficient rainfall.

Nevertheless, 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 dry up, 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 availability of water resources.

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. Accordingly, the goal of this article is to analyze farmers' decisions to adopt borewell technology in the face of rapid urbanization and changing weather. Urbanization and weather changes are part of a global phenomenon and exhibit strong, temporal as well as spatial characteristics. Therefore, to better understand their effects on agricultural management decisions, there is a need for more flexible, theoretical and empirical models that incorporate the dimensions of both space and time.

To achieve this objective, we first developed a microeconomic model that captures how weather and location can influence farmers' decision-making towards technology adoption. Secondly, in our empirical analysis, we applied 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 (Dadi et al., 2004;

Abdulai and Huffman, 2005; Euler et al., 2016). However, to our knowledge, none of these studies included an explicit location effect. If space was considered in previous studies, it was generally limited to one-dimensional proxies, such as distance to markets (Chamberlin and Jayne, 2013). Our two-dimensional location effects have two considerable advantages. Firstly, they allow for more complex and systematic spatial patterns, for example if there are several market centers accessible to a household. Secondly, 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: We first give a short overview of irrigation in South India and technology adoption. Then we develop a conceptual framework (section 3) and describe our survey design and data set (section 4). In section 5 we present our empirical strategy with a brief introduction to duration models and the particular model specification applied in our study. Finally, we discuss our results (section 6) and summarize our findings (section 7).

2. Background on irrigation in South India and technology adoption

The adoption of borewells has been 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 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. The reasons are manifold. Firstly, 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. Secondly, the maintenance of local water bodies requires high labor inputs. Thirdly, 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. However, increased output prices for agricultural products have lowered the relative price of groundwater irrigation (Kajisa et al., 2007). Due to the aforementioned reasons, India is now the biggest user of groundwater globally.

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 individual farm level, several factors were 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 as well as increased volatility in weather events (for rainfalls in the Bangalore area see Appendix 2) (Alcon et al., 2011; Genius et al., 2014). At farm level, unfavorable slopes and soil characteristics (Koundouri et al., 2006; Genius et al., 2014) as well as farm size and the degree of commercialization increases the probability to adopt (Feder et al., 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 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 she will adopt earlier than other producers. Since learning and implementation may require traveling, opportunity costs can be high and impede technology adoption (Sunding and Zilberman, 2001). More recently, the interconnectedness of market access and technology adoption has been studied. Damania et al. (2017) found 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, unclear. While off-farm income may have a positive effect on adoption due to income security, it might also have a negative effect if it reduces the need to generate more farm income (Pannell et al., 2006).

3. Conceptual framework

To identify mechanisms of technology adoption in the context of weather variability and urban proximity and to motivate the duration model applied in section 5, we provide some microeconomic intuition in this section. Irwin and Bockstael (2004), Abdulai and Huffman (2005), and Genius et al. (2014), for example, presented frameworks in their studies. However, they did not address the issue of household location in an urbanization setting or the effect of weather on household's decision making.

We assume smallholders to be 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, i.e. 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 $A_{s,i}$ is generated by either system as function of time period t and household i's location l.[8]

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

$A_s(t,l)$, 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 input prices $c(t,l)$ and expected used inputs a_s.[9]

According to equation (1), farmers' expectations are determined by three factors, namely time (t), location (l), and the chosen production system (s). Note that both prices $p(t,l)$ and $c(t,l)$ depend on time t. Furthermore, 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 input 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 (Minten et al., 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

[8] For better clarity we drop the subscript i in equations (1) to (5), but we want to emphasize that all these equations refer to farmers' expectations and, thus, depend on i.

[9] Note that we purposefully use the term of operating cash flows because we do not consider any installation costs of the borewell technology in equation (1), i.e. operating cash flows can be understood as yearly profits only considering variable input costs.

sophisticated inputs. Therefore, the quantity of inputs used, a_s, depends on the chosen production system s but is assumed to be independent of time and location. Furthermore, a system with a borewell as a water source (s=1) is likely to generate a higher output as 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) are very likely to vary with changing weather patterns, i.e. time. For example, if a farmer expects decreasing rainfall, the expected outputs from a rainfed production system will also decrease. Therefore, the weather component of our research objective is captured by allowing farmers' expectations regarding output quantities to vary over time.

In addition, one could argue that q_s also depends on location, i.e. rainfall might show spatial patterns, or alternative and location specific water sources, such as reservoirs, lead to differences in farmers' expectations. However, a simplified model with $q_s(t)$ instead of $q_s(t, l)$ was chosen for the following two reasons. Firstly, the research transects are rather small (maximum lengths about 40 km). Thus, considerable spatial differences in rain patterns are unlikely. Secondly, all possible alternative water sources (primarily water reservoirs) in the research area are rainwater dependent. That means farmers' expectations concerning their reliability also depend on their expectations about weather, rather than the location as such. In that way, a management system without borewell (s=0) does not necessarily mean rainfed agriculture, but agriculture dependent on resources dependent on rainfalls.

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.

Equation (1) and the one-time installation costs, $C(t, l)$, are the basic building blocks that we use to formalize the decision of a profit maximizing farmer. By modeling decision dynamics, the study was not so much interested in the adoption decision itself but its timing (*optimal timing problem*). Therefore, we assume that—based on the farmers' expectations—the farmer optimizes the time of adoption. For simplicity, we limit the time horizon of the decision to T+1, i.e. until the technology is adopted, the farmer decides every year whether to adopt a borewell now or wait another year[10]. This decision is based on the comparison of the expected net returns, $V(T, l)$, of adopting a borewell in time period T (equation 2a), and the expected net returns, $V(T+1, l)$, of adopting a borewell in time period T+1 (equation 2b).

$$V(T, l) = \sum_{h=0}^{\infty} A_1(T+h, l)\delta(h) - C(T, l) - \sum_{h=0}^{\infty} A_0(T+h, l)\delta(h) \tag{2a}$$

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

$$-A_1(T, l) - \sum_{h=1}^{\infty} A_0(T+h, l)\delta(h) \tag{2b}$$

If the technology is adopted in T (equation 2a), the expected net returns are given by the expected 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 expected net present value of the production system without the technology. The net present value of a production system with a borewell (s=1) represents the farmer's expectation of all potential profits, which she makes after the installation of the 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 the well. Analogously, in equation (2b) the first two elements depict the profits from one more year in the management system without the borewell plus all profits after the installation 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 (2a) and (2b) are the basis on which household i makes its decision, two decision criteria were defined, which have to be fulfilled so that the adoption

[10] We are aware that there exists a full strand of literature on *optimal stopping problems* and *stochastic dynamic optimization* (Dixit and Pindyck, 1994; Abdulai and Huffman, 2005). However, based on our experience and conversation with farmers in the field, the simplification we propose represents the time horizon of decision-making in our research area. For instance, many farmers make cropping decision from season to season which underlines farmers' short-term decision-making.

of the borewell technology takes place in year T. First, the net returns of adopting the borewell technology in T have to be positive:

$$V(T,l) \geq 0 \Leftrightarrow \sum_{h=0}^{\infty} A_1(T+h,l)\delta(h) - C(T,l) - \sum_{h=0}^{\infty} A_0(T+h,l)\delta(h) \geq 0 \tag{3}$$

Secondly, given the first criterion in equation (3), the technology is adopted in T, if the net returns in time T exceed the net returns of waiting for another year T+1:

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

$$\Leftrightarrow \sum_{h=0}^{\infty} A_1(T+h,l)\delta(h) - C(T,l) - \sum_{h=0}^{\infty} A_0(T+h,l)\delta(h) \geq$$
$$A_0(T,l) + \sum_{h=1}^{\infty} A_1(T+h,l)\delta(h) - C(T+1,l)\delta(1) - A_1(T,l) - \sum_{h=1}^{\infty} A_0(T+h,l)\delta(h)$$

$$\Leftrightarrow A_1(T,l) - A_0(T,l) - C(T,l) \geq A_0(T,l) - A_1(T,l) - C(T+1,l)\delta(1)$$

$$\Leftrightarrow A_1(T,l) - A_0(T,l) \geq \frac{1}{2}[C(T,l) - C(T+1,l)\delta(1)] \tag{4}$$

Furthermore, plugging equations (1), (2a), and (2b) into the last line of equation (4) and rearranging (see appendix 1) leads to:

$$q_1(T) - q_0(T) \geq \frac{C(T,l) - C(T+1,l)}{2p(T,l)} + \frac{c(T,l)(a_1 - a_0)}{p(T,l)} \tag{5}$$

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 her 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 and timely 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 two times the price of one output unit q_s.

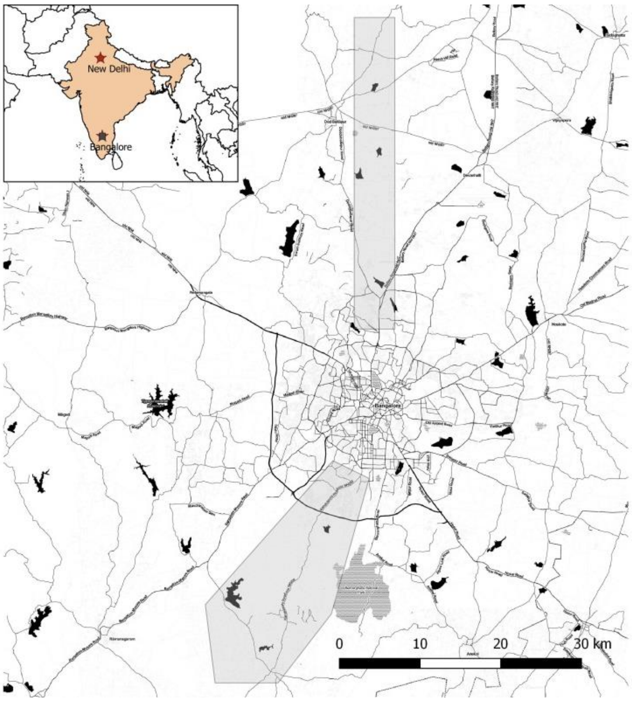
Similarly, the second term describes the difference between the variable inputs of both production systems normalized by the unit output price. Note that this representation places all variables that are influenced by farmers' expectations concerning weather and water availability in general on one side, and all variables that are affected by the household's location on the other side. Thus, the household will adopt the 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 can be achieved for the output gain. Therefore, the more pessimistic a farmer is about weather prospects, and the greater the access to borewell technology and input and output markets, the higher the likelihood that she adopts the technology in *T*.

4. Survey design and data set

The empirical analysis is based on data collected in a survey of 1,275 households in two transects following the rural-urban gradient of Bangalore (Fig. 1) and thus capturing potential 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 (SSI) was used to classify all villages in the transects into three strata (rural, peri-urban, urban) (Hoffmann et al., 2017). Then, ten villages in each stratum per transect were randomly selected. This equates to about one third of all villages located in the transects. Afterwards, on average 20 households[11] were randomly drawn from the household lists of the selected villages. All households were interviewed between December 2016 and May 2017.

Because the focus is on the adoption of borewells for agricultural purpose, in the following analysis only households that grew at least one crop in 2016 were considered (farm households). Therefore, our sample comprises a total of 574[12] households of which 315 are located in the transect north of Bangalore (northern transect) and 259 in the transect south of Bangalore (southern transect).

[11] We adjusted the number of households interviewed according to the total population of the respective village.
[12] This number already excludes all observations (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.



Source: Survey data.

Fig. 1. Research area, grey polygons indicate northern and southern transect, respectively

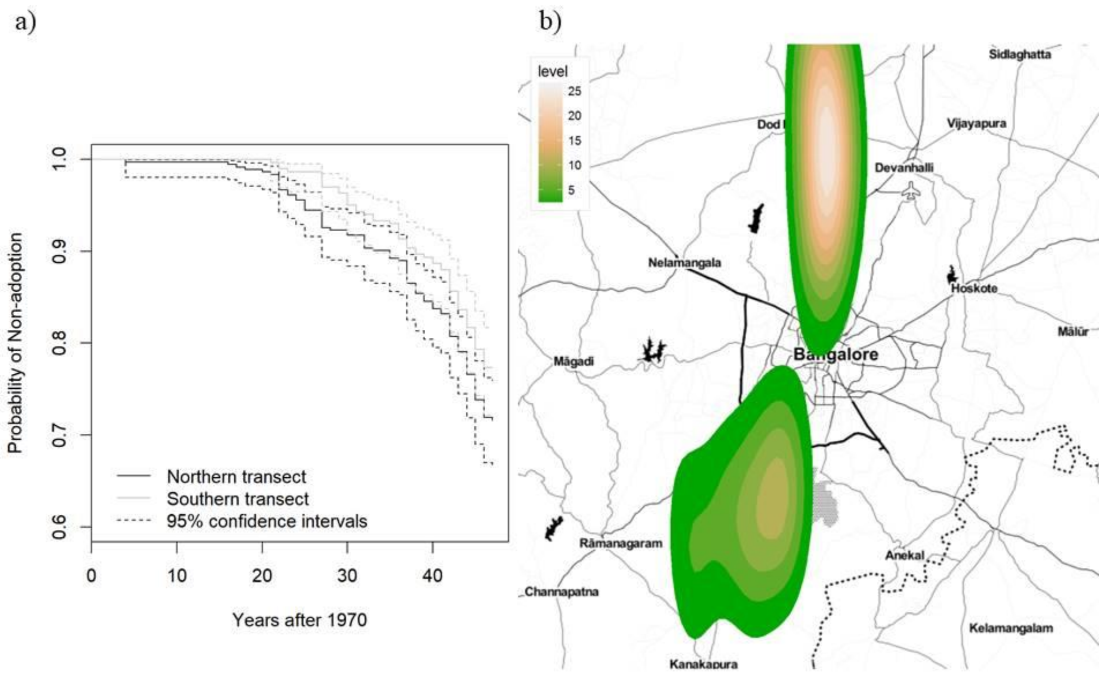
All 574 farm households were asked whether they have a borewell and, if yes, when they installed it. This information was used to estimate adoption probabilities and the hazard rate, which is the dependent variable in the duration model framework. To prevent recall bias and heaping effects[13], i.e. a farmer is more likely to give responses such as five or ten years than seven years, we asked farmers to give the year of adoption instead of the number of years that they have a borewell. In addition the histogram in appendix 3, shows that that there is no obvious heaping. Therefore, we are confident that recall bias in the dependent variable is no issue in our empirical analysis and hence strategies such as interval censoring to correct it were not applied. Fig. 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 (Fig. 2b), which is confirmed by the Kaplan-Meier estimates[14] of non-adoption probabilities (Fig. 2a).

[13] 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 appendix 4).
[14] 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).

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	0.47	0.56	0.49	0.43	0.48	0.44	0.51	0.68	0.55
SC	0.19	0.11	0.17	0.17	0.11	0.15	0.22	0.11	0.19
ST	0.07	0.04	0.07	0.08	0.05	0.07	0.07	0.02	0.05
OBC	0.22	0.26	0.23	0.26	0.34	0.28	0.18	0.15	0.17
Other	0.04	0.03	0.04	0.05	0.02	0.05	0.03	0.05	0.03
Age (t)	50.2 (13.31)	43.93 (13.7)	48.57 (13.67)	49.39 (13.49)	43.94 (13.13)	47.87 (13.59)	51.1 (13.07)	43.9 (14.61)	49.43 (13.75)
Gender (Dummy)	0.19	0.10	0.17	0.21	0.07	0.17	0.16	0.15	0.16
Education (Dummy)	5.97 (4.83)	6.53 (4.91)	6.12 (4.85)	6.54 (4.69)	6.63 (4.69)	6.57 (4.68)	5.32 (4.91)	6.4 (5.24)	5.57 (5.0)
Durable assets (t)	2.81 (1.25)	1.45 (1.54)	2.46 (1.46)	2.85 (1.24)	1.24 (1.46)	2.4 (1.49)	2.77 (1.26)	1.75 (1.6)	2.54 (1.41)
Transport equipment (t)	0.76 (0.58)	0.37 (0.56)	0.66 (0.6)	0.83 (0.57)	0.43 (0.58)	0.72 (0.6)	0.69 (0.57)	0.27 (0.52)	0.59 (0.59)
Off-farm employment (Dummy)	0.59	0.21	0.49	0.63	0.11	0.49	0.54	0.35	0.50
Farm characteristics									
Dairy (Dummy)	0.74	0.86	0.78	0.73	0.89	0.77	0.76	0.83	0.78
Experience (t)	27.69 (13.91)	30.28 (14.35)	28.36 (14.06)	26.78 (13.65)	30.24 (13.4)	27.74 (13.64)	28.73 (14.16)	30.35 (15.77)	29.11 (14.53)
Farm size (ha)	2.34 (0.49)	4.92 (7.68)	3.01 (5.41)	2.08 (3.39)	5.37 (7.61)	3.0 (5.15)	2.64 (4.9)	4.26 (7.8)	3.02 (5.73)

Source: Survey data.
Note: Std. Deviation in brackets. For dummy and factor variables percentages are given. Statistics were derived based on variable values in 2016 for non-adopters, and variable values at the time of adoption for adopters.



Source: Survey data.

Fig. 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 (N=148, households)

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.

To address the two major points of interest of our study, we needed variables capturing weather variability and spatial heterogeneity in the rural-urban interface. Because rainfalls have become more and more volatile in recent years in the Bangalore area (appendix 2), substantially increasing the drought pressure in the respective years, we believe the amount of rainfall is a good proxy to capture 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, not only the amount of total yearly rainfalls, but also the amount of pre-monsoon rainfalls and of rainfalls during the southwest monsoon (major growing season) was included in our dataset. A summary of the rainfall variables are presented in Table 2. Furthermore, we consider current and previous years' rainfalls. Obtaining data on rainfalls in India can be challenging in terms of availability and quality. Hence rainfall data for the *Bangalore urban* district published on the website of the Agrometerology Department of the University of Agricultural Sciences, Bangalore (UASB) was used. This was because the department collects daily real-time data on an entire set of meteorological variables and presents disaggregated measures such as pre-monsoon or southwest monsoons on a yearly basis. Therefore, we are confident that their data sufficiently represents rainfalls in the research area.

A common approach to model systematic spatial heterogeneity caused by a city in the research area is to use measures, such as distance or travel times to the city. These serve as proxies for access to markets and other infrastructure (Chamberlin and Jayne, 2013). Particularly, the access to input and output markets has been identified as an important channel by which cities influence smallholders' decision making processes (Minten et al., 2013; Damania et al., 2017). However, urbanization dynamics in the rural-urban interface of Bangalore are likely to be 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 one-dimensional proxy such as distance or travel time for every household. Therefore a household's explicit location in two-dimensional space was used to capture market access, i.e. all households were geo-referenced so that we could use their GPS coordinates to directly model two-dimensional location effects (see section 5.3).

Table 2
Summary of Rainfall Variables, 1970-2016

	Mean	Min	Max
Total Rainfall (mm)	777	475	1,200
Pre-monsoon (mm)	158	60	313
Southwest monsoon (mm)	445	129	730

Source: Rainfall data (Department of Agrometerology, UASB).

Furthermore information was collected on standard control variables, such as age of household head, gender and caste, but also dummies representing income composition, namely dairy production and off-farm employment (for descriptive statistics see Table 1). To capture the wealth or living standard of a household, a count of assets was used and applied to classify households in the *New Socio-Economic Classification (SEC) system*

(MRSI, Market Research Society of India, 2011). The assets included transport equipment, such as a car or two wheelers, and other durable assets like TVs, laundry machines or air conditioners.

5. Empirical strategy

5.1. Introduction to duration models

Traditionally, duration analysis—often also called survival analysis—originates from the fields of biology or medicine. It is applied when researchers are interested in the timing of certain events such as the outbreak of a decease or the time of death after a particular treatment (Moore, 2016). However, this type of model has been applied to explain technology adoption, and its ability to capture dynamics in time is highlighted as one of its biggest advantages (see for example Dadi et al., 2004; Abdulai and Huffman, 2005; Euler et al., 2016). That means we cannot only identify determinants of farmers' decisions to adopt a technology but also farmer's time preference—hazards—to adopt a new technology.

The general idea is that as 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 $t+h$, $h=1,\dots n$. In our analysis it is assumed that t_0 = 1970 when borewell technology started to become broadly available (*Green Revolution*). One important technical assumption of duration models is that there exist a time t_n when all households adopted the technology. Based on the observed adoption time spells it is possible to estimate the probability of (non-)adoption at all different points in time t. In the framework of duration analysis this probability is referred to as hazard rate $\lambda_i(t)$ and serves as dependent variable for estimating covariate effects:

$$\lambda_i(t) = \frac{\lim_{h\to 0} \Pr(t \leq T^* < t + h \mid T^* \geq t)}{h} \tag{6}$$

In this particular case, the hazard rate $\lambda_i(t)$ can be understood as follows: the probability that a household will adopt a borewell in the next time interval h, if it has not adopted the borewell until t, divided by the length of interval h. T is a non-negative random number and the non-adoption spell ends if $T = t$.

Furthermore, we can directly link the decision criterion (equation (5)) derived in the conceptual framework to the hazard rate (equation (6)), if we rewrite it in its probabilistic terms:

$$P_i(t) = \Pr\Big(p(T,l)\big(q_1(T) - q_0(T)\big) - c(T,l)(a_1 - a_0) - \frac{1}{2}[C(T,l) - C(T+1,l)\delta(1)]) > 0\Big) \quad (7)$$

The farmer's true expectations on profits defined in equation (7) are unobservable. However, we observed whether and at what time a household did adopt the borewell technology. This information can then be used to estimate the hazard rate (equation (6)). Assuming that the decision to adopt is based on equation (7), effects of covariates on the hazard rate defined in equation (6) can be estimated and used to validate the mechanisms derived in the end of section 3.

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

$$\lambda_i(t) = \lambda(t, x_i) = \lambda_0(t)\exp(x_i'\beta) \quad (8)$$

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 and Grambsch, 2000).

The overall framework of the Cox model was used in the empirical analysis. However, to accommodate more flexible effects, an extension with a semi-parametric predictor was applied, which will be introduced in section 5.3.

5.2. Preparation of the data set

The maximum adoption spell in our analysis lasts from 1970 to 2016 and is measured in years. Because we decided to include time-varying covariates in our analysis the data set had to be augmented in a way that there is one observation per year and household, i.e. a maximum number of 47 observations per household.

Note that the consideration of time-varying covariates has two important methodological advantages. Firstly, one general assumption of the Cox model is that the hazard ratio of different subjects stays constant throughout the entire time spell (proportional hazard).

Therefore, the baseline hazard can be left unspecified for estimating the covariate effects β. This is a big advantage over other duration models because no a priori assumptions about the functional form of the baseline hazard are necessary. However, it is unlikely that the hazard ratio is actually constant over longer periods such as the 47 years in our case. One possibility to counter the proportional hazard assumption is to include time-variant variables as covariates in $x_i'\beta$ (Therneau and Grambsch, 2000). Therefore, the control variables age, experience, SEC assets, and off-farm employment as well as all three rainfall variables were considered as time-variant (appendix 5). Secondly, covariates such as off-farm employment or wealth insdicators (durable assets or transport equipment) might cause some problems of reverse causality or endogeneity if they are included in a cross-sectional fashion. For example, wealth cannot only influence the adoption of a borewell due to more available capital, but a borewell might also have a wealth effect due to high agricultural output. However, if we include these covariates as time varying, we establish temporal causality and, thus, avoid these issues.

Furthermore, an indicator variable (1/0) for each year observation that signals whether or not the household adopted the borewell technology was implemented in the respective year. Once the household adopted the technology (*t*=*T*) all subsequent year observations were dropped; the adoption spell of the respective household ended. Comparably, year observations were omitted, if households entered the adoption spell later due to migration or age. These observations are called left-truncated. As a consequence, our final data set for estimation included 7,601 observations for the northern and 6,547 observations for the southern transect. Another aspect that is important, especially for applied studies, is right-censoring. Both Table 1 and Fig. 2 show that a large share of the households in our sample has 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). In the data set this was handled by the indicator variable, which remains zero in the last year observation (year 47) of the household.

5.3. Model specification

The effect of household location in the rural-urban interface was modeled in a two-dimensional non-linear fashion and, thus, the linear predictor $x_i'\beta$ in equation (8) was extended to a geo-additive predictor η_i (Kneib and Fahrmeir, 2007). Furthermore, by transforming $g_0(t) = \log(\lambda_0(t))$, the following semiparametric hazard rate model was specified:

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

with

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

Thus, the geo-additive predictor consisted of the log-baseline hazard $g_0(t)$[15], standard linear effects β of time-invariant covariates x_i, linear effects γ of time-variant covariates $u_i(t)$, effects of household location s_i, and the household and village random effects b_{g_i}.

The effect of household location $f_{geo}(s_i)$ was modeled as two-dimensional panelized spline (P-spline) with ten knots and a two-dimensional first order random walk penalty. Consequently, the model yielded a non-linear two-dimensional estimate of the effect that a particular position in the research area has on the adoption hazard rate (AHR). Because the P-spline was our attempt to model the effect of urbanization, i.e. market access, on the timing of adoption decisions of households, we had to ensure that the spline only captures urban influences. Thus, we had to rule our other exogenous spatial (e.g. biophysical) heterogeneity among the observation points. We accounted for this issue by allowing for household and village random effects[16], which correct for omitted variables, such as local variation in soil quality and other small-scale biophysical characteristics.

In addition, these random effects correct for other time-varying variables on household and village level that are omitted because they are very difficult to collect, especially over the time of 47 year. Examples would be crops, which have been grown in the past years, or other information concerning the agricultural management system. By allowing for the random intercepts on household and village level, the group-specific unobserved variation

[15] The log-baseline is estimated as one-dimensional penalized spline (P-spline) with 3 degrees of freedom and 20 knots (appendix 4).

[16] 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. Household random effects were excluded after primary estimations because they did not improve the model fit (AIC). We also included an elevation variable in our empirical analysis to capture geo-physical variability. However, estimation results did not show any significance (10% level). Additionally, the model fit (AIC) improved after excluding the variable. Therefore, it is no longer considered in the presented empirical results.

was controlled for and we could be confident that the estimated coefficients of other covariates are valid.

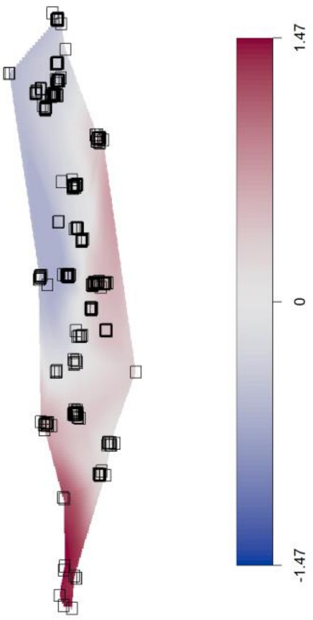
For the inferences of the additive regression model in equation (9), we relied on a mixed model approach introduced by Kneib and Fahrmeir (2007). The model was implemented in the software *BayesX* and the respective R-package *R2BayesX* (Umlauf et al., 2015). The estimation of smoothing parameters for non-linear effects was conducted via restricted maximum likelihood. This estimation approach relies on a Laplace approximation and, thus, no Markov chain Monte Carlo (MCMC) simulation techniques as in a fully Bayesian approach was 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 and Fahrmeir, 2007)[17].

Different model specifications were estimated including different sets of covariates. Starting with a base model that only included the control variables, we added the village fixed effects and the location effect. Afterwards the rainfall data was 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 year's values (Spatial Model III). To compare the model fit, we used the Akaike information criterion (AIC).

6. Results and discussion

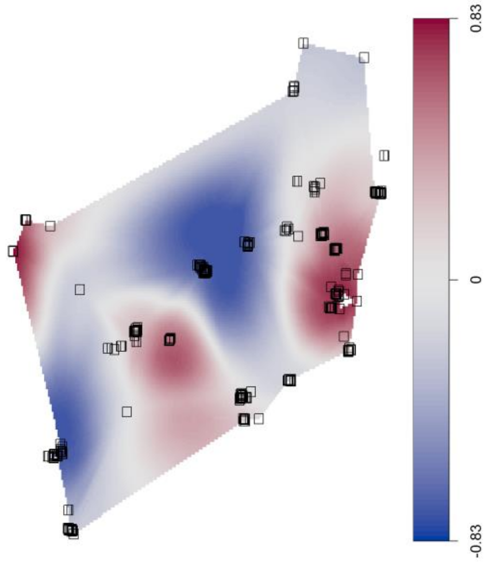
Table 3 and 4 present the estimation results for the three model specifications (Spatial Model I-III) as described above for the northern and southern transect, respectively. Fig. 3 and 4 depict the location effect of Spatial Model I as it had the lowest AIC value. Since the hazard rate was modeled as an exponential function of the geo-additive predictor $\eta_i(t)$, Tables 3 and 4 do not show the estimated coefficients but their exponentials. These 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 whereas a value smaller than one decelerates.

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



Source: Survey data and rainfall data (Department of Agrometerology, UASB).

Fig. 3. Location effect (two-dimensional P-spline) of Spatial Model I on the Adoption Hazard Rate in the northern transect (values are original coefficients, not exponentials, N=7,601))



Source: Survey data and rainfall data (Department of Agrometerology, UASB).

Fig. 4. Location effect (two-dimensional P-spline) of Spatial Model I on the Adoption Hazard Rate in the southern transect (values are original coefficients, not exponentials, N=6,547)

The main interest of this analysis is the location effect as well as the effects of the different rainfall variables on the AHR of borewell technology. Considering the spatial effect in the northern transect in Fig. 3, we find the highest coefficients in the transect areas closest to Bangalore. This is in line with the conceptual framework. In terms of equation (5), the right-hand side decreases for households located closer to the city as market access increases and transport costs decrease. In contrast, the location effect for the southern transect in Fig. 4 shows two adoption clusters in its center. However, one should notice that adoption rates are already lower in the southern transect (Fig. 2). In particular, the area with the most negative effect on adoption rates is located close to the largest water reservoir in the south. This result suggests that water demand is covered by sources which are cheaper to establish. Moreover, adoption rates are highest on locations next to the highway that cuts through the east side of the transect in north-south direction. This supports the argument that adoption occurs faster in areas with better infrastructure.

Concerning the effects of the rainfall variables on the AHR of borewell technology, the effects are very similar in both transects (Tables 3 and 4). 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 pre-monsoon rainfall in period t-1. According to the conceptual framework (in particular equation (5)) the value of waiting increases when the amount of rainfall also increases. The farmer has then 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 observe an accelerating effect of increasing pre-monsoon rainfalls in both transects in year t as well as with the southwest monsoon in year t-1. A year with more monsoon rains usually generates higher agricultural output as the monsoon season is the principal growing season. Thus, the 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 risks (Koundouri et al., 2006).

Table 3
Estimation Results, Northern Transect

	Exp(Coefficients)		
	Spatial Model I	Spatial Model II	Spatial Model III
Intercept	0.004* (0.026)	0.001** (0.001)	0.001** (0.001)
Household characteristics			
Age (years)	0.956*** (<0.001)	0.949*** (<0.001)	0.949*** (<0.001)
Caste			
SC	0.542 (0.127)	0.476 (0.066)	0.488 (0.076)
ST	0.827 (0.715)	0.797 (0.664)	0.785 (0.642)
OBC	0.850 (0.54)	0.814 (0.44)	0.831 (0.487)
Other	0.529 (0.391)	0.517 (0.377)	0.531 (0.395)
Durable assets (count)	0.630*** (<0.001)	0.569*** (<0.001)	0.577*** (<0.001)
Education (years)	0.983 (0.568)	0.971 (0.342)	0.974 (0.392)
Gender			
Female	0.356* (0.021)	0.333* (0.015)	0.341* (0.017)
Off-farm employment			
Yes	0.192*** (<0.001)	0.168*** (<0.001)	0.176*** (<0.001)
Transport equipment (count)	1.495 (0.116)	1.389 (0.2)	1.401 (0.193)
Farm characteristics			
Dairy			
Yes	1.921 (0.071)	1.890 (0.077)	1.884 (0.078)
Experience (years)	1.050*** (<0.001)	1.048*** (<0.001)	1.049*** (<0.001)
Farm size (ha)	1.040** (0.004)	1.050*** (<0.001)	1.045** (0.001)
Year t			
Total rainfall (mm)	0.995*** (<0.001)	0.999* (0.042)	
Pre-monsoon (mm)	1.010** (0.005)	1.002 (0.276)	
Southwest monsoon(mm)	1.001 (0.551)	0.999 (0.471)	
Year t-1			
Total rainfall (mm)	0.998* (0.023)		0.999 (0.401)
Pre-monsoon (mm)	0.990*** (<0.001)		0.993** (0.001)
Southwest monsoon(mm)	1.006*** (<0.001)		1.002** (0.005)
AIC	1,115.33	1,148.58	1,133.75
N	7,601	7,601	7,601

Source: Survey data and rainfall data (Department of Agrometerology, UASB).
Note: Asterisks *, **, and *** denote significance levels below 5%, 1%, and 0.1% respectively. 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.

Table 4
Estimation Results, Southern Transect

	Exp(Coefficients)		
	Spatial Model I	Spatial Model II	Spatial Model III
Intercept	0.000* (0.012)	0.000*** (0.001)	0.000** (0.003)
Household characteristics			
Age (years)	0.941*** (<0.001)	0.932*** (<0.001)	0.936*** (<0.001)
Caste			
SC	0.411 (0.057)	0.418 (0.069)	0.406 (0.056)
ST	0.152 (0.071)	0.147 (0.067)	0.148 (0.068)
OBC	0.591 (0.185)	0.528 (0.114)	0.561 (0.148)
Other	0.405 (0.212)	0.369 (0.181)	0.400 (0.213)
Durable assets (count)	1.011 (0.927)	0.935 (0.552)	0.950 (0.647)
Education (years)	1.059 (0.084)	1.051 (0.142)	1.056 (0.104)
Gender			
Female	0.876 (0.749)	0.813 (0.625)	0.826 (0.647)
Off-farm employment			
Yes	1.162 (0.608)	1.041 (0.892)	1.115 (0.71)
Transport equipment (count)	0.548 (0.087)	0.477* (0.035)	0.504* (0.048)
Farm characteristics			
Dairy			
Yes	1.238 (0.585)	1.172 (0.689)	1.199 (0.646)
Experience (years)	1.086*** (<0.001)	1.088*** (<0.001)	1.087*** (<0.001)
Farm size (ha)	1.060*** (<0.001)	1.060*** (<0.001)	1.061*** (<0.001)
Year t			
Total rainfall (mm)	0.997* (0.023)	1.000 (0.702)	
Pre-monsoon (mm)	1.009* (0.024)	1.000 (0.936)	
Southwest monsoon(mm)	1.001 (0.589)	1.000 (0.658)	
Year t-1			
Total rainfall (mm)	0.997* (0.02)		0.999 (0.157)
Pre-monsoon (mm)	0.994* (0.031)		0.995* (0.036)
Southwest monsoon(mm)	1.006*** (<0.001)		1.003** (0.002)
AIC	819.876	836.508	822.746
N	6,547	6,547	6,547

Source: Survey data and rainfall data (Department of Agrometerology, UASB).
Note: Asterisks *, **, and *** denote significance levels below 5%, 1%, and 0.1% respectively. 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

Controlling for socio-demographic and farm characteristics, results show almost identical effects for age, experience and farm size in both transects. There is a decelerating effect on the AHR with increasing age of the household head and an accelerating effect with increasing experience and farm size. The effect of gender differs as it is significantly negative in the northern transect but not significant in the southern transect. However, since the share of female households in the 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 effects of durable assets are only significant and negative in the northern transect but not statistically significant in the southern transect. Transport equipment is only statistically significant in Spatial Model I and II of Table 4 which have higher AIC values than Spatial Model I. 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 effect. Even though we only consider farm households in our sample, these households likely have additional off-farm income sources. In the northern transect, we find that off-farm employment significantly reduces the AHR. Also, the high magnitude of the effect of more than 80 percent in all three model specifications is quite substantial. 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 et al., 2001; De Jaunvry et al., 2005), or the relevance of the agricultural production for the income of the household decreases (Huang et al., 2009). In our case, at least in the northern transect, the latter seems to be the case. A number of studies show that smallholders—if they have access to a labor market—will diversify their income sources (Fafchamps and Shilpi 2003; Deichmann et al., 2009; Imai et al., 2015). Furthermore, if we assume that off-farm employment eventually yields equal or greater income 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).

Moreover, 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. The dummy for dairy production in this study showed an accelerating effect, however it is not statistically significant in both transects (though with a p-value of 0.07 in the northern transect).

7. Conclusions

Our analysis aims to understand how farmers' locations along the rural-urban interface of Bangalore and changing climate conditions affect decision-making to adopt borewell technology over time. Understanding the need for dynamic theoretical and empirical models that capture both temporal and spatial effects of urbanization and weather changes, we developed a flexible conceptual framework to model farmers' adoption decisions and applied duration models with geo-additive predictors in our empirical analysis.

Our results show that household location matters. In the northern transect, adoption rates decelerate with distance to the city. Hence market access and decreased transportation cost seem to accelerate adoption rates. This argument is also supported by the finding that adoption rates accelerate along main roads in the southern transect. In addition, the proximity to alternative water sources—such as the water reservoir south of Bangalore—decelerate adoption rates.

Considering the climate conditions, we find that the amount of rainfall affects decisions in two ways. First, we observe a decelerating effect with the amount total rainfall in year t as well as in the lagged time period t-1. Hence, dry spells accelerate the adoption of borewell technology. Second, we observe an accelerating effect with the amount of rainfall during the southwest monsoon in period t-1. As the monsoon season is the most important growing period, the adoption rate also depends on the household's additional income.

In light of these results, we can derive some policy implications. Support for the 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. If households diversify their income sources, they can hedge against losses in agricultural production due to droughts and changing weather conditions. In addition, a stronger focus on off-farm employment leads to a decreasing relevance of agricultural production among households and in the area in general. Thus, groundwater extraction might decrease, and aquifers can recover.

Nevertheless, there is room for further research. 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 agricultural production for households and their decision-making process 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.

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Appendix

Appendix 1. Derivation of equation (5)

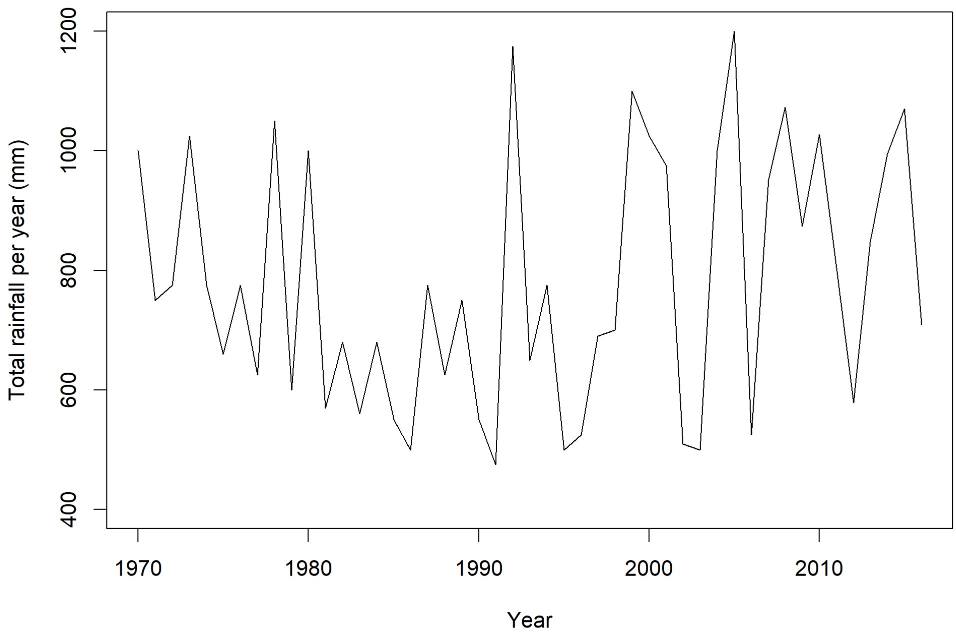
$$A_1(T,l) - A_0(T,l) \geq \frac{1}{2}[C(T,l) - C(T+1,l)\delta(1)]$$

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

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

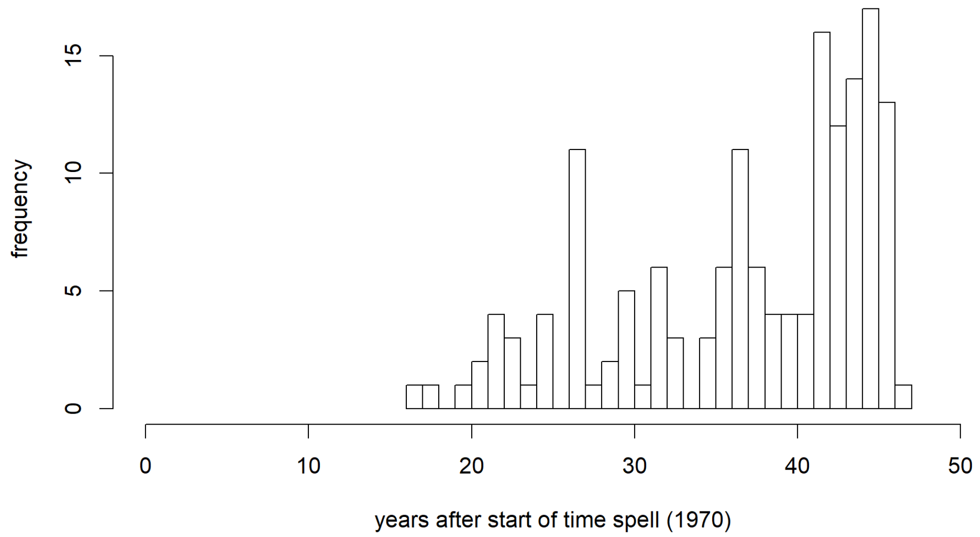
$$\Leftrightarrow p(T,l)(q_1(T) - q_0(T)) \geq \frac{1}{2}[C(T,l) - C(T+1,l)\delta(1)] + c(T,l)(a_1 - a_0)$$

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



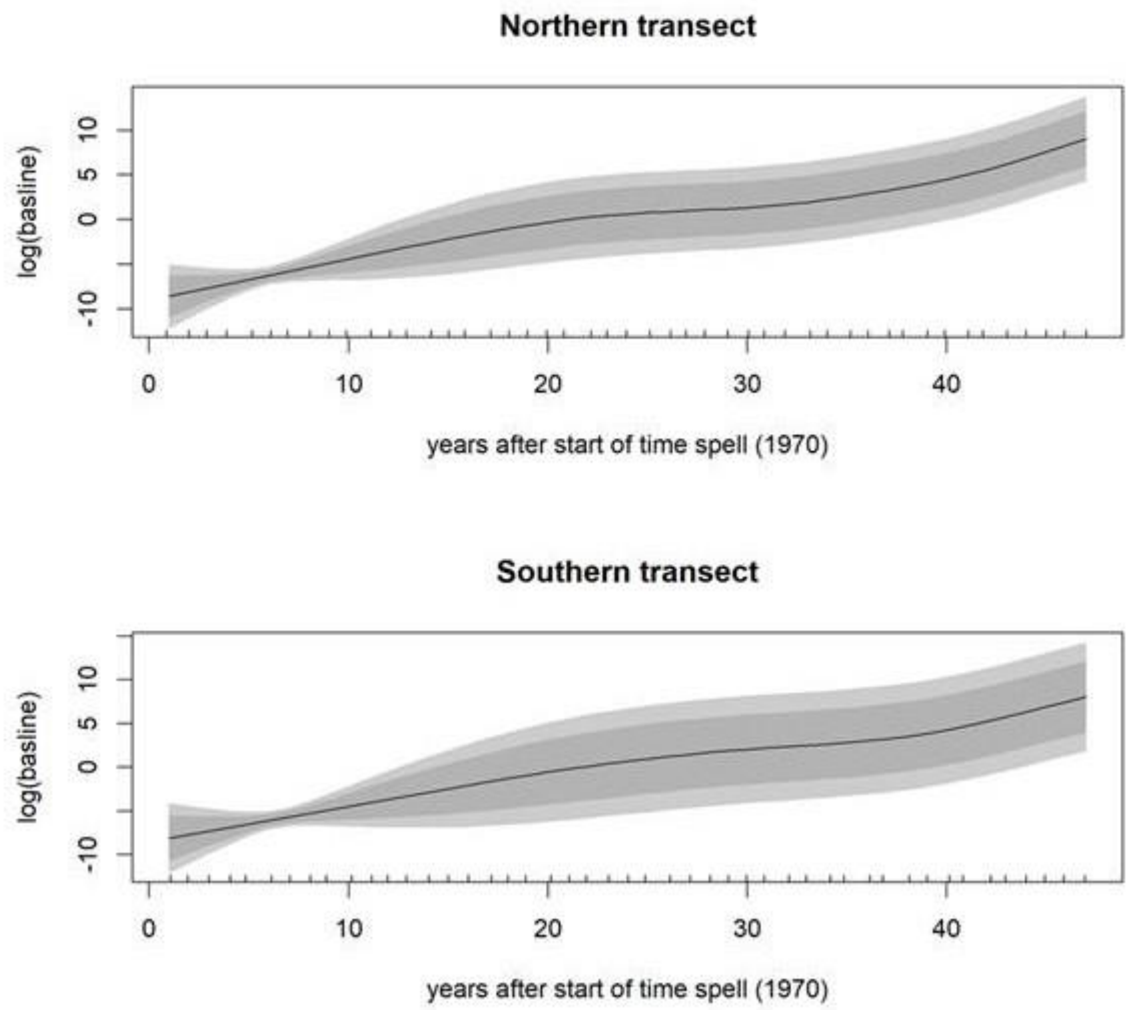
Source: Rainfall data (Department of Agrometerology, UASB).

Appendix 2. Total rainfall in the *Bengaluru urban* district, 1970-2016



Source: Survey data.

Appendix 3. Response frequency of when borewell was adopted (N=148, households)



Source: Survey data and rainfall data (Department of Agrometerology, UASB).

Appendix 4. Estimated log-baseline of Spatial Model I (P-Spline), Northern and Southern transect (N_{North}=7,601, N_{South}=6,547)

Appendix 5. Covariates included in Geo-additive Predictor

	Variable	Description
Time-invariant	Caste	1:General, 2:SC, 3:ST, 4:OBC, 5:Other
	Dairy	0:No dairy production, 1:Dairy production
	Education	Years of education (household head)
	Farm size	Acres under management
	Gender	0:Male household head, 1:Female household head
	Location	GPS coordinates of household
Time-variant	Age(t)	Age household head (years)
	Durable assets(t)	Number of durable assets available to household (*SEC*)
	Experience(t)	Years of farming experience (household head)
	Off-farm employment(t)	0: No household member involved in off-farm employment, 1: at least one member involved in off-farm employment
	Transport equipment(t)	Number of transport equipment available to household (*SEC*)
	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

IV. Groundwater management institutions in the face of rapid urbanization – results of a framed field experiment in Bengaluru, India

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Abstract

Many aquifers in semi-arid and arid regions with rapid urbanization are over-exploited or even at the point of depletion. Driven by the increased demand for food and other agricultural products, irrigated agriculture constitutes the biggest user of groundwater, and has thus contributed to this critical situation. In this paper, we compare different designs of groundwater management institutions in order to avoid aquifer over-exploitation and ensure secure water sources. We assess externally imposed reward-based and punishment rules as well as communication on their effectiveness to reduce water extraction behavior of groundwater users. Moreover, we evaluate how different user types affect the outcome of these institutional designs. To do so, we conducted a framed field experiment with 600 households along the rural-urban interface of the fast growing city of Bengaluru, India. Results indicate that all treatments can prolong the life of the resource but reward-based and punishment rules seem to be more effective than communication. Moreover, we find that user type behavior identified in the baseline trial is persistent in the treatment trial despite interventions.

Keywords: Common Pool Resource Management, Monitoring, Sanctioning; Urbanization

V. Conclusion

Bengaluru exemplifies many rapidly urbanizing areas in semi-arid or arid regions of the Global South as it is growing and expanding at a fast pace and has experienced socio-economic development. However, the city's growth in population, area and per capita income has spurred the demand for natural resources particularly for water. Like many cities with similar characteristics, large parts of Bengaluru depend on groundwater provided by the rural-urban interface. Due to the increase in consumption, many aquifers are over-exploited or are even threatened to deplete. Groundwater is mainly extracted by a large number of wells which are operated individually. This dissertation contributes to the understanding how individual extraction decisions of groundwater users are made and what drives their decisions. Particular emphasis was put on how urbanization shapes decision making behavior in terms of groundwater use and management.

The dissertation consists of three papers. The first paper examines the evolution of risk and time preferences along the rural-urban interface. As groundwater extraction involves decision making on uncertain outcomes over time, the outcome of these studies can be of relevance to better understand extraction or investment decisions in groundwater lifting technologies. To elicit these preferences, the Holt and Laury (Holt & Laury, 2002) task as well as the Coller and William (Coller & Williams, 1999) task were conducted with 1,160 households. To obtain risk-adjusted, unbiased estimates of discount rates, a joint estimation technique by Andersen, Harrison, Lau, and Rutström (2008) was used. The results reveal that on average the participants are slightly risk averse but highly impatient which is consistent with the literature in other low-medium income countries (Vieider, Martinsson, Nam, & Truong, 2018). As urban population has more income opportunities, we hypothesized, in accordance with the literature (Haushofer & Fehr, 2014), that the rural population would be more risk averse and reveal higher discount rates than the urban population, i.e. a higher level of impatience. The results show, however, that urban households are more impatient than rural households while no considerable difference was found for risk attitudes. The result is quite puzzling as rural households possess fewer assets - an indicator for wealth – than urban households. The results even suggest that the possession of assets increase discount rates. To study which individual and household characteristics determine risk attitudes and time preferences, several additional variables were added in the estimation. In particular, three hypotheses were tested; that income diversification of households, remittances receivers as well as agricultural intensification would reduce risk aversion and lower impatience. However, these hypotheses cannot be supported.

The puzzling results that impatience increases with the number of assets leave space for future research. One explanation might be that consumption opportunities in urban areas is a stimuli for impatience. Furthermore, the results of the study could be validated by using different methods to elicit risk and time preferences and expanded to other cultural contexts. One limitation to the results of the first paper is the cross sectional data set. For example, out-migration of the study area cannot be addressed which is a possible source of endogeneity.

The second paper provides an analysis with the aim to understand the determinants of farmers' decision to adopt borewell technology in the face of rapid urbanization and changing rain patterns. To address the objective a flexible conceptual framework to model farmers' adoption decisions was set up. The model was estimated using a duration models with geoadditive predictors. Results show that proximity towards the city center of Bengaluru and to major roads accelerates adoption rates. Moreover, the results suggest that adoption rates decrease for households with an income source in the nonagricultural sector. Where other sources of water for irrigation are available such as waste or grey waters from the city, adoption rates decelerate. In terms of weather variability, the results suggest that dry spells accelerate adoption of borewell technology. Moreover, adoption rate accelerates with high amounts of rainfall during the southwest monsoon. As this is the most important cropping season for agricultural households, sufficient funds to make a substantial investment of establishing a borewell are also an important factor for the adoption decision.

Nevertheless, there is room for further research. For instance the theoretical framework puts emphasizes on agricultural production. As more and more households might exit agriculture, models should be improved to account for this fact. Moreover, the adoption of private households or industrial sector was not incorporated in the analysis. As these might become relevant players for groundwater extraction decisions, future work should also consider these sectors.

The third paper focuses on the analysis of groundwater use and the design of management institutions to secure the sustainability of the resource. In a framed field experiment three different designs were tested on their effectiveness to reduce water extraction from aquifer and increase the sustainability of the resource: an externally imposed reward rule, an externally imposed punishment rule and a communication rule to reach internal arrangements. Without any treatments in place, the outcome of the experiment suggests that unmanaged groundwater extraction will lead to a rapid decline in groundwater level. In terms of the institutional designs, the reward and punishment rules, i.e. both externally imposed institutions, with a monitoring and sanctioning design are very effective in reducing groundwater extraction. One explanation is that deviating from a social norm is less attractive even if imperfect sanctioning and monitoring is at place. For the internal arrangement treatment in which participants were allowed to communicate with each other, the effect on reduced pumping decisions was statistically significantly lower than in the control group and the effect size was minor. The result suggests that internal arrangements need at least some sort of enforcement mechanism to prolong the life of the resource. Analyzing how different user types react on different institutional designs was another objective of the third paper. Five different user types were identified according to their pumping behavior: an excessive, a myopic, an individual rational, a social optimal, and a conservative. Users' attitudes were measured during the baseline trial of the experiment and remained stable across different treatments. This means for instance that myopic users would make short-sighted decisions under all treatments and ignore the externality of their decisions. Interacting different behavioral types with the treatment variables, all interaction coefficients with the social optimal type show a positive and statistically significant effect. This result indicates that all treatments have a crowing-out effect on users who were categorized as social optimal. The third objective of the study was to analyze whether the three institutional designs have a different effect at different stages of urbanization. However, no difference was found on the effectiveness of these designs along the rural-urban interface representing the different stages of urbanization.

Framed field experiments are a useful tool to analyze CPR management institutions. However, the number of treatments applied is limited and leave room for future research. More work is necessary to analyze why internal arrangements were not as effective as the externally imposed rules. Moreover, different types of internal arrangements could be evaluated. The literature provides examples of costly punishment within a user group, for example. Moreover, the underlying model could be improved by taking into account more complex hydrological models.

A comparison of these three studies reveals some interesting insights. The observation that groundwater level decline rapidly in the experiment when no interventions are at place matches the observation that decision makers are on average highly impatient along the rural-urban interface as highlighted in the first paper. It also matches the observation that impatience is less pronounced in more rural areas where adoption rates of borewell technology decreased as shown in the second paper. While it has been argued that groundwater monitoring is too costly due to a large number of small wells, focal points of improved groundwater management could be established even with imperfect monitoring and sanctioning. These could be in areas where adoption rates of borewells are accelerating. As many livelihoods depend on groundwater extraction policy makers should try to avoid borewell failures and ensure the groundwater access for future generations. Furthermore, the three papers show that urbanization affects decision making behavior as well as attitudes and preferences. However, the effect is often not straightforward. For example, extraction decisions in the experiment did not considerably differ across the rural-urban interface while the decision to adopt borewell technology accelerates with proximity to the city center. Moreover, the result that impatience is higher in more urban areas than in rural areas was also not an expected result.

In the dissertation, the focus was set on the availability of groundwater mostly in terms for irrigated agriculture – the world largest user of freshwater. Yet more research can be done and the scope of the research be expanded. For example, overexploitation of aquifer often has an effect on the quality of water as these are then prone to pollution. The causes range from excessive use of fertilizers and pesticides to industrial pollution or natural salinization. This can further reduce the availability of water and increase water stress. Therefore, further studies should also take into account groundwater pollution into the analysis of groundwater usage and management. Another important issue, which was not the scope of this dissertation, is equity and distribution of groundwater access. Clearly, access to groundwater is open to everybody if land is available. However, many households do not possess land and cannot access groundwater or are dependent on communal water pumps. However, many subsidies are available to drill and extract groundwater. This double burden of landless households needs also be addressed and discussed if groundwater policies are meant to be inclusive.

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Publication List

Papers published in peer-reviewed journals:

Wegmann, J.; Mußhoff, O. (2019): Groundwater management institutions in the face of rapid urbanization – results of a framed field experiment in Bengaluru, India, *Ecological Economics*

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Discussion/working papers:

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Wegmann, J.; Hermann, D.; Mußhoff, O. (2019): The evolution of risk attitudes and time preferences along the rural-urban interface – Results from Bengaluru, India. *168th EAAE seminar on "Behavioural Perspectives in Agricultural Economics and Management", 6-7 February, 2019, in Uppsala, Sweden.*

Wegmann, J.; Mußhoff, O. (2018): Addressing the Institutional Challenges of Groundwater Management in Semi-arid Areas with Rapid Urbanization - Results from a Framed Field Experiment. *30th International Conference of Agricultural Economists (ICAE), July 28 - August 02, 2018, in Vancouver, Canada.*

Wegmann, J.; Mußhoff, O. (2018): Addressing the Institutional Challenges of Groundwater Management in Semi-arid Areas with Rapid Urbanization - Results from a Framed Field Experiment. *6th World Congress of Environmental and Re-source Economists (WCERE), June 25-29, 2018, in Gothenburg, Sweden.*

Wegmann, J.; Steinhübel L. (2018) Struggle for water in times of Climate Change – technology adoption of farmers in the rural-urban interface of Bengaluru. *Annual meeting of the The Swiss Society for Agricultural Economics and Rural Sociology (SGA), April 12-13, 2018, in Gränichen, Switzerland.*

Wegmann, J.; Mußhoff, O. (2018): Addressing the Institutional Challenges of Groundwater Management in Semi-arid Areas with Rapid Urbanization - Results from a Framed Field Experiment. *AARES Annual Conference, February 7-9, 2018, in Adelaide, Australia.*

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Erklärung über den geleisteten Eigenanteil der Arbeit

Im ersten Beitrag „The evolution of risk attitudes and time preferences along the rural-urban interface – results from Bengaluru, India“, der in Zusammenarbeit mit Herrn Prof. Dr. Oliver Mußhoff verfasst wurde, sind folgende Bereiche von mir übernommen worden: konzeptionelle Entwicklung des Beitrags in enger Zusammenarbeit mit Herrn Prof. Dr. Oliver Mußhoff und Herrn Dr. Dr. Daniel Hermann. Datenerhebung, Durchführung der Berechnungen, Interpretation der Ergebnisse und Verfassen des Beitrags unter der Beratung von Prof. Dr. Oliver Mußhoff und Herrn Dr. Dr. Daniel Hermann.

Im zweiten Beitrag mit dem Titel „Digging deep and running dry – the adoption of borewell technology in the face of climate change and urbanization“, der in Zusammenarbeit mit Frau Linda Steinhübel und Herrn Prof. Dr. Oliver Mußhoff verfasst wurde, sind folgende Bereiche von mir übernommen worden: Erstellung des Fragebogens für den Wassernutzungsteil, sowie Interpretation der Ergebnisse und Verfassen des Beitrags in enger Zusammenarbeit mit Linda Steinhübel und Beratung von Herrn Prof Dr. Mußhoff.

Im dritten Beitrag „Groundwater management institutions in the face of rapid urbanization – results of a framed field experiment in Bengaluru, India“, der in Zusammenarbeit mit Herrn Prof. Dr. Oliver Mußhoff verfasst wurde, sind folgende Bereiche von mir übernommen worden: konzeptionelle Entwicklung des Beitrags in enger Zusammenarbeit mit Herrn Prof. Dr. Oliver Mußhoff. Datenerhebung, Durchführung der Berechnungen, Interpretation der Ergebnisse und Verfassen des Beitrags unter der Beratung von Prof. Dr. Oliver Mußhoff.

Eidesstattliche Erklärungen

Hiermit erkläre ich eidesstaatlich, dass:

1. Diese Arbeit weder in gleicher noch in ähnlicher Form bereits anderen Prüfungsbehörden vorgelegen hat.
2. Ich mich an keiner anderen Hochschule um einen Doktorgrad beworben habe.

Göttingen, den 21. Mai 2019 ________________________

(Unterschrift)

Hiermit erkläre ich eidesstaatlich, dass diese Dissertation selbstständig und ohne unerlaubte Hilfe angefertigt wurde.

Göttingen, den 21. Mai 2019 ________________________

(Unterschrift)