Watering the Seeds of the Rural Economy: Impact of Tube-Well Irrigation in India

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Abstract

We study the average village level effects of access to groundwater for irrigation on the structural transformation of the rural economy. Using newly-assembled data on irrigation practices, we exploit an absolute technological constraint imposed by the laws of physics on the operational capacity of pumps with depth of the water table in a *fuzzy* regression kink design. Our results show that increased access to irrigation – measured as an additional standard deviation unit ($\equiv 103$ $litres/ha/day$) of groundwater – significantly boosts agricultural land production. Farmers respond to an increase in groundwater for irrigation by expanding their cultivated land area by over 12%, and shifting away from drought tolerant crops. Furthermore, within the agricultural sector, we find that approximately 6 to 10% of cultivators and manual labourers respectively shift from part-time to full-time employment. This substantial shift in agricultural production translates into significant consumption gains including: (1) 0.35 standard deviation units increase in an index of durable assets, (2) 4% drop in the share of the village population living below the poverty line, and (3) increase in economic activity measured through night light. While we find no evidence of labour re-allocation between different sectors of the local village economy, there is a significant increase in village population density. Our results suggest that a positive shock to agricultural productivity – from access to irrigation – has important returns to income and employment opportunities within the agricultural sector, but little impact on structural transformation between sectors.

JEL Codes: O12, O13, O18, Q15, Q18, Q25

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1 . Introduction

A rich theoretical literature continues to debate the mechanism through which industrial growth is often preceded by unprecedented increases in agricultural output (Kuznets and Murphy, 1966; Johnston, 1970; Syrquin, 1988; Herrendorf et al., 2014). Various theoretical models suggest that in a closed economy, a boost to agricultural productivity generates demand for manufacturing goods which leads to a re-allocation of labour away from agriculture (Gollin et al., 2002; Kongsamut et al., 2001; Ngai and Pissarides, 2007). However this view has been challenged by research on open economies, which demonstrate that improved agricultural productivity can retard industrial growth as the economy specialises in the comparative advantage sector (Matsuyama, 1992; Field, 1978). Despite the centrality of this discussion in understanding the development process of low-middle income countries, there has been very little accompanying empirical evidence identifying the process by which shifts in agricultural productivity can alter the shape of the wider economy.

In this paper we provide direct empirical evidence on the effect of access to groundwater irrigation on agricultural production and the consequent structural transformation of the rural economy in India. Irrigation is one of the most conspicuous technologies for stimulating agricultural output. Primarily, improved productivity occurs through a direct yield effect – irrigated agriculture is on average at least twice as productive as rainfed (Faurès et al., 2002). Furthermore, the technology has also been found to (1) minimise inter-annual income variability by reducing exposure to rainfall shocks (Sarsons, 2015), (2) augment land endowments by introducing the possibility of a second harvest (Blakeslee et al., 2020), and (3) complement other key inputs such as high yielding varieties (Gollin et al., 2021).

Groundwater contributes the largest supply of irrigation water globally (Siebert et al., 2010). In India, groundwater has been the main source of irrigation since the 1970s (Mukherji et al., 2013). Unlike dam and canal infrastructure which require government support for building and maintenance of the networks, groundwater can be accessed independently by farmers through private investment in tubewells. Recent estimates suggest that groundwater now accounts for over 60% of irrigated area across the country; compared to only 20% by canals (Jain et al., 2019). Exploitation of this resource however, is a growing concern – India has the fastest depleting aquifers in the world (Famiglietti, 2014; Rodell et al., 2018). An understanding of how access to groundwater irrigation affects the village economy, is therefore of crucial contemporaneous relevance.

In order to accurately ascertain the causal effect of irrigation on structural shifts in the rural economy we require an exogenous source of variation in access to groundwater. An absolute technological constraint imposed by the laws of physics on the operational capacity of centrifugal pumps with depth of the water table provides one such source of variation. There are two types of pump technologies available – centrifugal and submersible. Centrifugal pumps are installed on the surface and generate a pressure differential between the water table and the pumping mechanism. The maximum pressure differential achievable is created by a perfect vacuum in the pump mechanism. In this ideal state, Bernoulli's principle of fluid dynamics dictates that the maximum depth from which water can be extracted is a constant at any given atmospheric pressure (Faber, 1995). For instance, at sea level a pump generating a perfect vacuum will only be able to extract water from up to 10.33 meters below ground level. Extracting water from greater depths requires significantly more expensive submersible pumps,[1] which are placed at the bottom of a tubewell and pushes the water to the surface.

If all centrifugal pumps were homogenous in their ability to generate a perfect vacuum, we would expect to see a sharp discontinuity in access to irrigation at a specific groundwater depth with altitude. However, not all pumps operate at the same efficiency. For instance at sea level, the operational depth of a centrifugal pump falls from 10.33 to 5.18 meters as pump efficiency falls to half of its maximum potential. Consequently, there only exists a pump specific operational threshold; which we do not observe in the data. To guide our identification strategy, we therefore propose a simple decision making framework faced by farmers when deciding which irrigation technology to adopt. For groundwater depths shallower than 10.33 meters, the more cost effective centrifugal pumps are the farmers preferred choice. However as we approach the maximum theoretical depth for extracting water, fewer and fewer of these pumps will be operational. As a result, we predict a decline in centrifugal pump adoption with groundwater depth, culminating in zero adoption at the maximum theoretical threshold. Furthermore, under liquidity constraints, we predict an incomplete substitution to the more expensive submersible pumps. Given this trend in adoption of irrigation technology, we expect a kink in the mapping between groundwater depth and water extraction for agricultural irrigation to coincide with the maximum theoretical threshold. We exploit this quasi-random between-village variation in access to irrigation at an exogenous groundwater depth in a *fuzzy* regression kink design.

[1] Based on an online search, centrifugal pumps cost approximately INR 16,000 (GBP 160), half the price of submersible pumps.

Our empirical analysis makes use of both existing and newly-assembled datasets. Our assignment variable – groundwater level – is compiled using data published by the Central Ground Water Board (CGWB) of India which monitors wells four times a year across the country. We use the geographic positioning system (GPS) locations of these wells to match this data to multiple external contemporaneous datasets. Irrigation data, including ownership of centrifugal and submersible pumps, is compiled from the Minor Irrigation Census. These censuses form the longest spanning database of information on irrigation infrastructure at the village level. We draw from remote sensing, population and economic censuses, as well as administrative micro-data in order to describe village level agricultural production, amenities, demographics, sectoral labour allocation, as well as various measures of consumption. The benefit of a village-identified dataset is that it enables us to leverage spatial variation in groundwater at a high resolution and across a large geographic area. This is especially important in our empirical approach, as regression kink designs are notoriously demanding of sample size. However, a disadvantage of this data is that we are limited to broad categories of outcomes of interest and cannot disentangle our results on a finer scale.

We estimate the impact of access to irrigation as an additional standard deviation unit ($\equiv 103\ litres/ha/day$) of groundwater on our outcomes of interest. We find that increases in groundwater irrigation significantly boosts agricultural land production. Specifically, agricultural yield (derived from remote sensing vegetation indices) increases by 9.1% in the dry winter/*Rabi* growing season. Furthermore, farmers appear to re-optimise their production strategies by moving away from drought tolerant crops, as well as bringing an additional 12% of land area under cultivation. In accordance with other studies analysing the impact of irrigation on poverty, we find significant gains to consumption (Duflo and Pande, 2007; Sekhri, 2014). These are captured through four key variables: (1) share of the village population living below the poverty line drops by 4.4%, (2) durable asset index increases by 0.34 standard deviation units, (3) average night-light intensity over a five-year period (a remote sensing proxy for economic activity) rises by 16%, and finally (4) variance of night-light intensity over a five-year period falls by 3%. Together, these results provide evidence for important returns to irrigation on consumption and the stabilising of inter-annual economic activity within the village.

The impact of increased access to irrigation on the labour market includes a shift from part-time to full-time employment in the agricultural sector. Specifically, we find that groundwater irrigation increases the share of both cultivators and manual labourers

working full-time by 6% and 10% respectively. In the case of manual labourers, this increase is experienced by both male and female workers. An increase in agricultural productivity from access to irrigation, does not however appear to have strong effects on the sectoral transformation of the village economy. We find no evidence of increased employment across a range of sectors within village businesses.[2] The lack of support for structural transformation within the village, does not rule out the possibility of increased migration to find employment in nearby small towns with agglomerate economies. In an attempt to capture migration outcomes, we analyse the effect of irrigation on population density within the village as well as the nearest urban centre. While we find a significant increase in population density at the village level, we cannot detect any changes in nearby towns.[3]

Our paper is linked to a recent and growing literature providing empirical evidence on how productivity shocks in agriculture affect structural shifts in the economy. This literature builds on macro-economic models which demonstrate how agricultural productivity growth plays a key role in subsequent industrialisation, explaining cross-country disparities in income (Gollin et al., 2002, 2007; Córdoba and Ripoll, 2009; Vollrath, 2011). These results have been corroborated empirically by two quasi-experimental, cross-country studies on the impact of improved seed varieties (Gollin et al., 2021) and fertilizer use (McArthur and McCord, 2017). Specifically, Gollin et al. (2021) find that the impact of high yielding varieties on per capita GDP are associated with a rise in total factor productivity beyond those simply derived from a boost in crop yields, therefore partially attributing these to structural transformation. Analysing the effect of an increase in staple yields introduced by improved fertiliser use, McArthur and McCord (2017) show that this generated a minimum rise of 14% in GDP per capita and led to a 5% decline in the agriculture labour share over a five year period.

Evidence of the role that agriculture plays in structural transformation at a more micro level is mixed. In a study exploiting the spread of improved seed varieties in Brazil, Bustos et al. (2016) are able to isolate two different types of productivity shocks – labour-saving and land-augmenting. The authors find that adoption of labour-saving hybrid soy led to an expansion of employment in the local manufacturing sector. Conversely, land-augmenting

[2] We conduct the same analysis with share of employment in different sectors as our outcome variables, but within nearby towns. Here again we find no evidence of shifts in labour allocation.

[3] In an attempt to further investigate the results on population density so as to identify the source of the increase in population, we estimate the impact of irrigation on a range of age cohorts. We also test for the share of the male population in each of these age brackets. None of these results are statistically different from zero, however they are also not precisely estimated to zero.

maize led to an increase in the marginal product of labour in agriculture and consequently a reduction in industrial employment. Leveraging shocks to agricultural productivity caused by unusually high levels of precipitation in rural India, Emerick (2018) show that farming households shift their labour towards the non-agricultural sector in years of agricultural boom. However in earlier work estimating structural change from panel data on Indian villages, Foster and Rosenzweig (2004) show that boosts in agricultural productivity raise local wages and thereby hinder the potential for non-farm sectoral growth.

In two concurrent papers, Asher et al. (2021a) and Blakeslee et al. (2021) also aim to estimate the impact of access to irrigation on the structural transformation of the Indian rural economy. The identification in both of these papers relies on the unique geography of canal irrigation networks. As a result, they both identify the treatment effect of being in the command area of a canal. Blakeslee et al. (2021) find that structural transformation from access to canal irrigation depends largely on the presence of a nearby town. Specifically, they find that villages within a 2km distance of a town experience a drop in population density and employment in non-agricultural sectors, while villages further away experience a positive shift. Evaluating the long-run effects of canals, Asher et al. (2021a) find that structural change from agricultural productivity increases is associated with the formation and population growth of nearby towns. In contrast to these papers, our work focuses on the dominant source of irrigation – groundwater – which requires significant private investment from farmers. Consequently, we make use of more detailed census data on irrigation practices to capture the intensive margin; providing insight into water-use efficiency. Regardless of the type of irrigation, all three papers find very little evidence for within village labour reallocation while geographic movement of labour is dependent on access to outside opportunities.

Our paper is also closely linked to a strand of causally interpretable evidence on the impacts of access to irrigation. The scarcity of such research is due in large part to the empirical challenges involved in establishing reliable estimates. Our paper contributes to a limited literature using quasi-experimental methods to evaluate the impact of this key technology. Duflo and Pande (2007) analyse the distributional effects of irrigation dams in India – the authors found that while beneficiaries living downstream from irrigation dams increased their agricultural productivity and experienced lower levels of poverty, this was counter balanced by increases in poverty in upstream populations. Evidence from private investment in tube-wells for irrigation has been found to reduced water related conflict (Sekhri, 2014). Furthermore, using randomly located geological formations that

store pockets of water in the bedrock, Blakeslee et al. (2020) explore farmer adaptations to a drying up of these pockets of groundwater for irrigation. The authors found that in such cases, there is a consequential decline in farm income, however households appear to successfully offset these losses by reallocating labour to off-farm employment.

The rest of the paper is structured as follows. Section 2 describes the different technologies available to farmers for groundwater extraction, and outlines a simple decision making framework for the adoption of these technologies. Our data sources are explained in Section 3, and the empirical strategy including graphical evidence is presented in Section 4. Section 5 contains results on the impact of access to irrigation on the rural economy. Finally, Section 6 concludes.

2 . Background

Private investment in groundwater irrigation, the focus of this paper, is the fastest growing source of irrigation water accounting for over 60% of the irrigated land in India. In this section, we first describe the technologies available to farmers for extracting groundwater. In particular, the role of groundwater depth in determining the most suitable pump for water extraction. We then outline a simple decision making framework faced by farmers when deciding which technology to adopt.

A . Irrigation Pumps

The technology most suitable for extracting groundwater depends on the depth of the water table in a given location. There are two main types of pump available, centrifugal and submersible. Centrifugal pumps are the most widely adopted due to their affordability. They are installed on the ground and create a vacuum with water moving up the tube from an area of high pressure at the bottom of the well, to an area of low pressure in the pumping mechanism (Figure 1). The extraction of water from a well using a centrifugal pump can be described by Bernoulli's principle of fluid dynamics (Faber, 1995) (Equation 1):

$$P_1 + \frac{1}{2}\rho v_1^2 + \rho g h_1 = P_2 + \frac{1}{2}\rho v_2^2 + \rho g h_2 \tag{1}$$

Where the variables P_i, v_i, and h_i refer respectively to the pressure ($kg/m/s^2$), velocity (m/s), and height (m), between the pump ($i = 2$) and the water table ($i = 1$). The constants, ρ and g are the density of water (997 kg/m^3) and gravitational force (9.81 m/s^2) respectively. Assuming constant flow velocity we can rewrite Equation 1 in the following form:

$$h_2 - h_1 = \frac{P_1 - P_2}{\rho g} \tag{2}$$

As can be interpreted from Equation 2, under a perfect vacuum ($P_2 = 0\ kg/m/s^2$) and a given atmospheric pressure, the depth from which water can be extracted with a centrifugal pump is a constant. At sea level ($P_1 = 101,325\ kg/m/s^2$) this depth is 10.33 meters. In real world circumstances however, it is unlikely that all pumps are able to create a perfect vacuum. Specifically, as we demonstrate in Figure 2, the maximum pumping depth at sea level falls from 10.33 to 5.18 meters as pump efficiency falls to half its maximum potential. We can therefore expect that once the groundwater level falls below a pump efficiency specific threshold, a centrifugal pump can no longer be used to access groundwater for irrigation.

In a scenario where a centrifugal pump can no longer operate, submersible pumps can provide an alternative technology for water extraction. A submersible pump is placed at the bottom of the tube-well and pushes the water to the surface. Consequently, provided it has sufficient horsepower, a submersible pump can extract water from any depth. This functionality however, comes at more than twice the price of a centrifugal pump.[4]

B. Decision Making Framework

In this section we introduce a simple decision making framework for the adoption of different irrigation technologies available to farmers. Consider a population of N farmers indexed by $i \in 1, ..., N$, living in a geographically diverse set of V villages indexed by $v \in 1, ..., V$. Each village has a given groundwater level λ_v.[5] In this context, farmer i decides whether or not to invest in a single unit of irrigation when faced with his exogenous groundwater level. We assume that one unit of irrigation is sufficient to irrigate the entire land endowment, l_i, of the farmer. Consequently, farmers with the most land get the highest returns from investment.

Based on Bernoulli's principle of fluid dynamics, we know from Equation 2 that the depth from which water can be extracted is a constant. At sea level, this depth is 10.33

[4]Based on an online search for a range of pump models for the Indian market, we found that the entry price for a centrifugal pump is approximately INR 16,000 (equivalent to GBP 160), while a submersible pump costs over INR 30,000 (GBP 300). To put these costs into context – the mean annual per capita consumption in our sample of villages is approximately INR 18,000 (GBP 180).

[5]In reality the water table fluctuates temporally, however for ease of exposition we will just consider a one time choice when faced with a fixed groundwater level.

meters. Below this threshold, k, no centrifugal pump can operate.[6] If the water table depth in a given village exceeds k, the farmer must incur the cost r_s of a submersible pump if he chooses to irrigate. Conversely, when $\lambda_v < k$, a centrifugal pump will operate and thus enter the farmers' set of choices as a more cost effective technology; $r_c < r_s$. However, the functionality of a centrifugal pump will depend on its' efficiency. This efficiency is random with known probability distribution $G(.)$ (and associated CDF $g(.)$) revealed to the farmer only at the time of purchase. Additionally, there exists a groundwater specific efficiency threshold, $e(\lambda)$, below which a centrifugal pump will not function. As such, there is a probability, $g(e(\lambda_v))$, that a farmer purchases a centrifugal pump which will not work.

When deciding on a technology, a farmer leverages all his current information. He also considers his forward looking expectations, including pump efficiency, relative costs, and yield increases from irrigation (which are assumed to be known to him). Specifically, a risk neutral farmer will choose an irrigation technology simply to maximise his profits. In doing so, he compares the following profit functions – irrigating with a submersible pump ($\pi_{iv}^{I_s}(p, r_s, l_i)$), irrigating with a centrifugal pump ($\pi_{iv}^{I_c}(\lambda_v, p, r_c, l_i)$), or no irrigation ($\pi_{iv}^{N}(p, l_i)$) – which can be written as:

$$\begin{aligned}
\pi_{iv}^{I_s} &= pY_i^I l_i - r_s \\
\pi_{iv}^{I_c} &= (1 - g(e(\lambda_v)))(pY_i^I l_i - r_c) + g(e(\lambda_v))(pY_i^N l_i - r_c) \\
\pi_{iv}^{N} &= pY_i^N l_i
\end{aligned} \tag{3}$$

Where p, r_s, and r_c are the prices of output, a submersible pump, and a centrifugal pump respectively. Y_i^I denotes agricultural yields when irrigating, and Y_i^N is for yields under no irrigation. As explained previously, a farmer is subject to a technology constraint such that $g(e(\lambda_v)) = 1$ if $\lambda_v > k$.

Given this framework, we consider three representative case scenarios: (1) a farmer whose liquidity constraint binds for both pump types, (2) a farmer who faces a liquidity constraint only for the more expensive submersible pump type, and (3) a farmer that is not liquidity constrained at all.

Case 1: Liquidity constrained for all irrigation technology. In this scenario, a farmer cannot access either irrigation technology. He therefore receives π_{iv}^{N} regardless of groundwater depth.

[6] k corresponds to the difference in height outlined in Equation 2.

Case 2: Liquidity constrained for submersible pumps only. The farmer cannot afford the more expensive submersible pump. Therefore, if $\lambda_v > k$, he cannot access any irrigation technology. Alternatively, if $\lambda_v \leq k$, he will adopt a centrifugal pump when $\pi_{iv}^{I_c} > \pi_{iv}^{N}$. Expanding on these profit functions we show that:

$$(1 - g(e(\lambda_v)))(pY_i^I l_i - r_c) + g(e(\lambda_v))(pY_i^N l_i - r_c) > pY_i^N l_i \tag{4}$$

Rearranging Equation 4 demonstrates that a farmer will adopt a centrifugal pump if the increase in revenue with irrigation multiplied by the probability of the pump working is larger than the cost of the pump:

$$(1 - g(e(\lambda_v)))(pY_i^I l_i - pY_i^N l_i) > r_c \tag{5}$$

The probability of adoption therefore declines in $g(e(\lambda_v))$, up to the threshold $\lambda_v = k$. Above this threshold, adoption is zero. Assuming $G(.)$ is uniformly distributed and the distribution of land holdings is orthogonal to λ_v, the decline in probability of adoption will be linear with a kink in the slope marginally before the threshold.[7] Furthermore, as previously noted, given their higher marginal returns, farmers with the largest landholdings are most likely to adopt even when $\lambda_v - k$ is small.

Case 3: Not liquidity constrained. The farmer can purchase either of the irrigation technologies. If $\lambda_v > k$ a farmer will adopt a more expensive submersible pump when $\pi_{iv}^{I_s} > \pi_{iv}^{N}$ – that is, when the increase in revenue from irrigation is greater than the cost of a submersible pump. As a result, adoption above the threshold is not dependent on groundwater depth:

$$(pY_i^I l_i - pY_i^N l_i) > r_s \tag{6}$$

If $\lambda_v \leq k$ a farmer will adopt a submersible pump if $\pi_{iv}^{I_s} > \pi_{iv}^{I_c} > \pi_{iv}^{N}$. Therefore, a farmer who is not liquidity constrained, and satisfies the condition in Equation 5, is now left to consider whether the certainty in submersible pump functionality justifies the difference in cost:

$$(1 - g(e(\lambda_v)))(pY_i^I l_i - pY_i^N l_i) > r_s - r_c \tag{7}$$

Similar to Case 2 when the increase in revenue with irrigation multiplied by the prob-

[7] Adoption will be zero when the largest farm is indifferent between adopting or not. That is, when: $(1 - g(e(\lambda_v)))(pY_{max}^I l_{max} - pY_{max}^N l_{max}) = r_c$

ability of the centrifugal pump working is larger than the difference in cost between the two types of irrigation technology, a farmer will adopt the submersible pump. This condition leads to a substitution from centrifugal to submersible pumps as groundwater depth increases and the probability of the centrifugal pump working declines.

Figure 3 sketches how we expect adoption may evolve with groundwater depth within our decision making framework. Specifically, it is the subset of farmers that can afford a centrifugal pump but not a submersible (i.e. Case 2) that generates a kink in overall pump adoption and consequently irrigation. Additionally, under the assumption that when $g(e(\lambda_v)) = 0$ – that is, centrifugal pumps work with certainty – then Equations 5 and 6 hold even for the smallest farmers. On the other hand, as $\lambda_v - k$ becomes very small, only the farmers with the largest landholdings are most likely to adopt centrifugal pumps.[8]

In the data we only observe what happens at aggregate; when combining populations regardless of their liquidity constraints. However, our model suggests that as long as a large proportion of the population are partially liquidity constrained (i.e. Case 2) then we can expect to observe a kink in pump adoption and consequently groundwater irrigation close to the threshold k. We empirically demonstrate the presence and validity of this relationship in Section 4.

3 . Data

For the purpose of this study, we have assembled a high resolution dataset including information on irrigation practices, as well as a range of features describing the rural economy. We link observational groundwater data from wells across the country with multiple external contemporaneous datasets to obtain a village level cross-section. Importantly for our empirical approach, this enables us to leverage spatial variation in groundwater at a high-resolution over a large geographical area.

Data on our assignment variable - groundwater level - come from the official website of the Central Ground Water Board (CGWB).[9] Since 1996, the CGWB has kept digitised records from groundwater monitoring wells evenly spread across the entire country. In 2013, the CGWB had a total of 17,116 monitoring wells covering 511 districts across 21 States. Wells are identified by Global Positioning System (GPS) coordinates and are monitored four times in the year – pre-monsoon, mid-monsoon, pre-winter, and post-winter[10] – so as

[8] In Figure 3, we index the decision equation for small farmers as min, and for large farmers as max.

[9] Data can be downloaded in excel format from:http://cgwb.gov.in. We accessed this data in June 2020.

[10] With some regional variation, the monsoon/$Kharif$ season is from June to October and the

to capture both seasonal and inter-annual variation. We construct our assignment variable as the maximum groundwater depth recorded at any point over a three year period covering 2011-2013.[11] As the water table fluctuates temporally, taking a three year horizon allows us to account for some of this variation. As a robustness test, we present results when constructing our assignment variable using a one and five year time period. Combining village boundary shapefiles offered by the Socioeconomic Data and Applications Center (SEDAC) of NASA,[12] along with the GPS coordinates of wells, we create a village level match. Specifically, we attribute the measure of our assignment variable to a village if the well falls within the village boundary.[13] Figure 4 presents a map of our final sample of matched wells across the country, as well as whether these fall below or above the operational threshold for centrifugal pumps. As Figure 4 plainly demonstrates, our data on groundwater level provide the basis of our empirical approach – evenly distributed high-resolution spatial variation across a large geographic coverage.

We compile data on irrigation practices from the Fifth Minor Irrigation (MI) Census conducted in 2013.[14] With the objective of collecting information to be used for the planning and management of water resources in the agricultural sector, the Government of India has implemented a MI Census every 7 years since 1986-87.[15] These Censuses provide a countrywide database of groundwater and surface water infrastructure that have a culturable command area of less than 2,000 hectares – known as minor irrigation schemes.[16] Specific to the needs of our study, the Fifth MI Census has data on ownership of different pump types, including submersible and centrifugal. Importantly, there also exists information on pump capacity (horse power) and usage (pumping hours), which allow us to calculate water input in litres following a standard engineering formula (Manring, 2013) (see Appendix B for detail on the construction of this variable). This measure of irriga-

winter/*Rabi* season is from November to March.

[11] Of the total groundwater monitoring wells sampled by the CGWB, not all are monitored four times a year. As a result, our assignment variable can only be calculated for a subset of 8,549 wells.

[12] Shapefiles mapping the whole of India are available at:https://sedac.ciesin.columbia.edu/data/set/india-india-village-level-geospatial-socio-econ-1991-2001.

[13] If more then one well was matched to the same village, an average of our assignment variable was taken.

[14] Village level data from the MI Censuses are publicly available in excel format on the Government of India open data platform at:http://data.gov.in. We accessed this data in June 2020.

[15] Background information on each Census (e.g. questionnaires and instruction manuals on data collection) as well as official reports and aggregated statistical tables can be found on the official website of the MI Census at:http://micensus.gov.in.

[16] In contrast, medium and large irrigation schemes have a culturable command area of 2,000-10,000 ha and above 10,000 ha respectively. These largely include dam and canal irrigation projects.

tion is also used in the recent work of Ryan and Sudarshan (2020) evaluating the effect of groundwater rationing in Rajasthan.

Data on agricultural production based on direct field measurements is - to the best of our knowledge - not available at the village level in India. We therefore rely on measures of vegetation cover calculated from satellite images as a proxy for agricultural yield at the village. Specifically, we use data from the Normalised Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) estimated from images taken by the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor aboard NASA's Terra satellite. This data was used in the recent work by Asher and Novosad (2020) for their evaluation of India's national rural road expansion programme, and was made available by the authors as part of their replication dataset.[17] The authors extracted information on NDVI and EVI from gridded datasets across India for nine 16-day periods from June to October – covering the monsoon/$Kharif$ growing season – and similarly from November to March – covering the winter/$Rabi$ growing season – over a fourteen year period (2000-2014). This data was then matched to village boundary shapefiles. We leverage this raw data to calculate three proxies for each vegetation index in each season – mean, maximum, and the difference between early-season (taken as the mean of the first three 16-day periods) and the maximum value observed. By differencing out non-crop vegetation (such as forest cover) this latter proxy provides the most reliable measure of crop production. Appendix B includes further information on how the indices and proxies are constructed, a discussion of the literature on using remote sensing imagery to predict crop yields, as well as results from validation tests showing the correlation between the indices and district level estimates of agricultural production.

In this study we are not only interested in capturing changes to agricultural production in response to irrigation access, but importantly changes in agricultural production choices. We therefore leverage data from multiple external sources in order to obtain a range of village level indicators on input use and crop choice. The Village Directory, administered as part of the 2011 Population Census, keeps records of the three principle crops grown in each village.[18] We use this information to create three binary measures of crop choice: does a village grow winter crops, drought tolerant crops, or cash crops.[19] In terms of

[17]The paper by Asher and Novosad (2020) and its associated dataset is available at:https://www.aeaweb.org/articles?id=10.1257/aer.20180268

[18]Data from the 2011 Population Census Village Directory can be downloaded from:https://censusindia.gov.in/2011census/censusdata2k11.aspx. We accessed this data in June 2020.

[19]Winter season crops include: wheat, barley, potato, oilseed, and chickpea. Drought tolerant crops

agricultural inputs, we also draw upon the 2011 Village Directory for our measures of land area cultivated. Finally, we compile data on two indicators of technology adoption – water-saving technology (drip and sprinklers) is obtained from the Fifth MI Census (2013) and mechanised farm equipment collected as part of the Socio Economic Caste Census (SECC) of India in 2012. The Government of India regularly conducts SECC surveys at the individual and household level so as to determine eligibility into social programmes. Village level aggregates of this survey, including household assets, are made available online as part of the work of Asher and Novosad (2020).[20]

We draw on the 2011 Population Census for information on labour allocation of village residents.[21] Specifically, we obtain data on total employment, as well as for two occupational categories of employment in the agricultural sector – cultivators and manual labourers. Cultivators are those that cultivate their own land, while manual labourers work for a daily wage. Data on these categories is available disaggregated by gender, enabling us to test for shifts in labour allocation for men and women separately. Furthermore, the data can also be disaggregated by time spent employed. Specifically, the Census of India considers two types of workers – main/full-time workers are defined as those that are economically active in an employment category for more than 6 months of the year, while marginal/part-time workers are active for less than 6 months. We also leverage the Population Census to obtain data on the population of villages and their nearest town to capture shifts in people across space.[22]

So as to obtain information on businesses at the village level, we make use of data from the Sixth Economic Census conducted in 2013.[23] The Economic Census is the only complete enumeration of all economic establishments in India, formal and informal, with

(based on classification by the International Crops Research Institute for Semi-Arid Tropics) include: millet, sorghum, maize, pigeon pea, and groundnut. Cash crops (these cannot be directly used for household consumption as they require post-harvest processing, but are generally considered to be more profitable) include: sugarcane, oilseed, cotton, and tobacco.

[20] As mentioned previously, the paper by Asher and Novosad (2020) evaluating India's national rural road construction programme and its associated dataset is available at:https://www.aeaweb.org/articles?id=10.1257/aer.20180268

[21] Data from the 2011 Population Census can be downloaded at: https://censusindia.gov.in/2011-Common/CensusData2011.html. We accessed this data in June 2020.

[22] Towns are identified according to the census definition of a minimum population of 5,000 and density of 400 persons per square kilometre or higher. We identify the nearest town as the shortest distance as the crow flies.

[23] This data is available on the National Data Archive site: http://microdata.gov.in/nada43/index.php/catalog/47. We accessed this data in June 2020.

no restrictions on size or location.[24] Detailed records are kept on employment and business characteristics (such as industry classification), but not on wages, inputs, or outputs. Compared to the Population Census which includes employment records for village residents even if these take place outside the village, the Economic Census concentrates on economic activity only in village businesses. We consider total employment in all village businesses, as well as the share of those employed in the following sectors: agro-processing (this excludes crop production), livestock, construction, manufacturing, and services. Among our sample, these five industries account for over 70% of those employed in village businesses. We also measure employment in these same industries for the nearest town, allowing us to capture labour re-allocation outside of villages.

As a final set of outcomes of interest, we look at a range of consumption indicators. These are all obtained from the Socioeconomic High-resolution Rural-Urban Geographic Dataset on India (SHRUG, Version 1.5).[25] Night light, measured by satellites as the pixel luminosity in a geographic polygon, is widely used as a proxy for economic activity when direct measures are otherwise unavailable (Henderson et al., 2011) (see Appendix B for a detailed discussion of this variable). For a more direct measure, we leverage household micro-data collected by the India Human Development Survey-II in 2012 to predict consumption on a range of asset and income variables equivalent to those recorded in the SECC 2012 (these predicted variables are available in the SHRUG). Following the methodology suggested by Elbers et al. (2003), we can then impute consumption using the SECC asset and income data to generate village-level statistics for predicted consumption per capita and the poverty rate (refer to Appendix B for further detail on how these indicators are generated and a discussion of the literature on the methodology). Finally, we look at an index of asset ownership – as recorded by the SECC 2012 – as well as each individual major asset independently.

As a robustness test to our identification strategy, we show that there does not exist a kink in the relationship between groundwater level and a range of covariates. These covariates include village level literacy rate, electrification for agriculture, paved road network, and distance to nearest town. These variables are all obtained from the 2011 Population Census Village Directory.

[24] An establishment refers to any unit where an economic activity is carried out; with the exception of those engaged in crop production, defence, and government administration.

[25] For detailed information on the SHRUG, please refer to Asher et al. (2021b). The dataset, including codebooks and references, can be found at:http://www.devdatalab.org/shrug

We link all our different datasets at the village level. For variables coming from the Population Census or Economic Census, these are directly matched to the SHRUG Dataset of India (Version 1.5) using Census village identifiers. However for the wells and irrigation data, we use a combination of Python and Stata code for fuzzy matching on names adapted to the local Indian languages.[26] This method resulted in a matching success of approximately 80%. Table 1 provides summary statistics of all key variables on the final sample size of 4,974 villages across 478 districts for 19 States of India. These statistics suggest that in an average village, the share of the population living below the poverty line is approximately 30%. Around 13% of households are engaged as cultivators, though only 4% own mechanised farm equipment. The share of agricultural irrigated land area which is irrigated by tubewells is on average 38%. Only 9% of the workforce are engaged in village businesses, with services having the largest employment share.

4 . Empirical Approach

In this paper, we are interested in capturing the effects of access to groundwater irrigation on the structural transformation of the rural economy. Irrigation practices however, are likely to be endogenous. For instance, we might expect that villages with better access to markets are more likely to adopt irrigation. Any naive correlation estimates between irrigation and economic outcomes will in such a case be biased; partially attributing the effect of irrigation to markets rather than the technology itself. In this section we introduce our proposed empirical approach – *fuzzy* Regression Kink (RK) Design – to circumvent this endogeneity issue. Furthermore, we present graphical evidence and estimation results corroborating the validity of this method.

A . Regression Kink Design

To identify the true causal effect of irrigation, we use a *fuzzy* RK design which relies on quasi-experimental variation in the likelihood of having access to groundwater around a specific threshold.[27] In our empirical model, the assignment function determining the

[26] We use the *Masala Merge* algorithm developed by Paul Novosad, which modifies the Levenshtein edit distance to lower the cost of certain substitutions that are common to Hindi. The code and information on this algorithm is available on the authors' website: `https://www.dartmouth.edu/~novosad/code.html`

[27] There has been increasing interest in adopting RK designs in the applied economics literature. The most common application so far has been the use of kinks in unemployment benefit schedules to capture the effect of these on labour market outcomes (Card et al., 2015a; Landais, 2015). A small but growing literature has also used this method to evaluate a range of topics including, but not limited to, the effect of coalition governments on fiscal policies (Garmann, 2014), financial aid on educational outcomes (Nielsen et al., 2010), and demand for prescription drugs (Simonsen et al., 2016).

probability of being treated – that is having access to irrigation – is driven by a technological constraint in centrifugal pump capacity with groundwater depth. Specifically, 10.33 meters is the maximum theoretical groundwater depth – k – at which a centrifugal pump can extract water for irrigation at sea level.[28] Below this depth, the cost of irrigating increases significantly due to the price differential of the more expensive submersible pumps.[29] As described further in the next subsection; we demonstrate that for our sample of villages, there is in fact a discontinuity in the first-derivative of our assignment function at the given threshold.

In our analysis, the change in slope of the assignment function at the kink is unknown and must therefore be estimated based on observed data. Accordingly, we employ a *fuzzy* RK design, in which both the assignment variable and the treatment variable may be observed with error (Card et al., 2015b).[30] Specifically, we expect a kink in the deterministic relation between our treatment variable – irrigation, I – and our assignment variable – groundwater depth, W – at k. It follows that if irrigation exerts a causal effect on our outcome of interest – Y – we should expect to see an induced kink in the relationship between Y and W at k. Accordingly, the causal impact can be estimated by dividing the change in slope of the conditional expectation function for an outcome variable of interest (Equation 8), by the corresponding change in slope of the conditional expectation function for the assignment function (Equation 9) at the kink point. Specifically, we obtain the numerator of the *fuzzy* RK design estimand from the following parametric polynomial model:

$$E[Y|W = w] = \mu_0 + \left[\sum_{p=1}^{\bar{p}} \gamma_p (w-k)^p + \nu_p (w-k)^p \cdot D \right] \tag{8}$$

where $D = \mathbb{1}[W \geq k]$ is a binary variable indicating whether the village experienced a groundwater level deeper than the threshold k at any point between 2011 to 2013. The change in slope of the conditional expectation function of Y at the kink point is given by ν_1.

Similarly, we estimate the denominator of the *fuzzy* RK design estimand using the following parametric polynomial form:

[28] k corresponds to the difference in height explained by Bernoulli's principle of fluid dynamics outlined in Equation 2.

[29] For detailed information on irrigation pump technologies available to farmers, including their costs, refer to Section 2.

[30] The difference between a *sharp* and *fuzzy* RK design is that the $fuzzy$ RK design estimand replaces the known change in slope of the assignment rule at the kink with an estimate based on the observed data.

$$E[I|W = w] = \alpha_0 + \left[\sum_{p=1}^{\bar{p}} \omega_p (w-k)^p + \pi_p (w-k)^p \cdot D \right] \tag{9}$$

The change in slope of our treatment variable – I – at the kink point of the assignment variable W is captured by π_1. The impact of irrigation is therefore the ratio of the coefficients – $\beta = \nu_1/\pi_1$, and should be interpreted as the average treatment effect on the treated. Standard errors for β are recovered using the Delta method.

All our main regressions are estimated using a linear functional form ($\bar{p} = 1$). However as a robustness test, we compare our results when using a quadratic and cubic function. As suggested by Ando (2017), our regressions include covariates as controls (even though these are shown not to be affected by the assignment function at the kink point), as well as state fixed effects. In a robustness test, we compare results on our main outcome variables when excluding the controls. Furthermore, all main regressions use a bandwidth (b) of 7 metres, such that $|w - k| \leq b$. Our results however, are shown to be robust to a range of bandwidth (down to 3 metres).

B . Impact of Groundwater Depth on Irrigation

Identification in a *fuzzy* RK design, requires two key assumptions (Card et al., 2015b): (1) the conditional density of the assignment variable, given the unobserved error in the outcome, is continuously differentiable at the kink point, and (2) the treatment assignment function is continuous at the kink point (i.e., there is no jump in the direct marginal effect of the assignment variable on the outcome of interest at the kink).[31]

Graphical evidence: We begin by showing graphical evidence to validate the *fuzzy* RK design assumptions. In response to the first assumption on the smooth density condition, we plot the probability density function of our assignment variable to check for manipulation of ones' position at the kink point. Note first that the exact location of the kink point is village specific as it varies with air pressure at different altitudes, as shown in Panel A of Figure 5.[32] Panel B of Figure 5 shows the number of observations in each bin for groundwater depth normalised at the kink point. The evolution of the distribution of our assignment variable shows no signs of discontinuity at the kink point. This is further

[31] As explained by Card et al. (2015b), this condition is what differentiates an RK to an RD design. In absence of this condition, wherein there exists a jump rather than a kink, an RD design would be used.

[32] Data on altitude was extracted from raster files for the whole of India, obtained from the ALOS Global Digital Surface Model. A barometric formula was used to calculate atmospheric pressure with varying altitude.

supported by the McCrary test, commonly used in the RD literature, which estimates the log change in height between bins at the kink point. Results from this test (displayed directly on the graph) confirm that we cannot detect a significant discontinuity at the kink point.

The evolution of the relationship between centrifugal pump ownership and our assignment variable normalised at the kink point, provides evidence towards the second assumption. Corroborating the technological constraint faced by centrifugal pumps with groundwater depth, Panel A of Figure 6 demonstrates a clear kink in the slope of the relationship at the given threshold. As hypothesised in our decision making framework, we find a decline in the adoption of centrifugal pumps as groundwater depth increases, followed by a sharp visible switch to a constant near zero adoption when groundwater depth exceeds the threshold ($w \geq k$). Furthermore, Panel B of Figure 6 shows a gradual increase in submersible pump ownership – likely driven by bigger wealthier farmers switching to this more expensive technology as the probability of a centrifugal pump operating declines. However, it is also clear that this technology substitution is incomplete. Specifically, centrifugal pump adoption (nb/ha) declines from 0.07 to 0.01, while submersible pump adoption only increases from 0.03 to 0.05 on the left of the threshold.

Importantly for our empirical approach, Panel C and D of Figure 6 exhibit a kink in the relationship between irrigation (measured as $litres/ha/day$) and our assignment variable. Specifically, as the depth of the water table increases, access to agricultural irrigation declines up to the maximum theoretical threshold followed a sharp switch to a constant near zero groundwater extraction. This result provides confirmation that our empirical approach is capturing a shift in irrigation at a given threshold driven by an exogenous factor – the operational capacity of centrifugal pumps with groundwater depth.

Observing the pattern in the relationship between covariates unrelated to irrigation and our assignment variable provides further validation to our *fuzzy* RK design. The implication of the design suggests that the conditional expectation of any such covariate should be twice continuously differentiable at the kink. Plotting the mean values of covariates in each bin of the assignment variable as presented in Figure 7 provides a valuable visual test. Access to a paved approach road, distance to nearest town, literacy rate, and electricity for agricultural use, reported in Panels A, B, C and D of Figure 7 respectively, all suggest that these covariates evolve smoothly at the kink point.

Estimation results: Table 2 shows the results from our empirical specification outlined in Equation 9. We report the estimate for π_1, which corresponds to the change in

slope of our treatment variable – irrigation from tubewells – at the kink point of the assignment variable – groundwater depth. Results based on a linear functional form suggests a statistically significant positive evolution of the relationship between groundwater depth and irrigation at the kink point. This result is consistent when considering the average irrigation over the year (Column 1), as well as during the monsoon/$Kharif$ (Column 2) and the winter/$Rabi$ season (Column 3) independently.

In support of our empirical strategy, we conduct various robustness tests. First, we demonstrate that for our covariates – access to a paved approach road, distance to nearest town, literacy rate, and electricity for agricultural use – there is no detectable change in the slope of the conditional expectation function at the kink point (see Columns 4 to 7 of Table 2). Second, we analyse the sensitivity of our results to the choice of polynomial order, reported in Panel B and C of Table A1. We find that the standard errors in the quadratic functional form increase substantially and the results in this form are no longer statistically significant. Third, we show that our results are consistent for our assignment variable calculated as the maximum groundwater depth recorded at any point over a one, three, or five year time horizon (see Table A2). Finally, we explore the sensitivity of the deterministic relation between irrigation and groundwater depth at $w = k$ to the choice of bandwidth level. As shown in Figure A1, our results are consistent across bandwidth size down to 4 meters either side of the kink.

5 . Results

In this section we report and discuss our results on the impact of groundwater irrigation on the structural transformation of the rural economy. For each outcome variable we report the beta estimate (with the heteroskedasticity robust standard errors in brackets) corresponding to the ratio of the coefficients capturing the conditional expectation function at the kink point from Equation 9 and Equation 8 (see Section 4 for more detail on the estimation strategy). Our explanatory variable for access to irrigation is calculated as $litres/ha/day$ and standardised such that all results can be interpreted as the effect of a one standard deviation ($\equiv 103$ $litres/ha/day$) increase in irrigation.

A . Agriculture

Before all else, we evaluate the impact of groundwater irrigation on agricultural yields. Leveraging two different vegetation cover indices – the Normalised Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) – we construct three alternative proxies of yield at the village level. These include the: mean, maximum, and difference

between early-season and the maximum. This latter proxy is our preferred outcome variable for crop production. Previous research has shown that by differencing out non-crop vegetation such as forest cover, it provides a more direct estimate of agricultural yield (Rasmussen, 1997). Table 3 presents results on the effect of irrigation on these proxies for both the monsoon/$Kharif$ and the dry winter/$Rabi$ growing season.

Focusing on the NDVI-derived differenced proxy for agricultural yield we find that irrigation has a positive impact on crop production. This effect is concentrated during the dry/$Rabi$ season. We estimate an impact of 9.1% higher agricultural yield during the winter/$Rabi$ season for a one standard deviation increase in groundwater irrigation use (Panel A Column 4 of Table 3). Graphical evidence presented in Panel A of Figure 8 corroborates this result. The plot demonstrates a sharp visible kink in the relationship between the winter/$Rabi$ differenced NDVI-derived value for agricultural yield and normalised groundwater depth at the given threshold. This increase in yield however, is not detected by the EVI-derived proxies (Panel B of Table 3). This is possibly because EVI was partly developed to compensate for the effects of NDVI saturation over high biomass areas such as forests (Huete et al., 2002; Gao et al., 2000). As a result, EVI tends to present relatively lower ranges over lower biomass sites, making it less sensitive in semi-arid agricultural settings (see Appendix B for further details including a discussion of the literature on using remote sensing imagery to predict crop yields).

During the monsoon/$Kharif$ season, irrigation does not appear to have a significant impact on yield (when considering the differenced proxy, see Column 1 of Table 3). This is to be expected, since unlike the dry winter months the monsoon season receives heavy rainfall; hence reducing the reliance on irrigation for cultivation. Interestingly however, the average groundwater irrigation use is similar in both the monsoon/$Kharif$ and winter/$Rabi$ season, (see summary statistics for irrigation in Table 1). This implies a comparative inefficiency of irrigating in the monsoon/$Kharif$ season. Evaluation of water use efficiency has become a subject of intense debate in India. Scientific evidence drawing from satellite imagery and field studies indicate that the Indian aquifers are being depleted at an unprecedented rate relative to other countries (Famiglietti, 2014; Rodell et al., 2018; Siebert et al., 2010). The treatment of groundwater as a common resource with very little regulation, along with highly subsidised electricity for agricultural, are seen as the leading factors of mismanagement (Shah, 2013; Dubash, 2007; Badiani-Magnusson and Jessoe, 2018).

Having established the overall effects of access to irrigation on agricultural production, we go on to analyse the pathways through which these effects may operate – over and above

the direct effect from watering. Improvements in agricultural yields could happen through two main channels: (1) farmers may re-optimise their production strategy in response to a reduced exposure to climate risk, and/or (2) conditional on higher yields translating to higher profits, farmers may increase investment in other inputs.

In response to the first channel, we analyse shifts in crop choice (reported in Columns 3 to 6 of Table 4). We consider three categories of crops – those grown in the dry winter/*Rabi* season, drought tolerant, and cash based – which are all characterised by an element of risk. The winter/*Rabi* season receives very little rainfall, hence crops grown in this season are much more vulnerable to weather shocks. Surprisingly, we find no significant shifts towards these type of crops. Drought tolerant crops are resistant to semi-arid conditions and are therefore an effective way of reducing exposure to rainfall shocks. We find that 25.6% fewer villages report one of their three most widely cultivated crops to be drought tolerant in response to an increase of one standard deviation of irrigation groundwater use. Finally, cash crops cannot be directly used for household consumption as they require post-harvest processing. While these crops are generally considered to be quite profitable they are also more susceptible to price fluctuations. For farmers who rely on their agricultural produce to feed their household, moving to cash crops can therefore often be considered risky. While our point estimate on cash crops is positive, it is not statistically significant.

We investigate the second channel by considering investments in a range of inputs (Columns 1 to 3 of Table 4). Our results suggest that there is no shift in the ownership of mechanised farm equipment. However, we do find that a one standard deviation increase in groundwater irrigation leads to a 4.4% drop in the adoption of water-saving technologies (such as drip and sprinklers). Water mismanagement would therefore appear to be more prevalent when groundwater is more readily available (Ostrom et al., 1991; Ostrom and Gardner, 1993). Finally, there appears to be a strong effect of irrigation on land extensification – an increase of one standard deviation in irrigation results in an extra 12.2% of available agricultural land being cultivated.

In a further investigation, we attempt to estimate the effects of irrigation on the size of landholdings. There is good reason to believe that shocks to land productivity could have significant implications on the land market. For instance, those farmers that invest in irrigation may buy out less productive non-irrigated farms. To test for this we analyse the impact of access to irrigation on the share of households in four different landholding categories – landless, 0-2, 2-4 and above 4 acres, reported in Table 5. While we see a positive point estimate for the landless category, this is not significantly different from

zero. All other measures report a negative point estimate, though again, not statistically significant.

B. Consumption

Table 6 reports results on the impact of irrigation on measures of consumption at the village level. Importantly, we find a 4.4% reduction in the village poverty rate for a one standard deviation increase in irrigation water use. This result agrees with other research which exploit a quasi-experimental empirical approach to analyse the effect of irrigation on poverty alleviation (Duflo and Pande, 2007; Blakeslee et al., 2020; Sekhri, 2014). This effect is further corroborated by our results on average night light intensity, measured over a 5 year period – a one standard deviation in irrigation leads to a 16% increase in night time light. We also test the effect of irrigation on the variance of night light intensity over this same time period – a one standard deviation in irrigation leads to a 3.1% drop in the standard deviation of night time light. Interestingly, this suggests that access to irrigation not only increases consumption, but is also effective in insulating rural economies from income shocks.

While our point estimate on consumption per capita is positive, it is not statistically significant. However, we further investigate the impact of irrigation on consumption using a more direct measure – household microdata from the Socio Economic Caste Census of India (2012) on asset ownership; reported in Table 7. We find a significant positive effect on the index of household assets. A one standard deviation in groundwater irrigation increases the asset index by 0.35 standard deviations. This result appears to be largely driven by solid house construction – the share of households that own a solid house increases by 17%. As explained in Duflo and Banerjee (2011), investment in solid house construction is a common form of informal savings among poor households. This implies that improved access to irrigation provides households with additional cash in hand.

C. Labour

An increase in agricultural production with improved access to irrigation, may simultaneously increase demand for labour in this sector. This effect however, may be small or even reversed if farmers switch to less labour intensive crops or replace labour activities with specialised mechanised tools such as transplanters and harvesters. Furthermore, labour demand for agriculture is likely to be influenced by market opportunities in other sectors. On-farm growth may spur production in off-farm sectors, therefore increasing demand for labour in those industries. Alternatively, irrigation may provide some villages

with a comparative advantage in farming, thereby attracting labour away from other sectors or less productive population centres. Characterised by these complex interactions, the overall effect of irrigation on the labour market is ambiguous. We attempt to identify the dominance of these different components by evaluating the impact of irrigation on aggregate employment rates as well as shifts in the sectoral share of the workforce.

We begin our analysis of structural shifts in labour allocation, by analysing the effect of irrigation on the share of the population employed at the village level (reported in Panel A of Table 8, Columns 1 to 3). We find a 2.2% reduction in the share of the population employed, which is statistically significant at the 10% level (Column 1). This decline appears to be driven by a statistically significant 4.6% decline in female employment due to irrigation (Column 3). In a time series analysis of employment trends in India spanning 3 decades (from 1990 to 2010), Mehrotra et al. (2014) describe women as the reserve army of labour for the agricultural sector, called upon only in times of distress. Irrigation, which appears to significantly improve agricultural sector productivity, may therefore be reducing the need for female labour force participation. This drop may also be related to the 'income effect'; a trend suggesting that women appear to drop out of the labour force as households become wealthier (Mehrotra and Sinha, 2017).

Approximately 30% of the workforce in our sample villages report their primary occupation to be either cultivation or manual agricultural labour. In order to capture sectoral shifts in labour allocation to the agricultural sector, we therefore present results on the share of the workforce employed in these categories. Results from this analysis are reported in Panel B of Table 8. We find that there is no statistically significant shifts in labour allocation either into or out of the agricultural sector. Specifically, we can only rule out a 0.43 standard deviation change in the share of the workforce employed as cultivators and a 0.32 standard deviation change in the workforce employed as manual labourers, with 95% confidence.

We complement this occupational data in the agricultural sector from the Indian Census, with data from the Economic Census on employment in village businesses, reported in Panel A of Table 9. We consider employment in the following sectors: agro-processing, livestock, construction, manufacturing, and services. The point estimates for employment in sectors aligned to agriculture (agro-processing and livestock) are negative, while point estimates in all the other sectors are positive. However, none are significantly different from zero at the 10% level. In the case of the services sector, we can only rule out a 0.4 standard deviation change in the dependent variable in response to a one standard deviation change

in irrigation. It may be however, that shifts in labour re-allocation outside of agriculture do not take place within the village but rather within nearby agglomerations which benefit from better infrastructure. In order to investigate this possibility, we consider employment in these same industries but within the nearest town; reported in Panel B of Table 9. Here again, we find no evidence of structural transformation, with similar precision on the point estimates. Taken together, it would appear that irrigation does not lead to substantive shifts in off-farm sectoral growth at the local level. These results add to evidence from two concurrent papers, showing that access to irrigation does not seem to cause significant shifts in structural transformation within villages in the context of rural India (Asher et al., 2021a; Blakeslee et al., 2021).

In our final set of outcome variables, we consider the effect of irrigation on the share of full-time workers (see Panel C of Table 8). Interestingly, these results point to a large and significant increase in the share of full time workers – defined as those employed for more than 6 months of the year. We find that a one standard deviation increase in groundwater irrigation increases the share of the population in full-time employment by 9.9% (Column 1). This appears to be driven by an increase in both cultivators (Column 3) and manual labourers (Column 6). This result would indicate that there is in fact an increase in labour demand within the agricultural sector, which is absorbed by the existing labour force extending there period of activity to cover both growing seasons.

Finally, as an additional measure of shifts in employment, we investigate the effect of irrigation on the population density of the village and its nearest town. These results are reported in 10. We find an increase in the village population density of approximately 39.1% due to a one standard deviation increase in irrigation (Column 5). This suggests a large and significant pooling in of labour. In an attempt to further disentangle these results, we estimate the effect of irrigation on the population in different age brackets as well as the share of the male population in each age group; reported in Table A4. Our point estimates are positive on the age groups below years 30, and negative for older cohorts. However these results are not statistically significant. The estimate on the 21-30 years group allows us to rule out a 0.37 standard deviation change with 95% confidence interval. With respect to the population density of the nearest town, the effects are not statistically different from zero. Conversely, Asher et al. (2021a) find that canals cause a 20% increase in the population density of urban centres. This disparity however may be due to two key factors. First the authors find this effect when considering the long-run impact of canals, while we only consider the cross-sectional effects of groundwater irrigation. It may be that

shifts in population take time to occur. Second, the authors use the command area of canals as their source of treatment. Our measure, irrigation based on pump functionality with groundwater, will have a much higher degree of spatial disaggregation relative to the large catchment area of a canal.

6 Conclusion

First documented with regards to the Industrial Revolution in England during the 18th century, scholars argued that an increase in agricultural productivity was a necessary precursor for industrial growth (Nurkse, 1953). Since then, a large literature has been devoted to chronicle the process of economic growth across countries, overwhelmingly finding that this is accompanied by a process of structural re-allocation of labour away from the agricultural sector towards the manufacturing and service industries (Herrendorf et al., 2014). Leveraging this information, a number of theoretical models on structural change have been formalised, placing agricultural growth as a catalyst for the process of industrialisation (Gollin et al., 2002; Ngai and Pissarides, 2007). Conversely, other models have suggested that agricultural productivity may in fact impede the process of growth if the sector has a comparative advantage; thereby pooling in labour (Matsuyama, 1992). Yet despite the centrality of this discussion in understanding the development process of low-income countries, there exists remarkably little empirical evidence to support the mechanisms suggested by these models.

In this paper, we estimate the impact of a shock to agricultural productivity – induced by access to groundwater irrigation – on the structural transformation of the rural economy in India. Primarily, we find that access to irrigation does in fact significantly boost agricultural production. Furthermore, farmers appear to significantly re-optimise their production strategies in terms of land area cultivated and types of crops grown. Secondly, this production shock has a large and positive effect on alleviation of poverty at the village level. Finally, irrigation appears to increase demand for labour in the agricultural sector – with 6% of cultivators and 10% of manual labourers shifting from part-time to full-time employment – as farmers now cultivate during the dry winter/*Rabi* season. However, it does not lead to any significant shifts in labour re-allocation between sectors.

Since the onset of the Green Revolution in India during the 1960s, the Government has adopted policies of providing free or largely subsidised electricity to farmers for irrigation in an effort to stimulate growth in the rural economy. Subsequently, the area irrigated by groundwater has increased by over 500 percent between 1960 and 2010, now accounting for

60% of the cultivated land area (Foster and Garduño, 2013). Exploitation of this resource however, is now becoming a growing concern – India has the fastest depleting aquifers in the world (Famiglietti, 2014). Given the seriousness and extent of these negative externalities from promoting groundwater use, they should be balanced with reliable evidence on the benefits of irrigation as an instrument to stimulate rural economic growth. The results from this paper suggest the irrigation in the monsoon/$Kharif$ season is relatively inefficient in terms of yield benefits and should therefore be regulated. The major benefits are accrued during the dry winter/*Rabi* season by allowing a reliable second cropping season. This increase in production is coupled with significant asset accumulation, reductions in poverty, and stabilisation of inter-annual economic activity within the village.

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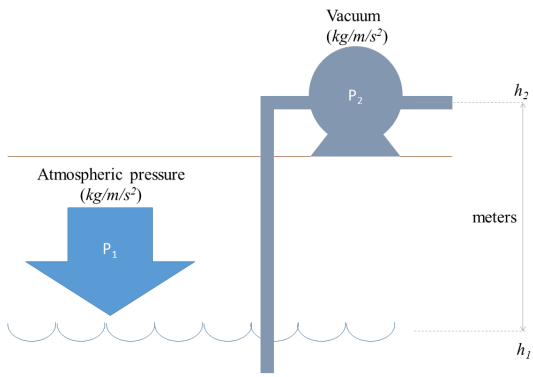
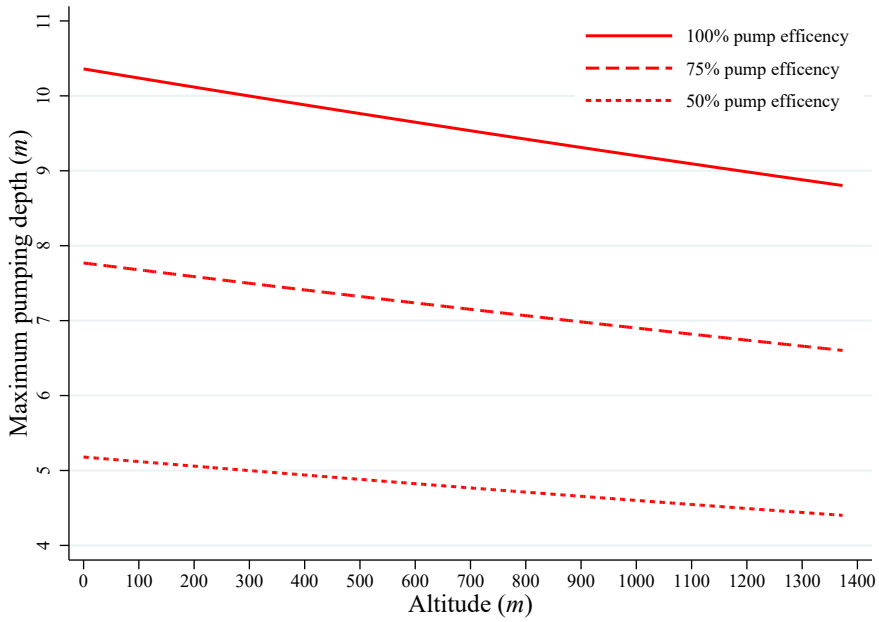
Figure 1: Pumping mechanism of a centrifugal pump



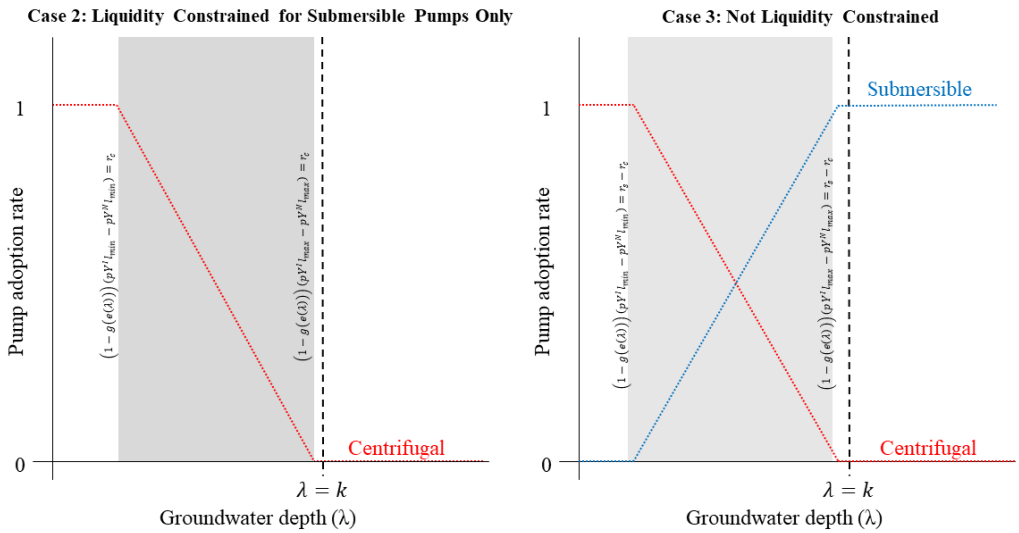
Notes: Extraction of water from a well using a centrifugal pump can be described by Bernoulli's principle of fluid dynamics (Equation 1). Assuming constant flow velocity, water extraction is defined by Equation 2: $h_2 - h_1 = \frac{P_1 - P_2}{\rho g}$, where P_1 and P_2 refers to pressure from the water table and the pump respectively, ρ is the density of water (997 kg/m^3), and g the gravitational force (9.81 m/s^2). The difference between h_1 and h_2 is the distance between the ground level and the water table. Under a perfect vacuum (P_2=0 $kg/m/s^2$) and atmospheric pressure at sea-level (P_1=101,325 $kg/m/s^2$), the depth from which water can be extracted is 10.33 meters.

Figure 2: Effect of efficiency and altitude on the maximum pumping depth of a centrifugal pump



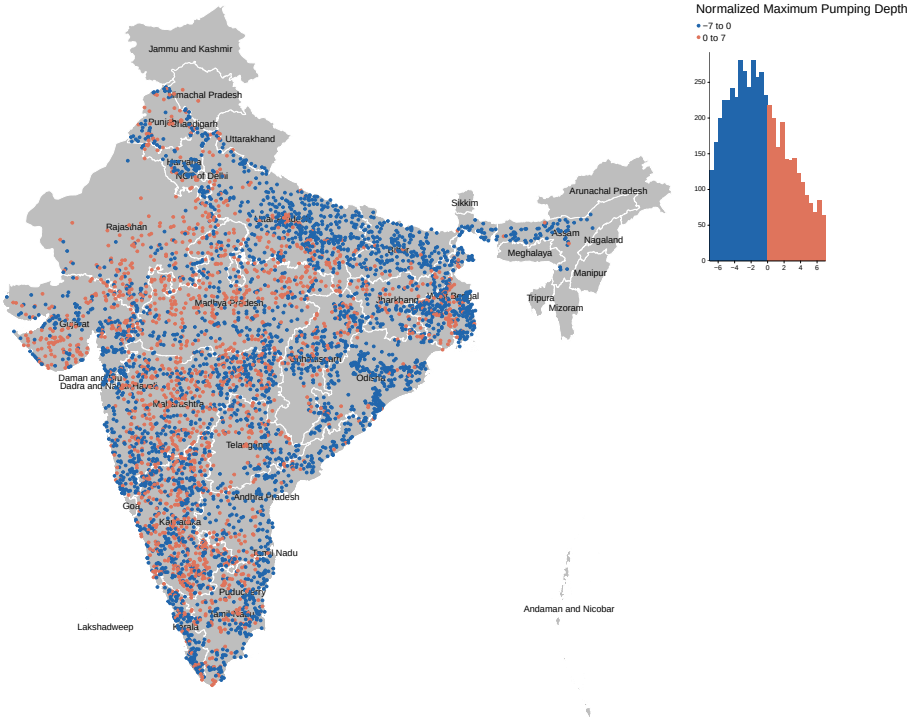
Notes: 100% pump efficiency occurs under a perfect vacuum (where P=0 $kg/m/s^2$). 75% and 50% pump efficiency indicates the corresponding percentage drop from a case of perfect vacuum. The range of altitude plotted correspond to those found in our sample of villages. Data on altitude was extracted from raster files for the whole of India, obtained from the ALOS Global Digital Surface Model. A barometric formula was used to calculate atmospheric pressure with varying altitude. Specifically, we estimate $P = P_b.exp[\frac{-gM(h-h_b)}{RT_b}]$, where P refers to pressure, g is the gravitational force, M is the molar mass of the Earth's air, h is height, R is the universal gas content, and T is temperature. Note that though the base values for P_b, h_b and T_b naturally evolve with altitude, these are in fact constant for the range of altitude found in our sample.

Figure 3: Illustrative diagram for the evolution of pump adoption with groundwater depth



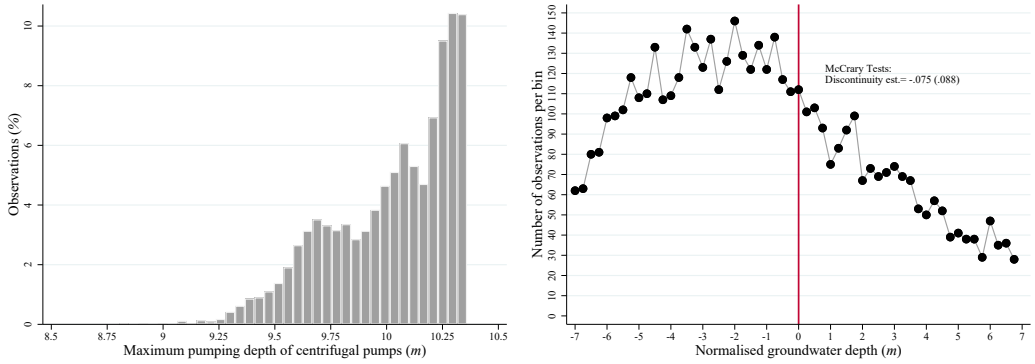
Notes: It is the subset of farmers that can afford a centrifugal pump but not a submersible (i.e. Case 2) that generates a kink in overall pump adoption and consequently irrigation. The linear functional form requires that pump efficiency and land are distributed uniformly. Additionally, under the assumption that $g(e(\lambda_v)) = 0$ – that is, centrifugal pumps work with certainty – even the smallest farmers (whose decision equation is indexed by min) will adopt centrifugal pumps. On the other hand, as $\lambda_v - k$ becomes very small, only the farmers with the largest landholdings (whose decision equation is indexed by max) are most likely to adopt centrifugal pumps.

Figure 4: Location of sample villages and their groundwater depth



Notes: Our total sample covers 4,974 villages across 478 districts amongst 19 States. Each point on the map represents a village in this sample. The maximum groundwater depth below which no centrifugal pump can operate is 10.33 meters. Red points correspond to villages with depths deeper than 10.33 metres, while blue points are shallower.

Figure 5: Distribution of the assignment variable across the kink point

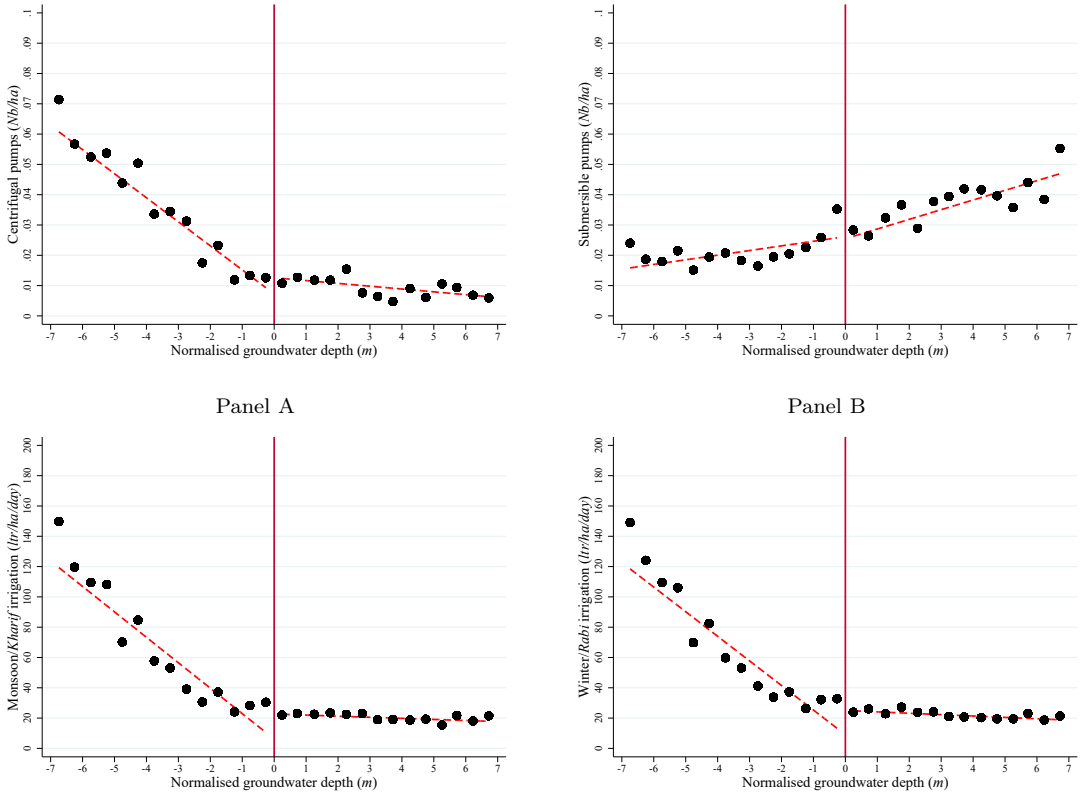


Panel A

Panel B

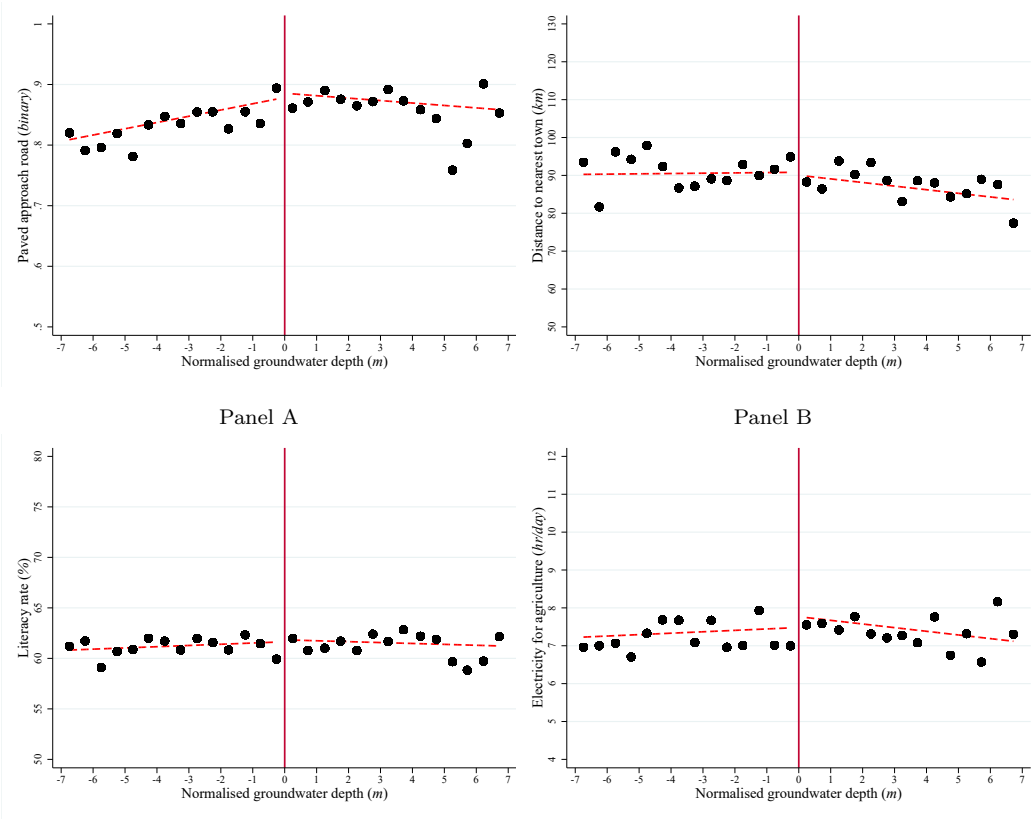
Notes: The kink point refers to the groundwater depth below which no centrifugal pump can operate – 10.33 meters. Panel A shows the distribution of the maximum pumping depth of a centrifugal pump for villages in our sample. Panel B plots the number of observations in each bin for groundwater depth normalised at the kink point. A *fuzzy* RK design requires for the conditional density of the assignment variable, given the unobserved error in the outcome, to be continuously differentiable at the kink point. The McCrary test, reported in Panel B, provides an additional validation test by estimating the log change in height between bins at the kink point.

Figure 6: Deterministic relation between groundwater depth and irrigation



Notes: The x-axis in each panel represents our assignment variable – the maximum groundwater depth recorded at any point between 2011-2013. This variable is normalised around the kink point of 10.33 metres – the operational threshold for a centrifugal pump. Points to the right of zero correspond to depths deeper than 10.33 metres, while those left of zero are shallower. Each panel reports results on the deterministic relation between our assignment variable and measures of pump adoption and irrigation. Pump adoption, calculated as the number of pumps per cultivated land area, is reported for centrifugal and submersible pumps in Panels A and B respectively. Irrigation, calculated as water input in litres (for a complete discussion on the construction of this variable see Appendix B), is reported for the monsoon/*Kharif* (June-October) and the dry winter/*Rabi* season (November-March) in Panels C and D respectively. Each panel shows the mean values of the variable of interest in each bin of the assignment variable. The bin size is 0.5. The red dashed lines display predicted values of the regressions in the linear case allowing for a discontinuous shift at the kink. Formal estimates of the kink for these variables using *fuzzy* RK regression analysis are reported in Table 2.

Figure 7: Deterministic relation between groundwater depth and covariates

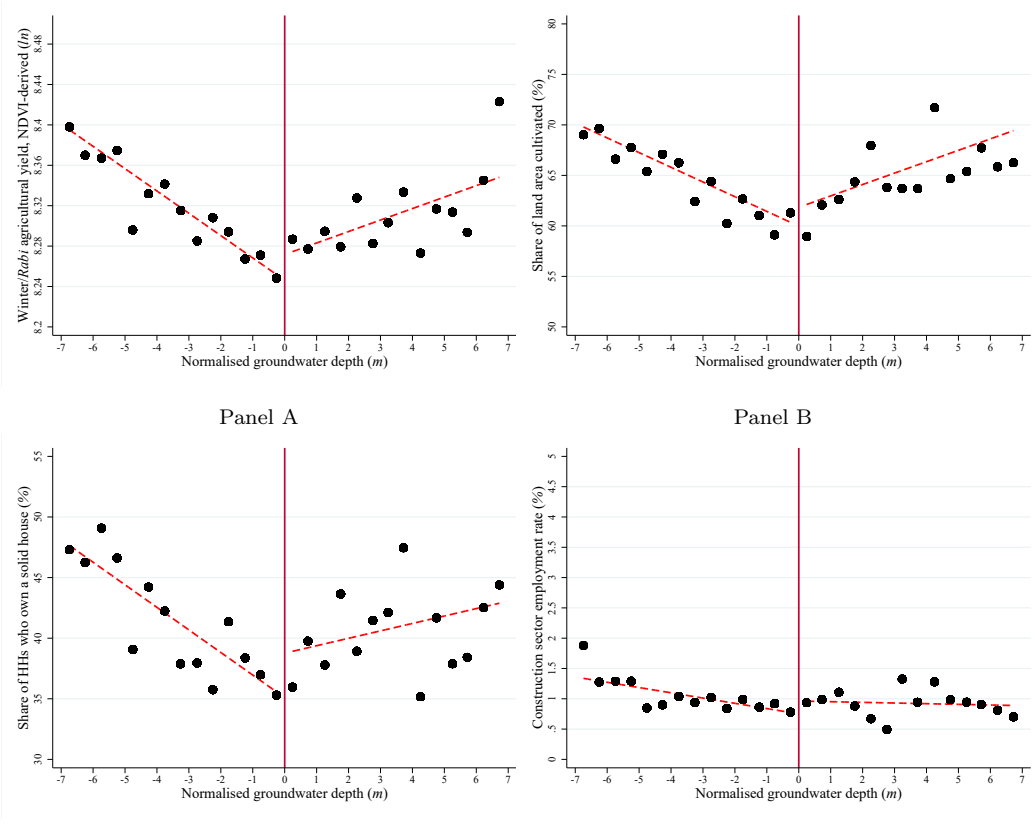


Panel A Panel B

Panel C Panel D

Notes: The x-axis in each panel represents our assignment variable – the maximum groundwater depth recorded at any point between 2011-2013. This variable is normalised around the kink point of 10.33 metres – the operational threshold for a centrifugal pump. Points to the right of zero correspond to depths deeper than 10.33 metres, while those left of zero are shallower. Each panel reports results on the deterministic relation between our assignment variable and village covariates unrelated to irrigation. The four covariates considered in our analysis include: whether a village has access to a paved road (Panel A), the minimum distance in kilometres to the closest agglomeration (town with population above 500,000) (Panel B), the percentage share of the literate population to the total population (Panel C), and the average power supply (hr/day) over the year for agricultural use (Panel D). Each panel shows the mean values of the variable of interest in each bin of the assignment variable. The bin size is 0.5. The red dashed lines display predicted values of the regressions in the linear case allowing for a discontinuous shift at the kink. Formal estimates of the kink for these variables using *fuzzy* RK regression analysis are reported in Table 2.

Figure 8: Deterministic relation between groundwater depth and a selection of outcomes



Panel A Panel B

Panel C Panel D

Notes: The x-axis in each panel represents our assignment variable – the maximum groundwater depth recorded at any point between 2011-2013. This variable is normalised around the kink point of 10.33 metres – the operational threshold for a centrifugal pump. Points to the right of zero correspond to depths deeper than 10.33 metres, while those left of zero are shallower. Each panel reports results on the deterministic relation between our assignment variable and a selection of our outcome variables. The four outcome variables reported here include: winter/*Rabi* agricultural yield (derived from NDVI – an index of vetegation cover based on satellite imagery, for a complete discussion on the construction of this variable see Appendix B) calculated as the log of the difference between early-season and the maximum value (Panel A), the share of village agricultural land area which is cultivated (Panel B), the percentage share of households in the village that own a solid house (Panel C), and the percentage share of workers employed in village construction businesses (Panel D). Each panel shows the mean values of the variable of interest in each bin of the assignment variable. The bin size is 0.5. The red dashed lines display predicted values of the regressions in the linear case allowing for a discontinuous shift at the kink. Formal estimates of the kink for these variables using $fuzzy$ RK regression analysis are reported in Tables 3, 4, 7, and 9 for Panels A, B, C and D respectively.

Table 1: Descriptive statistics

	Mean (1)	SD (2)	N (3)	Source (Year) (4)
Panel A: Irrigation				
Monsoon/*Kharif* irrigation (*ltr/ha/day*)	46.018	102.183	4971	MIC (2013)
Winter/*Rabi* irrigation (*ltr/ha/day*)	47.358	101.452	4971	MIC (2013)
Irrigation average (*ltr/ha/day*)	47.101	103.230	4971	MIC (2013)
Tube-wells (*Nb/ha*)	0.055	0.092	4971	MIC (2013)
Centrifugal pumps (*Nb/ha*)	0.025	0.068	4971	MIC (2013)
Share of irrigated area by tube-wells (%)	38.440	42.559	4971	MIC (2013)
Panel B: Demographics and amenities				
Population (*nb*)	4220.214	5244.649	4971	PC (2011)
Share of literate population (%)	61.372	11.754	4971	PC (2011)
Share of scheduled caste population (%)	18.232	15.802	4971	PC (2011)
Has a paved road (*binary*)	0.856	0.351	4971	PC (2011)
Panel C: Consumption				
Per capita consumption ('000 *Rs./annum*)	18.093	4.748	4971	SECC (2012)
Share of HHs BPL[a] (%)	30.891	18.443	4971	SECC (2012)
Share of HHs who own a solid house (%)	40.454	28.620	3682	SECC (2012)
Panel D: Agriculture				
Share of cultivated land sown (%)	61.468	30.759	4971	PC (2011)
Agricultural electricity usage (*hr/day*)	8.820	6.217	4971	PC (2011)
Share of HHs who own mechanised equipment (%)	4.067	6.936	3682	SECC (2012)
Share of workforce are cultivators (%)	13.254	10.219	4971	PC (2011)
Share of workforce are labourers (%)	18.321	11.957	4971	PC (2011)
Panel E: Industry				
Share of workforce employed(%)	9.732	9.655	4971	EC (2012)
Share of employment in agro-processing (%)	1.176	4.701	4971	EC (2012)
Share of employment in livestock (%)	16.863	24.929	4971	EC (2012)
Share of employment in manufacturing (%)	15.661	16.737	4971	EC (2012)
Share of employment in services (%)	45.812	23.519	4971	EC (2012)
Share of employment in construction (%)	0.996	2.733	4971	EC (2012)

Notes: For additional details on the source of data and construction of each variable, refer to Section 3. The total sample with non-missing observations across all our outcomes of interest and within our bandwidth (7 metres) covers 4,974 villages across 478 districts in 19 States. Variables obtained from the SECC however, have a slightly reduced sample covering 3,682 villages.
[a]Poverty line is set at Rs.31/day.

Table 2: Estimated kink in the deterministic relation of groundwater depth with irrigation and covariates

	Irrigation			Covariates			
	Average	Monsoon/*Kharif*	Winter/*Rabi*	Paved approach road	Distance to nearest town	Literacy rate	Electricity for agriculture
	(*standardised*)	(*standardised*)	(*standardised*)	(*binary*)	(*km*)	(%)	(*hr/day*)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
π_1	0.095***	0.096***	0.090***	-0.001	-0.324	0.083	-0.065
	(0.011)	(0.011)	(0.011)	(0.005)	(0.674)	(0.153)	(0.067)
Mean	0.000	0.000	0.000	0.856	89.418	61.372	8.820
SD	1.000	1.000	1.000	0.351	47.608	11.754	6.217
N	4971	4971	4971	4971	4971	4971	4971
Controls	Yes	Yes	Yes	No	No	No	No
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents estimates on the effect of groundwater depth on irrigation and covariates. π_1 is the estimated change in slope of the assignment rule at the kink (based on Equation 9). We calculate irrigation as water input in litres. However, for the purpose of interpretation across all regressions, we standardise these variables (for a complete discussion on the construction of these variables, see Appendix B). Our measure of irrigation is reported in Columns 1 to 3 as an average over the year, as well as independently for the Monsoon/*Kharif* (June-October) and the dry Winter/*Rabi* season (November-March) respectively. We consider four covariates (reported in Columns 4 to 7) capturing village-level amenities and demographics unrelated to irrigation. Paved road is a binary variable for whether the village has a tar road. Distance to nearest town captures the minimum distance, measured in kilometres, to the closest agglomeration (town with population above 500,000). Literacy rate is the percentage share of the literate population to the total population. Electricity for agriculture measures the average power supply (hr/day) over the year for agricultural use. Heteroskedasticity robust standard errors are reported in parentheses. * significant at 10% ** significant at 5% *** significant at 1%.

Table 3: Impact of tube-well irrigation on agricultural yield

	Monsoon/*Kharif*			Winter/*Rabi*		
	Differenced (*ln*)	Mean (*ln*)	Max (*ln*)	Differenced (*ln*)	Mean (*ln*)	Max (*ln*)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Agricultural yield, NDVI-derived						
Irrigation	0.058	0.049**	0.070***	0.091***	0.011	0.076***
(*standardised*)	(0.059)	(0.021)	(0.025)	(0.033)	(0.020)	(0.027)
Mean	3406.297	4330.978	6617.739	257.189	5018.756	5274.746
SD	1231.014	835.095	1063.499	1577.431	1200.420	1264.672
Panel B: Agricultural yield, EVI-derived						
Irrigation	0.052	0.032	0.045	-0.015	0.007	-0.001
(*standardised*)	(0.064)	(0.024)	(0.032)	(0.035)	(0.017)	(0.026)
Mean	2396.702	3049.590	4600.275	1737.821	2935.496	4672.270
SD	1013.289	626.923	964.476	958.657	758.271	1054.239
N	4971	4971	4971	4971	4971	4971
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents *fuzzy* RK estimates on the effect of irrigation on agricultural yield. Irrigation intensity is calculated as *litres/ha/day* and standardised. We rely on measures of vegetation cover using satellite imagery – NDVI (reported in Panel A) and EVI (reported in Panel B), as indicators for agricultural yield. Calculated over a three year period (2011-2013), we consider three proxies specific to each agricultural season – maximum, mean, and the difference between early season and the maximum value. The Monsoon/*Kharif* season (reported in Columns 1 to 3) is based on data from June to October, and the dry Winter/*Rabi* season (reported in Columns 4 to 6) covers November to March. For a complete discussion on the data and how each proxy is calculated, refer to Appendix B. Summary statistics for all our proxies are reported on the level form of the variables. Controls include the following covariates: paved approach road, distance to nearest town, literacy rate, and electricity for agriculture. Heteroskedasticity robust standard errors are presented in parenthesis. * significant at 10% ** significant at 5% *** significant at 1%.

Table 4: Impact of tube-well irrigation on agricultural production choices

	Inputs			Crop choice		
	Mechanised equipment (%) (1)	Water-saving technology (%) (2)	Cultivated land (%) (3)	Winter/ *Rabi* (*binary*) (4)	Drought tolerant (*binary*) (5)	Cash (*binary*) (6)
Irrigation	1.005	-4.357*	12.229***	0.062	-0.256***	0.040
(*standardised*)	(1.490)	(2.617)	(3.948)	(0.060)	(0.079)	(0.069)
Mean	4.067	3.224	64.760	0.243	0.316	0.198
SD	6.936	15.467	27.939	0.429	0.465	0.398
N	3681	4971	4971	3910	3910	3910
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents *fuzzy* RK estimates on the effect of irrigation on agricultural production choices. Irrigation intensity is measured as *litres/ha/day* and standardised. Columns 1 to 3 considers the effect of irrigation on three measures of inputs: mechanisation – calculated as the percentage share of households who own mechanised farm equipment (e.g. tractors, harvesters etc.), water-saving technology – calculated as the percentage share of tube-wells which are adapted to water-saving mechanisms (i.e. which use drip and sprinklers), and cultivated land – calculated as the percentage share of agricultural land area which is cultivated. Columns 4 to 6 present estimates on the effect of irrigation on three binary measures of crop choice: does a village grow winter crops (wheat, barley, potato, oilseed, and chickpea), drought tolerant crops (millet, sorghum, maize, pigeon pea, and groundnut), or cash crops (sugarcane, oilseed, cotton, and tobacco). Controls include the following covariates: paved approach road, distance to nearest town, literacy rate, and electricity for agriculture. Heteroskedasticity robust standard errors are presented in parenthesis. * significant at 10% ** significant at 5% *** significant at 1%.

Table 5: Impact of tube-well irrigation on the distribution of landholdings

	Landless (%) (1)	0-2 Acres (%) (2)	2-4 Acres (%) (3)	4+ Acres (%) (4)
Irrigation	4.717	-0.204	-2.417	-0.060
(*standardised*)	(4.640)	(3.658)	(1.496)	(2.932)
Mean	54.107	22.411	9.002	13.419
SD	23.145	19.333	7.257	14.955
N	3681	3681	3681	3681
Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

Notes: This table presents *fuzzy* RK estimates on the effect of irrigation on the distribution of landholdings. Irrigation intensity is measured as $litres/ha/day$ and standardised. Results are reported for four categories of land acreage – 0, 0-2, 2-4, and over 4. Each variable is calculated as the percentage share of households who own that specific landholding size. Controls include the following covariates: paved approach road, distance to nearest town, literacy rate, and electricity for agriculture. Heteroskedasticity robust standard errors are presented in parenthesis. * significant at 10% ** significant at 5% *** significant at 1%.

Table 6: Impact of tube-well irrigation on consumption

	Consumption per capita (*ln*) (1)	Poverty rate (*share*) (2)	Average mean night light (*ln*) (3)	SD mean night light (*ln*) (4)
Irrigation	0.046	-0.044*	0.165**	-0.031*
(*standardised*)	(0.033)	(0.024)	(0.073)	(0.016)
Mean	18.242	0.316	6.782	1.011
SD	4.936	0.191	4.756	0.881
N	4971	4971	4971	4971
Controls	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes

Notes: This table presents *fuzzy* RK estimates on the effect of irrigation on consumption. Irrigation intensity is measured as $litres/ha/day$ and standardised. We consider two household level measures of consumption (reported in Columns 1 and 2): imputed log consumption per capita, and the share of the population living below the poverty line (set at Rs.31/day). For a complete discussion on the data and construction of these variables, refer to Appendix B. Additionally, we rely on measures of night light luminosity from satellite images as indicators of consumption (reported in Columns 3 and 4). Using data on mean night light, we calculate two proxies: average of mean night light and the standard deviation of mean night light. These are calculated over a five year period (2009-2013). For a complete discussion on the data and construction of these variables, refer to Appendix B. Summary statistics for consumption per capita, as well as those for night light, are reported on the level form of the variable. Controls include the following covariates: paved approach road, distance to nearest town, literacy rate, and electricity for agriculture. Heteroskedasticity robust standard errors are presented in parenthesis, except for consumption and poverty which report bootstrapped standard errors. * significant at 10% ** significant at 5% *** significant at 1%.

Table 7: Impact of tube-well irrigation on ownership of assets

	Asset index	Solid house (%)	Refrigerator (%)	Vehicle (%)	Phone (%)
	(1)	(2)	(3)	(4)	(5)
Irrigation	0.348*	17.394***	1.296	1.903	3.056
(*standardised*)	(0.210)	(5.602)	(2.137)	(2.850)	(4.042)
Mean	0.313	40.454	8.758	19.637	67.586
SD	1.001	28.620	12.940	15.537	25.326
N	3681	3681	3681	3681	3681
Controls	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes

Notes: This table presents *fuzzy* RK estimates on the effect of irrigation on ownership of assets. Irrigation intensity is measured as $litres/ha/day$ and standardised. The variable for asset index reported in Column 1 is calculated as the village-level average of the primary component of indicator variables for all household assets captured in the Socio Economic Caste Census (2012). We further present estimates on the percentage share of households in the village that own each of the following specific assets: solid house, refrigerator, vehicle, and phone (reported in Columns 2 to 5 respectively). Controls include the following covariates: paved approach road, distance to nearest town, literacy rate, and electricity for agriculture. Heteroskedasticity robust standard errors are presented in parenthesis. * significant at 10% ** significant at 5% *** significant at 1%.

Table 8: Impact of tube-well irrigation on agricultural sector employment

	Total			Cultivators			Manual labourers		
	Person (%) (1)	Male (%) (2)	Female (%) (3)	Person (%) (4)	Male (%) (5)	Female (%) (6)	Person (%) (7)	Male (%) (8)	Female (%) (9)
Panel A: Share of population									
Irrigation	-2.228*	0.279	-4.632**	0.579	1.596	-0.420	-1.209	-0.707	-1.893
(*standardised*)	(1.350)	(0.871)	(2.276)	(1.497)	(1.743)	(1.562)	(1.670)	(1.702)	(1.984)
Mean	44.450	55.313	33.097	13.254	18.183	8.120	18.321	18.886	17.665
SD	10.471	6.768	17.448	10.219	11.722	10.712	11.957	11.677	14.579
Panel B: Share of workforce									
Irrigation	-	-	-	2.574	3.035	0.573	-0.971	-1.262	0.853
(*standardised*)	(-)	(-)	(-)	(2.919)	(3.036)	(3.210)	(3.105)	(2.925)	(4.008)
Mean	-	-	-	29.142	32.766	21.667	39.798	33.948	49.453
SD	-	-	-	19.612	20.463	21.556	21.604	20.174	27.184
Panel C: Share of full-time workers									
Irrigation	9.864***	8.426***	6.850	6.206**	5.228*	2.062	10.390**	8.660*	8.896*
(*standardised*)	(3.368)	(2.984)	(4.327)	(3.025)	(2.732)	(4.831)	(4.708)	(4.653)	(5.114)
Mean	73.674	81.011	59.451	84.630	89.099	67.128	61.810	68.411	51.967
SD	21.780	19.284	29.392	20.252	18.461	32.314	30.989	30.454	34.651
N	4971	4971	4971	4971	4971	4971	4971	4971	4971
Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents *fuzzy* RK estimates on the effect of irrigation on employment of the village population in the agricultural sector. Irrigation intensity is measured as *litres/ha/day* and standardised. Alongside total employment (reported in Columns 1 to 3), we consider two specific occupational categories in agriculture: cultivators (reported in Columns 4 to 6) are those who cultivate their own land, and manual labourers (reported in Columns 7 to 9) are those who work for a daily wage. Furthermore, we disaggregate each of our categories by gender. Panel A reports results on the percentage share of the population employed, calculated - for total employment as well as specific to each category - as the ratio of those employed to the total population of working age. Panel B reports results on the percentage share of the workforce engaged in each category, calculated as the ratio of those employed in that category to the total workforce. Panel C reports results on the percentage share of full-time workers (those that work for more than 6 months of the year), calculated - for total employment as well as specific to each category - as the ratio of full-time workers to the total workforce. Controls include the following covariates: paved approach road, distance to nearest town, literacy rate, and electricity for agriculture. Heteroskedasticity robust standard errors are presented in parenthesis. * significant at 10% ** significant at 5% *** significant at 1%.

Table 9: Impact of tube-well irrigation on industrial sectoral employment

	Total	Agro-processing	Livestock	Construction	Manufacturing	Services
	(*ln*)	(%)	(%)	(%)	(%)	(%)
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: In village businesses						
Irrigation	0.233	-0.494	-0.874	0.381	2.897	2.510
(*standardised*)	(0.227)	(0.770)	(3.686)	(0.434)	(2.721)	(3.641)
Mean	488.092	1.176	16.863	0.996	15.661	45.812
SD	918.049	4.701	24.929	2.733	16.737	23.519
N	4971	4971	4971	4971	4971	4971
Panel B: In nearest town businesses						
Irrigation	0.235	-0.028	0.580	0.138	3.044	-1.349
(*standardised*)	0.184	0.172	0.995	0.309	2.179	2.321
Mean	6681.337	0.370	2.956	1.447	19.314	64.725
SD	8487.485	0.959	5.614	1.794	12.034	13.030
N	4076	4076	4076	4076	4076	4076
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents *fuzzy* RK estimates on the effect of irrigation on employment in economic establishments. Irrigation intensity is measured as *litres/ha/day* and standardised. We consider sectoral employment both within the village, reported in Panel A, as well as within the nearest town, reported in Panel B. Results are reported for log of total employment across all sectors (Column 1), as well as the percentage share of employment in each of the following sectors: agro-processing (this excludes crop production), livestock, construction, manufacturing, and services (reported in Columns 2 to 6 respectively). Summary statistics for total employment are reported on the level form of the variable (*nb*). Controls include the following covariates: paved approach road, distance to nearest town, literacy rate, and electricity for agriculture. Heteroskedasticity robust standard errors are presented in parenthesis. * significant at 10% ** significant at 5% *** significant at 1%.

Table 10: Impact of tube-well irrigation on population

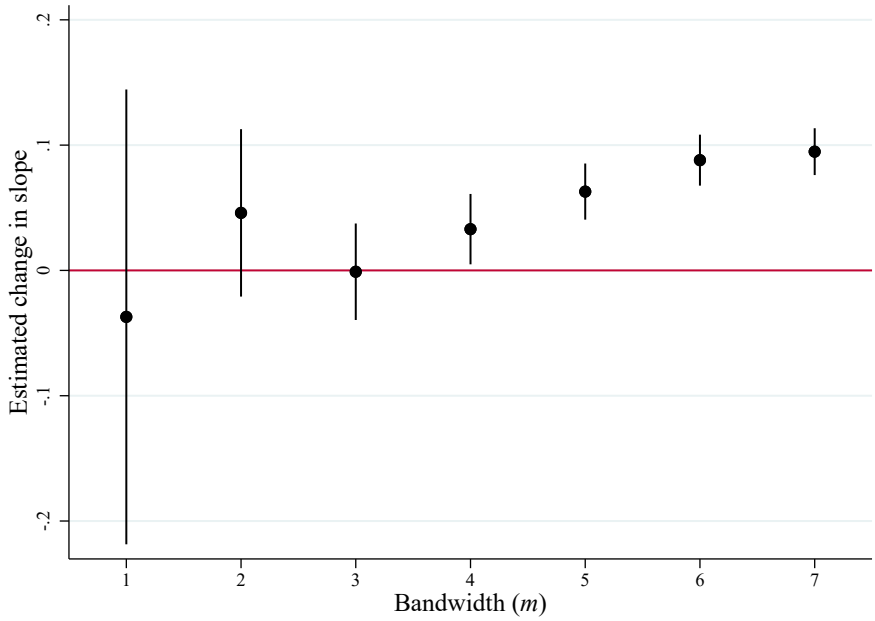
	Village			Nearest town		
	Population	Population density	Population growth	Population	Population density	Population growth
	(*ln*)	(*ln*)	(%)	(*ln*)	(*ln*)	(%)
	(1)	(2)	(3)	(4)	(5)	(6)
Irrigation	0.322*	0.391***	-2.070	0.142	0.055	-1.131
(*standardised*)	(0.167)	(0.126)	(2.821)	(0.159)	(0.143)	(2.045)
Mean	7.771	1.315	15.701	10.371	8.030	14.772
SD	1.117	0.909	18.426	1.003	0.911	12.542
N	4841	4841	4841	4841	4841	4841
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents *fuzzy* RK estimates on the effect of irrigation on population. Irrigation intensity is measured as *litres/ha/day* and standardised. Changes in population are captured for both the village (reported in Columns 1-3), and its nearest town (reported in Columns 4-6). We consider three measures of population - log of population in 2011, log of population density in 2011 (i.e. population divided by area), and the decadal rate of population growth (2001-11). Controls include the following covariates: paved approach road, distance to nearest town, literacy rate, and electricity for agriculture. Heteroskedasticity robust standard errors are presented in parenthesis. * significant at 10% ** significant at 5% *** significant at 1%.

Appendices

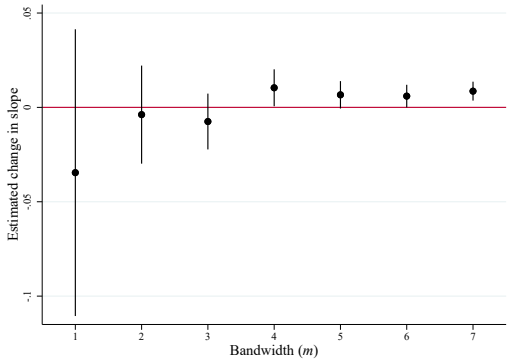
A . Appendix: Additional Tables and Figures

Figure A1: Estimated kink in the deterministic relation between irrigation and groundwater depth at a range of bandwidths

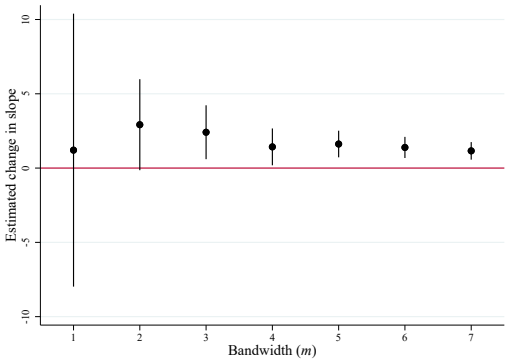


Notes: The plot presents point estimates and 90% confidence intervals for the linear specification of Equation 9 on our measure of irrigation at one meter interval bandwidths. Irrigation, is calculated as water input in litres measured as an average over the year and standardised for the purpose of all regressions (for a complete discussion on the construction of this variable see Appendix B). The regression is estimated using heteroskedasticity robust standard errors and includes both state fixed effects and the following controls: paved approach road, distance to nearest town, literacy rate, and electricity for agriculture.

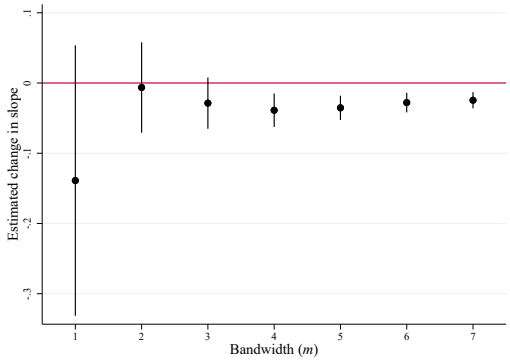
Figure A2: Estimated kink in the relation between key outcome variables and groundwater depth at a range of bandwidths



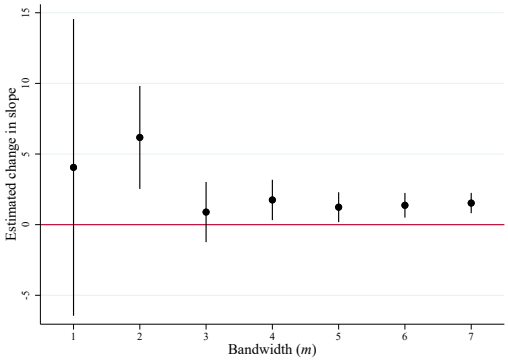
Panel A: Winter/*Rabi* agricultural yield, NDVI-derived (*ln*)



Panel B: Cultivated land (%)



Panel C: Drought tolerant crops (*binary*)



Panel D: Solid house (%)

Notes: Each plot presents point estimates and 90% confidence intervals for the linear specification of Equation 8 at one meter interval bandwidths for a selection of our outcome variables. The four outcome variables reported here include: winter/*Rabi* agricultural yield (derived from NDVI – an index of vetegation cover based on satellite imagery) calculated as the log of the difference between early-season and the maximum value (Panel A), the share of village agricultural land area which is cultivated (Panel B), whether the village grows drought tolerant crops (millet, sorghum, maize, pigeon pea, and groundnut) (Panel C), and the percentage share of households in the village that own a solid house (Panel D). All regressions are estimated using heteroskedasticity robust standard errors and include both state fixed effects and the following controls: paved approach road, distance to nearest town, literacy rate, and electricity for agriculture.

Table A1: Estimated kink in the deterministic relation of groundwater depth with irrigation and covariates for different functional forms

	Irrigation			Covariates			
	Average	Monsoon/*Kharif*	Winter/*Rabi*	Paved approach road	Distance to nearest town	Literacy rate	Electricity for agriculture
	(*standardised*)	(*standardised*)	(*standardised*)	(*binary*)	(*km*)	(%)	(*hr/day*)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Panel A: Linear							
π_1	0.096***	0.097***	0.091***	-0.001	-0.324	0.083	-0.065
	(0.011)	(0.011)	(0.012)	(0.005)	(0.674)	(0.153)	(0.067)
Panel B: Quadratic							
π_1	-0.046	-0.036	-0.053	-0.003	0.099	1.231**	-0.054
	(0.039)	(0.039)	(0.040)	(0.017)	(2.494)	(0.557)	(0.251)
Panel C: Cubic							
π_1	-0.170*	-0.167*	-0.176*	0.068	-1.950	1.732	0.152
	(0.089)	(0.089)	(0.090)	(0.042)	(6.083)	(1.346)	(0.612)
N	4971	4971	4971	4971	4971	4971	4971
Controls	No	No	No	No	No	No	No
State FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents estimates on the effect of groundwater depth on irrigation and covariates for varying functional form. π_1 is the estimated change in slope of the assignment rule at the kink (based on Equation 9). Panel A presents estimates using a linear functional form, Panel B is quadratic, and Panel C is cubic. We calculate irrigation as water input in litres. However, for the purpose of interpretation across all regressions, we standardise these variables (for a complete discussion on the construction of these variables, see Appendix B). Our measure of irrigation is reported in Columns 1 to 3 as an average over the year, as well as independently for the Monsoon/*Kharif* (June-October) and the dry Winter/*Rabi* season (November-March) respectively. We consider four covariates (reported in Columns 4 to 7) capturing village-level amenities and demographics unrelated to irrigation. Paved road is a binary variable for whether the village has a tar road. Distance to nearest town captures the minimum distance, measured in kilometres, to the closest agglomeration (town with population above 500,000). Literacy rate is the percentage share of the literate population to the total population. Electricity for agriculture measures the average power supply (hr/day) over the year for agricultural use. Heteroskedasticity robust standard errors are reported in parentheses. * significant at 10% ** significant at 5% *** significant at 1%.

Table A2: Estimated kink in the deterministic relation of groundwater depth with irrigation over varying time horizons

	Irrigation		
	Average (*standardised*) (1)	Monsoon/*Kharif* (*standardised*) (2)	Winter/*Rabi* (*standardised*) (3)
Panel A: 1 year			
π_1	0.033***	0.035***	0.028***
	(0.008)	(0.008)	(0.008)
Panel B: 3 years			
π_1	0.095***	0.096***	0.090***
	(0.011)	(0.011)	(0.011)
Panel C: 5 years			
π_1	0.089***	0.090***	0.085***
	(0.012)	(0.012)	(0.012)
N	4971	4971	4971
Controls	Yes	Yes	Yes
State FE	Yes	Yes	Yes

Notes: This table presents estimates on the effect of groundwater depth on irrigation for varying time horizons. π_1 is the estimated change in slope of the assignment rule at the kink (based on Equation 9). The assignment variable is defined as the maximum groundwater depth recorded at any point over a 1, 3, and 5 year time horizon preceding 2013. We calculate irrigation as water input in litres. However, for the purpose of interpretation across all regressions, we standardise these variables (for a complete discussion on the construction of these variables, see Appendix B). Our measure of irrigation is reported in Columns 1 to 3 as an average over the year, as well as independently for the Monsoon/*Kharif* (June-October) and the dry Winter/*Rabi* season (November-March) respectively. Controls include the following covariates: paved approach road, distance to nearest town, literacy rate, and electricity for agriculture. Heteroskedasticity robust standard errors are reported in parentheses. * significant at 10% ** significant at 5% *** significant at 1%.

Table A3: Impact of tube-well irrigation on outcome variables without controls

	Winter/*Rabi* agricultural yield, NDVI-derived	Cultivated land	Drought tolerant crop	Share of full time workers	SD mean night light	Solid house
	(*ln*)	(%)	(*binary*)	(%)	(*ln*)	(%)
	(1)	(2)	(3)	(4)	(5)	(6)
Irrigation	0.092***	12.250***	-0.257***	9.958***	-0.032**	16.825***
(*standardised*)	0.033	3.924	0.079	3.363	0.016	4.972
Mean	8.312	64.760	0.316	73.674	0.158	40.762
SD	0.332	27.939	0.465	21.780	0.116	28.589
N	4971	4971	4971	4971	4971	4971
Controls	No	No	No	No	No	No
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents *fuzzy* RK estimates on the effect of irrigation on a selection of our outcome variables without controls. Irrigation intensity is measured as *litres/ha/day* and standardised. The outcome variables reported here include: winter/*Rabi* agricultural yield (derived from NDVI – an index of vetegation cover based on satellite imagery, for a complete discussion on the construction of this variable see Appendix B) calculated as the log of the difference between early-season and the maximum value (Column 1), the share of village agricultural land area which is cultivated (Column 2), whether the village grows drought tolerant crops (millet, sorghum, maize, pigeon pea, and groundnut) (Column 3), the percentage share of full-time workers (total persons) (Column 4), the standard deviation of mean night light over a five year period (Column 5), and the percentage share of households in the village that own a solid house (Column 6). Summary statistics for agricultural yield are reported on the level form of the variable. Heteroskedasticity robust standard errors are presented in parenthesis. * significant at 10% ** significant at 5% *** significant at 1%.

Table A4: Impact of tube-well irrigation on the village age distribution and gender ratio

	1-10 (%) (1)	11-20 (%) (2)	21-30 (%) (3)	31-40 (%) (4)	41-50 (%) (5)	51-60 (%) (6)
Panel A: Population share in each age group						
Irrigation	0.827	0.087	0.009	-0.342	-0.643	-0.216
(*standardised*)	0.631	0.563	0.439	0.382	0.429	0.363
Mean	20.485	22.799	19.838	15.923	12.614	8.295
SD	4.602	3.132	2.311	2.105	2.572	2.274
Panel B: Male share in each age group						
Irrigation	-0.274	-0.075	0.202	0.670	0.327	-0.588
(*standardised*)	0.752	0.774	0.769	0.758	0.820	1.087
Mean	51.942	52.698	51.220	50.584	51.875	51.259
SD	3.480	3.608	3.723	3.555	3.956	5.128
N	3681	3681	3681	3681	3681	3681
Controls	Yes	Yes	Yes	Yes	Yes	Yes
State FE	Yes	Yes	Yes	Yes	Yes	Yes

Notes: This table presents *fuzzy* RK estimates on the effect of irrigation on the age distribution and gender ratio. Irrigation intensity is measured as $litres/ha/day$ and standardised. Panel A reports results on the percentage share of the population in each age group. Panel B reports results for the percentage share of the male population in each age group. Results are reported for ten-year age bins. Controls include the following covariates: paved approach road, distance to nearest town, literacy rate, and electricity for agriculture. Heteroskedasticity robust standard errors are presented in parenthesis. * significant at 10% ** significant at 5% *** significant at 1%.

B . Appendix: Data

B1 Irrigation

According to a standard engineering formula, three main factors affect water extraction from irrigation pumps – capacity, use, and well depth (Manring, 2013). We leverage data collected by the Fifth Minor Irrigation (MI) Census in 2013 on irrigation practices to calculate village-level indicators for pump capacity and usage.[33] Specifically, we measure pump capacity as the average horse power of pumps in a village. Usage is measured as the total number of pumping hours per day in a village.[34] We use our assignment variable – the maximum groundwater depth recorded at any point over a three year period covering 2011-2013 – as our measure for well depth.[35] Using these three factors as outlined in Equation 10, we are able to calculate our main variable for irrigation in terms of water input in litres:

$$W_i(H_i D_i) = \rho \frac{P_i H_i}{D_i} \tag{10}$$

where i denotes a village, P_i is pump capacity, H_i is usage, and D_i is the depth from which water is lifted. The physical constant ρ, is given by:

$$\rho = c \frac{E}{dg} \tag{11}$$

where c is a constant to correct units and account for friction, E is pump efficiency, d is density of water, and g is the gravitational constant. Values for the constants used in the calculation of ρ are provided below in Table A5.

Calculated in this manner, we obtain a litres/day measure of groundwater extraction for irrigation. We then scale this by village size, generating a litres/ha/day variable. For the purpose of all our regressions, we further standardise this variable such that all results can be interpreted as the effect of a one standard deviation increase in irrigation.[36] To provide some context, one standard deviation is approximately equivalent to 103 $litres/ha/day$.

[33] Background information on each Census (e.g. questionnaires and instruction manuals on data collection) as well as official reports and aggregated statistical tables can be found on the official website of the MI Censuses at:http://micensus.gov.in. Village level data from each MI Census is publicly available in excel format on the Government of India open data platform at:http://data.gov.in

[34] Data on usage is available disaggregated by season. This allows us to calculate water input independently for both the monsoon/$Kharif$ and the winter/$Rabi$ season. We obtain an annual measure by taking an average across the seasons.

[35] For information on how this data is compiled, refer to the part on groundwater in Section 3.

[36] To standardise the variable we subtract the mean and divide by the standard deviation of the sample for each observation.

Table A5: Constants used in water input calculation

Variable	Value	Units	Source
c	3.6×10^6		Ryan and Sudarshan (2020)
E	0.25		Ryan and Sudarshan (2020)
d	10^3	kg/m^2	Manring (2013)
g	9.81	m/s^2	Manring (2013)

Notes: The table shows the values of the constants used in the calculation of ρ in Equation 11. While density of water (d) and the gravitational constant (g) are standard in the literature (Manring, 2013), the values for pump efficiency (E) and friction (c) were obtained by Ryan and Sudarshan (2020) from case studies on irrigation pumping technology in India.

B2 Agricultural Production

Data on agricultural production based on direct field measurements is not available at the village level in India. We therefore rely on measures of vegetation cover calculated from satellite images as proxies for village agricultural yield. Specifically, we use data from the Normalised Difference Vegetation Index (NDVI) and the Enhanced Vegetation Index (EVI) estimated by the United States Geological Survey from images taken by the Moderate Resolution Imaging Spectroradiometer (MODIS) sensor aboard NASA's Terra satellite. Evidence suggests that NDVI values obtained from MODIS predict land use – to the extent of classifying general crop types – with 90% accuracy (Wardlow and Egbert, 2010). With respect to crop yields, Labus et al. (2002) find that NDVI values from MODIS are able to successfully predict the growth profile of wheat at both the regional and farm level in Montana, USA. In a study of millet in Senegal, Rasmussen (1997) estimates a correlation coefficient of 72% between NDVI and actual yield. Additionally, the author finds that subtracting early-season NDVI from the peak integral NDVI values significantly improves the level of explained yield variance – an approach we therefore adopt in our empirical analysis. Comparisons of EVI and NDVI have found that both indices produce equivalent crop classification results (Wardlow and Egbert, 2010) and are equally successful at predicting yields (Kouadio et al., 2014). EVI has been found to be especially sensitive to high biomass locations and tends to present relatively lower ranges over lower biomass sites (Gao et al., 2000).

In order to determine the spatial distribution of plants from satellite images, the vegetation indices exploit the natural strong differences in plant reflectance. Specifically, the green photosynthetically active pigment in plant leaves – chlorophyll – strongly absorbs visible red light (RED). Conversely, the cell structure of leaves, strongly reflects near-infrared

light (NIR). As a result, healthy vegetation absorbs most of the visible light that hits it and reflects a large portion of the near-infrared light. Therefore, in a given pixel, if there is more reflected radiation in the near-infrared wavelengths than in the visible wavelengths, we can concur that the vegetation cover is likely to be dense. Formally, NDVI is calculated as:

$$NDVI = \frac{\rho_{NIR} - \rho_{RED}}{\rho_{NIR} + \rho_{RED}} \tag{12}$$

where ρ_{NIR} (846–885 nm) and ρ_{RED} (600–680 nm) are the surface reflectance for the respective MODIS bands. MODIS captures data in 36 spectral bands ranging in wavelength from 0.4 to 14.4 μm. The bands covering the wavelengths of interest for the purpose of capturing vegetation cover are generated at a global scale and a resolution of 250 m. Each image represents a 16-day composite, such that the value of each pixel is optimised following an algorithm which accounts for cloud cover obstruction, image quality, and viewing geometry. The images are published by the IRI/LDEO Climate Data Library.[37] The EVI is estimated in the same manner as the NDVI, but uses additional wavelengths from the blue band so as to account for atmospheric disturbance and background corrections. For an in-depth review of the literature and methods on calculating vegetation indices based on satellite imagery, refer to Huete et al. (2002).

As part of their research evaluating India's national rural road expansion programme, Asher and Novosad (2020) compiled data on the NDVI and EVI at the village-level across India for the years spanning 2000-2014. Specifically, the authors downloaded composite images for nine 16-day periods from June to October so as to cover the monsoon/*Kharif* growing season, and similarly from November to March so as to capture the winter/*Rabi* season. Each composite image was then spatially averaged to village boundaries and a range of proxies for agricultural production – based on evidence from previous research evaluating the accuracy of vegetation indices from satellite imagery – were calculated for each year and season. This data is made publicly available as part of the replication material of their published paper.[38] We employ three proxies calculated for both the NDVI and EVI in each growing season: (i) the mean value (Mkhabela et al., 2005), (ii) the maximum value (Labus et al., 2002), and (iii) the difference between the maximum value and the early season value (taken as the average of the first three 16 day periods) (Rasmussen, 1997). This third proxy enables us to subtract interference from non-crop vegetation such as forest cover, thereby providing a more accurate measure for agricultural production. All our proxies are calculated as an average over a three-year period covering 2011-2013,

[37] Information on MODIS and images for Asia can be found on the site of the IRI/LDEO Climate Data Library:https://iridl.ldeo.columbia.edu/index.html?Set-Language=en

[38] The paper by Asher and Novosad (2020) and its associated dataset is available at:https://www.aeaweb.org/articles?id=10.1257/aer.20180268

coinciding with the time horizon of our assignment variable. Finally, for more interpretable results of our regression analysis, all proxies are log transformed.

As a validation test of these vegetation indices to proxy for agricultural production in the case of Indian villages, Asher and Novosad (2020) provide correlation estimates between the proxies and district level measures of agricultural output. Table A6 presents the replication of these results. Specifically, the authors ran panel regressions (2000-2006) of the differenced NDVI and EVI proxy on agricultural output obtained from the Planning Commission's district-wise domestic product data. An R-squared of over 70%, when using district-year fixed effects, suggests a strong correlation between the proxies and district level estimates of agricultural output.

Table A6: Correlates of NDVI and EVI proxies on district agricultural output

	Differenced NDVI (*ln*)		Differenced EVI (*ln*)	
	(1)	(2)	(3)	(4)
Output (*ln*)	0.331	0.233	0.235	0.197
	(0.042)	(0.040)	(0.046)	(0.041)
R^2	0.74	0.78	0.85	0.89
N	2124	2124	2124	2124
District FE	Yes	Yes	Yes	Yes
Year FE	No	Yes	No	Yes

Notes: This table replicates the results from Asher and Novosad (2020) evaluating the validity of vegetation indices as proxies of agricultural production. The NDVI and EVI proxy are based on satellite images, calculated as the difference between early season and the maximum value. Agricultural output is obtained from the Planning Commission's district-wise domestic product data. Heteroskedasticity robust standard errors are presented in parenthesis.

B3 Consumption

Most developing countries do not collect detailed information on income or consumption as part of their censuses. As such, estimates of these economic indicators at a high geographic resolution are often unavailable at regular time intervals. Policy makers (especially the World Bank) and researchers have therefore recently relied on a method developed by Elbers et al. (2003) which uses an imputation rule derived from a household survey to generate small-area estimates of consumption in census data (Bedi et al., 2007). In a comparison of methods, McKenzie (2005) show that this prediction method through aux-

iliary surveys most accurately predicts non-durable consumption. Hentschel et al. (2000), demonstrate that this method produces unbiased estimates of poverty.

Since the early 1990s the Government of India has conducted national socioeconomic censuses collecting information at both the individual and household level on caste, occupation, earnings, and assets, in order to determine the eligibility of households into various welfare schemes (Alkire and Seth, 2013). In 2012, the fourth such Socio Economic Caste Census (SECC) was implemented.[39] In that year, the India Human Development Survey-II (IHDS-II) was also conducted. It recorded direct measures of household consumption, as well as equivalent questions to the SECC on household assets and earnings.[40] Following the methodology of Elbers et al. (2003), Asher et al. (2021b) use the IHDS-II data to predict household level consumption in the SECC dataset. Specifically, the researchers first estimate regressions of total household consumption on dummy variables of assets and earnings in the IHDS-II.[41] Coefficients from these regressions are then used to impute household level consumption values in the SECC. Finally, based on these household level values the researchers generate village level statistics for mean predicted consumption per capita and the share of the population below the poverty line.[42] Bootstrap estimates of these village level indicators are made available by the research team on the Socioeconomic High-resolution Rural-Urban Geographic (SHRUG, Version 1.5) open data platform for India.[43] We take these 1000 bootstrapped variables for predicted consumption per capita (for the purpose of the regression, these variables are log transformed) and share of the population below the poverty line, and run an additional bootstrap process on our main sample of villages when estimating the effect of access to irrigation on these indicators. As outlined in the work of Elbers et al. (2003), this bootstrapping process is required to obtain correct standard errors and p-values on our estimates.

Specific to our setting of Indian villages, Asher et al. (2021b) provide three validation tests for the bootstrap estimates of consumption used in our analysis. First, the distribution of the consumption estimates at the village level matches broadly to that found in two

[39]Information on the census can be found on the SECC website:`https://secc.gov.in/welcome`. Though the Government initially made the raw data public, only aggregated information is now available on the website.

[40]Information and data related to this survey can be found on the platform of Data Sharing for Demographic Research:`https://www.icpsr.umich.edu/web/pages/DSDR/index.html`

[41]These are the exact same variables as those recorded in the SECC. They include: type of roof and wall material, number of rooms, ownership of phone, house, vehicle, land, kisan credit card, and refrigerator, as well as the highest individual income in the household.

[42]The official poverty line for rural India is set at Rs.27/day, based on the Planning Commission's Tendulkar Committee Report in 2014.

[43]For detailed information on consumption data using the SHRUG open data platform, please refer to Asher et al. (2021b). The dataset, including codebooks and references, can be found at:`http://www.devdatalab.org/shrug`

national surveys conducted at the same time and at the same geographic level (IHDS-II and the National Sample Survey-2012). Second, there is a strong covariance between the district level predicted consumption estimates and those in the original household survey (IHDS-II). Third, by identifying how each component used in the imputation rule affects the difference in average consumption between the estimates and the original survey (IHDS-II), the researchers find that the transformation of asset ownership to consumption assumes a similar relationship across datasets. These findings provide confirmation that the predicted consumption estimates are valid proxies of the direct survey measures.

B4 Night Light

As an additional proxy for consumption, we leverage remote sensing imagery on Night-Time Light (NLT) at the village level across India. Initiated by the work of Henderson et al. (2011), NTL has since become a widely used proxy for economic activity. Researchers have adopted night-time luminosity to effectively capture GDP growth (Henderson et al., 2011), cross-sectional GDP Bleakley and Lin (2012), urbanisation (Harari, 2020), public expenditure (Hodler and Raschky, 2014), and employment (Mellander et al., 2015). In an analysis of Indian villages, Asher et al. (2021b) find that night light is a highly statistically significant proxy for a range of development outcomes including - population, employment, per capita consumption, and electrification.

Night-time luminosity data is made available by the U.S. National Oceanographic and Atmospheric Administration (NOAA). The observations are assembled by the Operational Linescan System (OLS) aboard the Defense Meteorological Satellite Program (DMSP) satellites. A total luminosity value ranging from 0-63, is reported in grid cells covering a resolution of 1km x 1km. A description of the satellite instrumentation, data collection, and processing methods for NTL is detailed in the work of Elvidge et al. (1997). Asher et al. (2021b) leverage this data to verify the effectiveness of night-time luminosity as a proxy for development indicators at the village level in India. As part of this work, the researchers compile a panel of NTL from 1994 to 2013 matched and aggregated to villages and towns across the country.[44] This dataset is made available by the research team on the Socioeconomic High-resolution Rural-Urban Geographic (SHRUG, Version 1.5) open data platform for India.[45] We make use of data on the average pixel luminosity at the village level.[46] Specifically, we measure the average of mean night light for a village over a five year period, from 2009 to 2013, as our main proxy for economic activity (for the purpose of the

[44]The data is calibrated for consistent estimation across time, as suggested by Elvidge et al. (1997).

[45]For detailed information on NTL data using the SHRUG open data platform, please refer to Asher et al. (2021b). The dataset, including codebooks and references, can be found at:`http://www.devdatalab.org/shrug`

[46]Average luminosity in a given year is calculated by dividing total luminosity by the village area.

regression, this variable is log transformed). Furthermore, in order to capture variability over time, we also calculate the standard deviation of mean night light over this time period.