The treatment effect elasticity of demand: Estimating the welfare losses from groundwater depletion in India

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Abstract

I estimate an elasticity of irrigation adoption to its gross returns in rural India. Many approaches to estimating this elasticity fail when agents select into adopting irrigation on heterogeneous gross returns and costs. I develop a novel approach to correct for selection using two instrumental variable estimators that can be implemented with aggregate data on gross revenue and adoption of irrigation. I use climate and soil characteristics as an instrument for gross returns to irrigation, and hydrogeology as an instrument for irrigation to correct for selection. I estimate that a 1% increase in the gross returns to irrigation causes a 0.7% increase in adoption of irrigation. I use this elasticity to infer changes in profits from changes in adoption of irrigation caused by shocks to its profitability, and to conduct counterfactuals. First, groundwater depletion from 2000-2010 in northwestern India permanently reduced economic surplus by 1.2% of gross agricultural revenue. Second, I evaluate a policy that optimally reduces relative subsidies for groundwater irrigation in districts with large negative pumping externalities, while holding total subsidies fixed. Under the policy, depletion caused by subsidies decreases by 16%, but farmer surplus increases by only 0.07% of gross agricultural revenue.

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1 Introduction

A common parameter of interest in economics is the elasticity of adoption of a binary treatment to its treatment effect. In the classic Roy (1951) model, workers' relative potential wages across sectors determine their sectoral choice. Similarly, the effect of the skill premium on high school graduates' decisions to attend college is an important input to models of directed technical change (Acemoglu, 1998), as is the effect of firms' potential profits on entry decisions to many models in industrial organization and trade (Melitz, 2003). An estimate of this elasticity is useful both for counterfactuals, such as agents' responses to a tax, or for welfare analysis, such as inferring lost surplus from behavioral responses to a shock.

Selection complicates consistent estimation of this elasticity when economic agents select into treatment on both idiosyncratic treatment effects and perceived costs of adopting treatment. Existing approaches to estimating this elasticity require assuming selection on observables (as noted by Heckman (1979)), imposing strong parametric assumptions (Heckman, 1979), or access to sufficiently high powered instruments to estimate a control variable nonparametrically (Ahn & Powell, 1993; Das et al., 2003; Eisenhauer et al., 2015). This contrasts starkly with estimating treatment effects, where linear instrumental variables estimates a local average treatment effect in the presence of selection on unobservables and without imposing any parametric assumptions (Imbens & Angrist, 1994).

In this paper, I focus on the elasticity of irrigation adoption to its gross returns in India. Irrigation is of first order importance in Indian agriculture. From 1960 to 2010, during India's Green Revolution, the irrigated share of agricultural land grew from 18% to 54%; over 60% of this growth came from the expansion of tubewells for groundwater extraction. This extraction is not benign; Rodell et al. (2009) find extraction caused water tables in northwest India to fall 3.3m from 2000-2010, or 0.21 standard deviations of depth to water table across districts. Falling water tables, by increasing the costs of groundwater irrigation, have been shown to increase poverty (Sekhri, 2014), decrease land values (Jacoby, 2017), and cause outmigration and decrease area under irrigation (Fishman et al., 2017). This has important implications for economic efficiency: groundwater extraction is a classic example of "tragedy of the commons", as farmers do not internalize the increase in pumping costs their extraction causes for neighboring farmers through declining water tables (Jacoby, 2017).

Despite potentially large externalities from groundwater extraction, formulating optimal policy responses to declining water tables in India is difficult for two reasons. First, the elasticity of irrigation to many counterfactual policies is unknown. Second, empirical estimates of the impacts per unit decline in water tables on agricultural profits are not available, as agricultural profits in developing countries are notoriously difficult to measure reliably.[1] An estimate of the elasticity of groundwater irrigation for agriculture to its gross returns would solve both of these challenges. For the first, responses of irrigation to a policy are proportional to the elasticity of irrigation to its gross returns times the effect of the policy on relative profits under irrigation. For the second, effects of declining water tables on adoption of irrigation are proportional to their effects on farmer profits times the elasticity of irrigation to its gross returns.

I estimate an elasticity of irrigation adoption to its gross returns. To do so, I first build a generalized Roy model where farmers adopt irrigation if their gross returns to irrigation are greater than their costs of irrigation; this allows for selection into irrigation on unobservable heterogeneity in gross returns, and I make no parametric assumptions about the joint distribution of gross returns and costs. Under this model, I show that a linear instrumental variable estimator using an instrument for gross revenue under irrigation estimates the sum of weighted averages of gross returns to irrigation (a "local average treatment effect") and inverse semielasticities of demand for irrigation (a "local average surplus effect"). This builds on formulas for instrumental variables bias from Angrist et al. (1996); here, the "bias" is the estimand of interest, a local average surplus effect. Existing results imply the local average treatment effect, and therefore the local average surplus effect, is identified with a continuous instrument for irrigation (Heckman & Vytlacil, 2005) or bounded with a discrete instrument for irrigation (Mogstad et al., 2017).[2] Under stronger assumptions, which still allow sorting on unobserved heterogeneity in both gross returns and costs, I show weighted linear instrumental variables with an instrument for irrigation is a consistent estimator of this local average treatment effect; the weights adjust the compliers to the instrument for

[1] Challenges in the measurement of agricultural profits in developing countries are discussed at length in Foster & Rosenzweig (2010) and Karlan et al. (2014), among others. To list two, first, absent administrative data, long household surveys are required to capture the full set of inputs used in smallholder agriculture. Second, smallholder agriculture intensively uses non-marketed inputs (primarily household labor) which are difficult to value.

[2] An extra monotonicity assumption is needed; the marginal farmers induced to adopt irrigation by the instrument for irrigation and the instrument for gross revenue under irrigation are assumed to be the same conditional on the propensity score and observables; I discuss this assumption in Section 3.2. For point identification, conditions on the conditional support of the propensity score are needed as well.

irrigation to match the compliers to the instrument for gross revenue under irrigation on observables.[3]

The generalized Roy model I use to study selection into irrigation on its gross returns builds on a long literature surveyed in Heckman & Vytlacil (2007a,b); these models have been used to study sectoral choice and wage premia (Roy (1951)), education and skill premia (Willis & Rosen, 1979), and, closest to my setting, hybrid maize seed and its gross returns (Suri, 2011). I build most closely on Eisenhauer et al. (2015), who establish nonparametric identification of agents' willingness to pay for treatment (irrigation) from an instrument for treatment and an instrument for treatment effects (gross returns to irrigation). I instead assume the existence of an instrument for potential outcome under treatment (gross revenue under irrigation), and establish nonparametric identification of the inverse semielasticity of adoption of treatment to the treatment effect under weaker conditions. These weaker conditions are the union of the assumptions of the standard local average treatment effect framework (Imbens & Angrist, 1994) and the assumptions needed for point identification of economic surplus from a change in costs when potential outcomes are independent of treatment conditional on observables (Willig, 1978; Small & Rosen, 1981).

I estimate that a 1% increase in the gross returns to irrigation causes a 0.7% increase in the irrigated share of agricultural land. I estimate this elasticity using climate and soil characteristics as an instrument for gross revenue under irrigation, and using hydrogeology as an instrument for irrigation. I use this elasticity to infer changes in profits from changes in adoption of irrigation caused by shocks to profitability of irrigation. Fishman et al. (2017) estimate the effect of declining water tables on adoption of irrigation; with their estimate, my estimate of this elasticity implies that that the 3.3m decline in depth to groundwater observed in northwest India from 2000-2010 decreased economic surplus by 1.2% of gross revenue per hectare. These losses are large; for comparison, Government of India (2018) anticipate losses in India due to climate change of 1.8%/decade over the next century. I compare my estimate to a simple physics based back-of-the-envelope that considers losses only from farmers' increased electricity costs; my estimate is six times as large as that back of the envelope, consistent with farmers'

[3] This approach generalizes assumptions made in Angrist & Fernandez-Val (2010) under which linear instrumental variable estimators can be reweighted on observables to recover the same local average treatment effect. In doing so it contributes to a number of recent papers which enables comparison of compliers to different instruments under monotonicity by estimating marginal treatment effects (Kowalski, 2016; Arnold et al., 2018; Mountjoy, 2018)) or bounding local average treatment effects (Mogstad et al., 2017).

cost share of electricity in irrigation.

I incorporate my estimate of the economic costs of declining water tables into a model of optimal taxation of electricity for groundwater irrigation, following Allcott et al. (2014). A social planner chooses subsidies for electricity use, trading off the value of subsidies as a transfer to farmers with their deadweight loss and the negative externalities generated from induced marginal extraction. These externalities vary across districts, as water tables fall more rapidly in thinner aquifers, and these falls are experienced by more farmers when a larger share of land is irrigated. I calibrate the model using data on groundwater extraction and aquifer characteristics for districts in Rajasthan, the state in northwest India most known for falling water tables. I find the observed electricity subsidy in Rajasthan is responsible for a 1.5 meter fall in water tables, 46% of the observed rate of decline in northwest India. However, this subsidy increases farmer surplus by 5.9% of gross agricultural revenue, and on the margin implies the social planner is paying 1.56 Rs for 1.00 Rs in surplus transferred to farmers, not far from a similar shadow cost in the US from Hendren (2016). Externalities are important: of the 1.56 Rs, 0.31 Rs are lost to deadweight loss, while 0.25 Rs are lost to negative externalities from induced marginal extraction.

I consider a counterfactual where the social planner optimally varies subsidies across districts, relatively decreasing subsidies in high externality districts, while holding fixed total subsidy payments. This alternate policy reduces the effect of subsidies on water table declines by 16%, but it increases farmer surplus by only 0.07% of gross agricultural revenue. This increase in surplus is small in magnitude relative to the reallocation of surplus from subsidies from farmers in districts with high externalities to farmers in districts with low externalities, consistent with political economy motives for electricity subsidies (Dubash, 2007). However, the magnitude of surplus gains, and more generally the magnitude of externalities, are much larger under smaller calibrations of the discount rate: while transfers and deadweight loss are static, falls in the water table are permanent in the districts I consider, implying the social planner must trade off transfers to farmers today with lost profits for farmers in future decades.

In providing these estimates, I build on a deep literature on the economics of irrigation. Most directly, I contribute to existing results of the impacts of surface water irrigation (Duflo & Pande, 2007) and declining water tables (Sekhri, 2014; Fishman et al., 2017) on welfare proxies in India, and hedonic estimates of the value of access to groundwater in India (Jacoby, 2017) and in the US (Schlenker et al., 2007). In contrast, I estimate sufficient parameters for many optimal policy calculations: the economic losses from a 1 meter decline in the water table, and the elasticity of demand for irrigation to its gross returns. In this sense, I build on estimates of the elasticity of groundwater extraction to electricity subsidies (Badiani & Jessoe, 2017) and output subsidies for water intensive crops (Chatterjee et al., 2017). I use this estimated elasticity to build on the optimal control literature, summarized in Koundouri (2004a), and applied in India by Sayre & Taraz (2018); a large body of work has used complicated, calibrated dynamic models of management of aquifers to characterize optimal policy.[4] Contributing to this literature, I take a sufficient statistics approach, building a simple public economic model following Chetty (2009) and Allcott et al. (2014): empirical estimates of elasticities are used where possible, and calibrated parameters enter transparently into counterfactuals.

The rest of the paper is organized as follows. Section 2 describes the data used and the context. Section 3 presents the model, including results on identification and estimation. Section 4 describes the empirical strategy I use. Section 5 presents the main results, including the impacts of groundwater depletion on rural surplus, and Section 6 discusses their robustness. Section 7 considers optimal subsidies for electricity for groundwater irrigation, building on results from Section 5. Section 8 concludes.

2 Data and context

2.1 Context

India's Green Revolution, starting in the 1960's, was a time of rapid growth in agricultural productivity, driven by increased adoption of new high yielding varieties of seeds, fertilizers, pesticides, and irrigation (Evenson & Gollin, 2003). Irrigation was a particularly important component: large investments were made in the expansion of surface water irrigation, with over 2,400 large dams constructed from 1971-1999 (Duflo & Pande, 2007), but the majority of growth of irrigation was ground water irrigation (Gandhi & Bhamoriya, 2011). The irrigated share of agricultural land in India expanded from 18% to 54% from 1960 to 2008, while the share of agricultural land irrigated using tubewells grew from 0% to 22%, accounting for 63% of the overall growth in irrigation. Reduced form evidence suggests that access to groundwater has large impacts on social

[4] Results from these models can be sensitive to the calibration: Gisser & Sanchez (1980) famously find small gains from optimal policy relative to laissez faire, but Koundouri (2004b) argue their findings are driven by their steep calibrated marginal benefit curves, while Brozović et al. (2010) argue they are driven by the characteristics of the aquifer they study.

welfare (Sekhri, 2014; Fishman et al., 2017; Jacoby, 2017) and is an important driver of adoption of modern agricultural technologies (Sekhri, 2014). This evidence suggests a large share of agricultural productivity growth during the Green Revolution may have been caused by access to groundwater.

Groundwater is stored in underground aquifers, which are underground layers of permeable rock or other materials that hold water. The meters below ground level at which groundwater is available is often referred to as the depth to water table, and varies both across aquifers and within aquifer. For agriculture in India, as in much of the world, this groundwater is typically extracted using tubewells. In a tubewell, a narrow pipe, typically PVC or stainless steel, is bored into the ground, fitted with a strainer cap, and installed with a pump used to pump the water to the surface. Drilling tubewells is costly: according to the 2007 Minor Irrigation Census, the fixed cost of infrastructure for groundwater irrigation in the average district was 26,600 Rs/ha, just over 1 year of agricultural revenue per hectare. This cost varies substantially across districts, with a coefficient of variation of 0.55. This variation is partially driven by the accessibility of groundwater. At greater depths to water table, wells must be drilled deeper, which is more costly (Jacoby, 2017). Additionally, at these lower depths, more expensive and more powerful pumps are required (Sekhri, 2014). Moreover, different types of soils can store different quantities of water, and vary in their permeability. These hydrogeological characteristics affect the rate at which groundwater resources can be extracted that balances natural rates of recharge ("potential aquifer yield" or "safe yield"), the rate at which the water table falls per unit of water extracted ("specific yield"), and the number of wells required per unit of water extracted (Fishman et al., 2017).

Although some of this variation in accessibility of groundwater is driven by exogenous hydrogeological characteristics of the districts, human activity can impact this accessibility. In many districts, ancient groundwater resources are trapped in confined aquifers; these resources are exhaustible. Rodell et al. (2009) use satellite data to show declining water tables in northwestern India, while Suhag (2016) show that the Indian Central Groundwater Board's calculations based on hydrology models imply overexploitation of groundwater resources in the same region. Appendix Figure A.1 shows that this overexploitation (high withdrawals of groundwater as a percentage of natural rates of recharge) is most prevalent in states that experienced the largest increases in agricultural productivity during the Green Revolution, highlighting the link between agricultural productivity and groundwater extraction. In many places, declining water tables are believed to have significantly increased costs of groundwater extraction (Fishman et al., 2017; Jacoby, 2017). On the other hand, rainwater capture and surface water irrigation have the potential to replenish groundwater reserves and reduce dependency on groundwater (Sekhri, 2013).

This decline has been accelerated by implicit subsidies for groundwater irrigation. Most significantly, most states in India do not have volumetric pricing of electricity, but instead charge pump capacity fees. These fees partially substitute for volumetric pricing, since many farmers pump groundwater whenever electricity is available during the growing seasons. However, the levels of fees correspond to large subsidies for electricity, ranging from 52% to 100% subsidies (Fishman et al., 2016). Badiani & Jessoe (2017) use panel variation in these subsidies to estimate an elasticity of water use to the price of electricity of -0.18, suggesting these subsidies contribute meaningfully to declining water tables. However, they point out that this inelastic demand for electricity suggests limited deadweight loss from the subsidies. Since a commonly stated motivation for subsidies is as a transfer to farmers (Dubash, 2007), a social planner who places a high value on marginal consumption by farmers, potentially due to a lack of availability of other policy instruments for making such transfers, might find it optimal to trade off a small deadweight loss to increase transfers to farmers. Moreover, subsidies may correct for the presence of market power in water markets, which might cause socially suboptimal rates of groundwater extraction (Gine & Jacoby, 2016).

In addition to traditional concerns of inefficiency due to subsidies or other wedges, rates of groundwater extraction may be higher than is socially optimal due to negative externalities in pumping groundwater. As farmers extract groundwater, water is drawn from nearby parts of the aquifer, decreasing the water table for neighboring farmers (Theis, 1935), and increasing their costs of extracting groundwater. In the presence of such externalities, farmers will not internalize the increased costs their pumping causes to other farmers. Jacoby (2017) suggests externalities may be particularly important in confined aquifers in India; wells are frequently tightly clustered, and interference between wells is a concern, especially during the dry season.

An estimate of the magnitude of this externality is necessary to determine an optimal tax, or subsidy, for groundwater irrigation. To calculate this externality, one can decompose it into two terms. First, increased pumping of groundwater causes a decline in the water table. The impact of increased pumping on the water table varies significantly across aquifers: pumping one cubic meter of water causes the water table to decline by as much as 20,000 cubic meters in thin, confined aquifers, and by as little as 5 cubic meters in thick, unconfined aquifers (Gisser & Sanchez, 1980; Brozović et al., 2010).

Second, these declines in the water table cause decreases in the profitability of irrigated agriculture, as the cost of groundwater extraction increases. These increases in costs are an externality: they are almost completely experienced by farmers other than the farmer extracting the unit of water. Estimating this increase in costs is hard: costs are notoriously hard to observe in agricultural data (Foster & Rosenzweig, 2010; Karlan et al., 2014), and as a result empirical estimates of the economic costs of declining water tables are unavailable. In India, past work has estimated impacts of declining water tables on welfare proxies, including poverty headcount (Sekhri, 2014) and outmigration (Fishman et al., 2017). However, calculating the externality requires an estimate of the economic damages from a unit decline in water tables. Existing approaches to estimating this have focused largely on the United States, and have typically used hedonic regressions (see Koundouri (2004a) for a review); these approaches may not be feasible in developing country settings such as India, where the assumption of frictionless land markets and full information is less likely to hold.[5]

2.2 Data

I merge data from multiple sources on agriculture in India. Since district boundaries in India have changed multiple times over the past century, all analysis is done using 1961 state and district boundaries. Descriptive statistics for all variables used in analysis are presented in Table 1.

[5]Many studies have also used contingent valuation approaches, which can be severely biased. A noteable alternative approach is taken by Hagerty (2018), who studies water markets in the United States. However, they estimate the willingness to pay for one unit of water, which is different from the economic costs of a one unit decline in water tables. One notable exception is Jacoby (2017), who applies a hedonic regression in India to estimate the economic value of having a borewell using exogenous drilling failures as an instrument. Since the presence of a functioning borewell is easily observable, the assumptions underpinning a hedonic regression are likely to hold. However, this estimate cannot be converted into an estimate of the economic costs of a one unit decline in water tables without strong assumptions.

Table 1: Descriptive statistics

	Mean	SD	Min	Max	# of obs.	# of clu.
Ag '07-'11						
Y_n Agricultural productivity ('000 Rs/ha)	24.9	15.1	1.3	125.0	884	222
D_n Share irrigated	0.550	0.273	0.017	1.000	884	222
Z_n Potential aquifer yield (40 L/s)	0.336	0.349	0.025	1.000	884	222
W_n log relative potential irrigated crop yield	0.533	0.254	0.098	2.050	884	222
X_n log potential rainfed crop yield (log t/ha)	0.690	0.503	-2.234	1.285	884	222
Share rice	0.268	0.265	0.000	0.977	884	222
Share wheat	0.211	0.190	0.000	0.631	884	222
NSS '12						
Y_i Agricultural productivity ('000 Rs/ha)	36.6	26.1	0.0	100.0	33,778	222
$Y_i \vert D_i = 1$ Irrigated plots	44.9	26.3	0.0	100.0	23,957	220
$Y_i \vert D_i = 0$ Rainfed plots	22.0	18.3	0.0	100.0	9,821	189
Area (ha)	1.778	2.540	0.001	40.823	33,778	222
D_i Irrigated	0.637		0.000	1.000	33,778	222
Agricultural inputs net irrigation ('000 Rs/ha)	15.4	15.5	0.0	100.0	26,280	222
Any bank loan	0.310		0.000	1.000	26,280	222
Irr '07						
Infrastructure costs/irrigated ha ('000 Rs/ha)	26.6	14.5	3.4	85.1	222	222
Groundwater share of irrigation	0.658	0.257	0.022	1.000	222	222
Deep tubewells/irrigated ha	0.025	0.057	0.000	0.616	222	222
Shallow tubewells/irrigated ha	0.130	0.213	0.000	1.821	222	222
Dugwells/irrigated ha	0.251	0.401	0.000	2.961	222	222
Well '95-'17						
Depth to water table (mbgl)	14.3	15.4	-1.1	534.0	123,199	203

Notes: Descriptive statistics on the primary datasets are presented here. Units are in parentheses, and standard deviations are omitted for binary variables. Observations in Ag '07-'11 are district-year, observations in NSS '12 are household-plot (for agricultural productivity, area, and irrigated) or household (for agricultural inputs and any bank loan), observations in Irr '07 are district, and observations in Well '95-'17 are well-season. Clusters are districts. To maintain comparability to Ag '07-'11 and Irr '07, statistics for the NSS '12 are calculated weighting using sampling weights times plot area, with weights scaled so each district receives identical weight. Similarly, statistics for Well '95-'17 are weighted so each district-year receives identical weight. All subsequent analysis maintains these weights.

Primary agricultural outcomes come from two sources. First, I merge together the World Bank India Agriculture and Climate Data Set, which contains data from 1956-1987, with the ICRISAT Village Dynamics in South Asia Macro-Meso Database, which contains data from 1966-2011. I refer to this merged dataset as "Ag '56-'11".[6] The merged dataset contains annual district level data on crop specific land allocations

[6]The former dataset has been used by many papers analyzing agriculture in India, including Duflo & Pande (2007) and Sekhri (2014) studying irrigation, while the latter dataset has been used by Allen & Atkin (2015) among others.

(rainfed and irrigated), prices, and yields. I use this to construct an imbalanced panel of 222 districts in 11 states from 1956-2011 of agricultural revenue per hectare and irrigated share of agricultural land. While more districts are observed in this data set, I restrict to districts which appear in all primary data sets used for analysis to maintain comparability across specifications.[7] For much of the analysis, I restrict to the most recent 5 year cross section in this data set.

I supplement this with the 2012 Agricultural National Sample Survey, which included questions on household level land allocations and agricultural production by crop, crucially both on irrigated and rainfed land; I refer to these observations as plots. The data also contain household level expenditures on agricultural inputs by category. I refer to this dataset as "NSS '12". 35,200 households were surveyed, and the survey is intended to be representative at the district level. The sampling of villages from which surveyed households were selected was stratified on share of village land irrigated; because this stratification is correlated with treatment (irrigation), I use survey weights in all analysis with this data. Moreover, to maintain comparability with Ag '56-'11, I weight plots by area, I restrict to crops observed in Ag '56-'11, and I reweight districts so each district receives the same weight. Both revenue per hectare and input expenditures per hectare are noisily measured at high quantiles; I winsorize them at 100,000 Rs/ha (95th percentile for revenue per hectare, 99th percentile for input expenditures per hectare).

For data on irrigation technologies, I use the 2007 Minor Irrigation Census. This survey censuses minor irrigation schemes (culturable command area less than 2000 hectares), which account for 65% of irrigated area and almost all groundwater irrigation. I refer to this dataset as "Irr '07". In this, I observe district level counts of minor irrigation schemes by type (dugwell, shallow tubewell, deep tubewell, surface flow scheme, surface lift scheme), hectares of potential created and used for surface water and ground water schemes, and counts of ground and surface water schemes by cost.[8]

I use potential aquifer yield as my instrument for costs of irrigation, a measure of

[7]Most notably, this restriction drops Chhattisgarh, Jharkhand, and West Bengal.

[8]I observe 5 categories, corresponding to [0 Rs., 10,000 Rs.), [10,000 Rs., 50,000 Rs.), [50,000 Rs., 100,000 Rs.), [100,000 Rs., 1,000,000 Rs.), [1,000,000 Rs., ∞). I code each of these as 10,000 Rs., 50,000 Rs., 100,000 Rs., 300,000 Rs., and 1,000,000 Rs. Alternative codings do not affect significance of any results nor magnitudes of any results in logs, but magnitudes in levels are sensitive to the coding of the [100,000 Rs., 1,000,000 Rs.) category. Estimates of the pseudo treatment effect elasticity of demand are unaffected.

the sustainable rate of extraction of groundwater from a typical tubewell. I constructed this measure by georeferencing a hydrogeological map of India from the Central Ground Water Board (CGWB) which categorizes all land by potential aquifer yield and aquifer type. The measure ranges from 0 L/s to 40 L/s.[9] In all analysis I divide by 40 to normalize this measure to range from 0 to 1, and I plot variation in this measure across districts in Panel (a) of Figure 1.

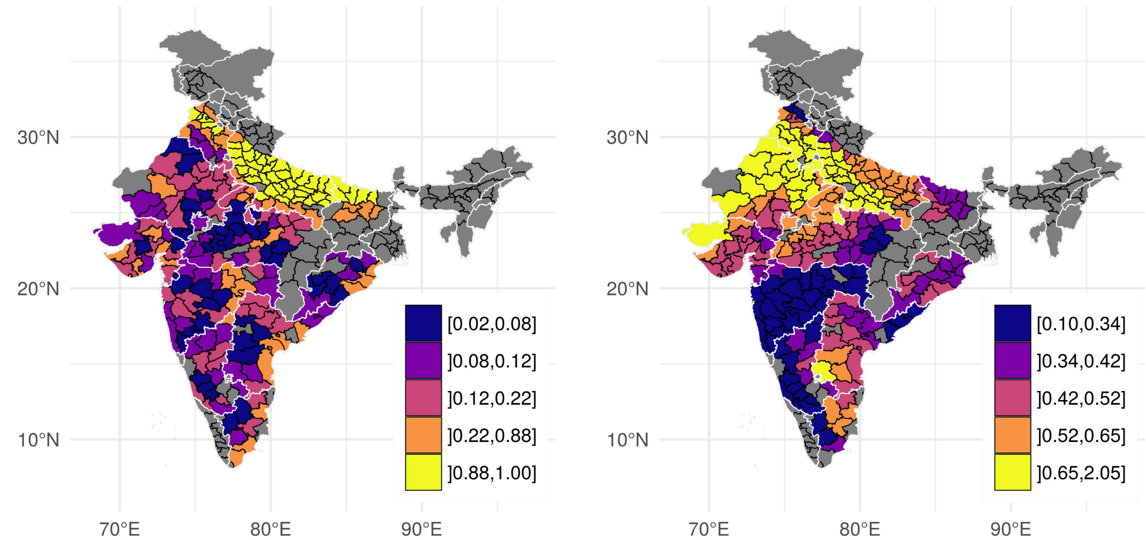
I use a measure of log relative potential irrigated crop yield as my instrument for potential gross revenue under irrigation. For data on potential crop yield, I use the FAO GAEZ database; this source is discussed at length in Costinot et al. (2016). Among other products, it includes constructed measures of potential yields under 5 input scenarios (low rainfed, intermediate rainfed/irrigated, high rainfed/irrigated) based on climate and soil characteristics. I construct potential rainfed crop yield as the weighted average of potential crop yields under the intermediate rainfed scenario. I construct relative potential irrigated crop yield as the ratio of the weighted average of potential crop yields under the intermediate irrigated scenario to potential rainfed crop yield.[10] I plot variation in log relative potential irrigated crop yield across districts in Panel (b) of Figure 1.[11] This measure is likely to be correlated with gross revenue under rainfed agriculture; I therefore control for log potential rainfed crop yield in all primary specifications. I discuss the construction of relative potential irrigated crop yield and potential rainfed crop yield in more detail in Appendix A.

[9]All land is cateogorized as unconsolidated formations (>40 L/s, 25-40 L/s, 10-25 L/s, <10 L/s), consolidated/semi-consolidated formations (1-25 L/s, 1-10 L/s, 1-5 L/s), and hilly areas (1 L/s), which I code as 40, 25, 10, 1, 25, 10, 1, and 1 L/s, respectively. This measure is strongly correlated with the measure of aquifer depth used by Sekhri (2014), and the measure of whether groundwater formations are unconsolidated or consolidated used by D'Agostino (2017).

[10]The weights used are state-by-state shares of land allocated to different crops. To identify effects from variation in potential crop yield, and not variation in weights, I control for state fixed effects in all analysis. Other work has used the difference in yields under different scenarios as an instrument for returns to technology adoption (Bustos et al., 2016).

[11]The measure is almost identical if I use the high input scenarios; in India, for almost all crops, potential yields under the high input scenario are closely approximated by a crop specific multiple of potential yields under the intermediate and low input scenarios. Regressing potential yields from the rainfed high input scenario on the rainfed intermediate input scenario yields R^2 ranging from 0.87 to 1, while regressing potential yields from the irrigated intermediate input scenario on the rainfed intermediate input scenario yields R^2 ranging from 0.04 and 0.06 on the low end (for water intensive sugarcane and rice) to 0.90 and 1 on the high end (for drought resilient sorghum and pearl millet).

Figure 1: Cost and benefit shifters



(a) Potential aquifer yield Z_n (b) log rel. potential irrigated crop yield W_n

Notes: Variation in the cost instrument Z_n (potential aquifer yield, Panel (a)) and the outcome instrument W_n (log relative potential irrigated crop yield, Panel (b)) across districts in India is presented here. Colors correspond to quintiles of their respective distributions. District boundaries are in black, and state boundaries are in white.

I make use of some supplementary datasets. I use data from the Indian Central Groundwater Board's network of monitoring tubewells on seasonal depth to water table from 1995 to 2017; I refer to this dataset as "Well '95-'17". Data on the groundwater share of irrigation by district in 2001 is from the FAO Global Map of Irrigation Areas. Data sources of all calibrated parameters for counterfactual exercises in Section 5.4 and Section 7 are cited in Table 7.

3 Model

I consider a model of profit maximizing farmers deciding whether to irrigate their land. Following Suri (2011), I use a generalized Roy model to model the selection decision: although only farmers' gross revenue conditional on their adoption decision is observed, farmers decide to irrigate if their gross revenue under irrigation minus gross revenue under rainfed agriculture (gross returns to irrigation) is greater than their relative costs of irrigating. Past work has established nonparametric identification of parameters of these models from panel data (Suri, 2011), instruments for costs (Heckman & Vytlacil, 2005), instruments for treatment effects (Adão (2016); in this context, treatment effects are the gross returns to irrigation), and instruments for both costs and treatment effects (Das et al., 2003; Eisenhauer et al., 2015).

In Section 3.1, I consider a simple econometric model to motivate the more general framework. In Section 3.2, I setup a generalized Roy model building on the work cited above. I assume the presence of a conventional cost instrument, but I also impose a novel exclusion restriction on an outcome instrument: I assume the outcome instrument does not affect gross revenue under rainfed agriculture (potential outcome under control). In Section 3.3, I define the marginal treatment effect (following Heckman & Vytlacil (2005)), and two novel parameters, the marginal surplus effect and the treatment effect elasticity of demand. The marginal surplus effect builds on Willig (1978) and Small & Rosen (1981): it is the inverse semielasticity of demand for irrigation, which equals the effect on profits caused by shifts to profitability of irrigation, as inferred by changes in adoption of irrigation. The treatment effect elasticity of demand captures the percentage increase in adoption of irrigation caused by a 1% increase in treatment on the treated (the effect of irrigation on gross revenue for inframarginal irrigators); it is inversely proportional to the marginal surplus effect and unitless, which facilitates interpretation and comparison across studies. In Section 3.4, I establish nonparametric identification of the marginal surplus effect. I show that the treatment effect elasticity of demand is not nonparametrically identified without strong assumptions on the instruments, but a pseudo treatment effect elasticity of demand, that serves as a reasonable approximation in many contexts, is. In Section 3.5, I discuss estimation of the marginal surplus effect. I show that linear instrumental variables using the outcome instrument estimates the sum of a local average treatment effect (a weighted average of marginal treatment effects) and a local average surplus effect (a weighted average of marginal surplus effects), and that these weights are nonparametrically identified. I compare the linear instrumental variables approach to a control function approach, and show that with the novel exclusion restriction the control function approach is overidentified.

3.1 A simplified econometric model

Consider the following econometric model

$$
\begin{aligned}
Y_i &= \beta_0 + \beta_1 D_i + \beta_2 D_i W_i + \epsilon_i \\
D_i &= \gamma_0 + \gamma_1 Z_i + \gamma_2 W_i + \eta_i
\end{aligned}
$$

where Y_i is an observed outcome for agent i and D_i is the agent's endogenous adoption of a binary treatment. I make the independence assumption that $(Z_i, W_i) \perp (\epsilon_i, \eta_i)$. Z_i shifts agents decisions to adopt treatment. W_i shifts agents decisions to adopt treatment through its effect on treatment effects; $\beta_1 + \beta_2 w$ is the treatment effect for agents with $W_i = w$. The estimand of interest is $\frac{\gamma_2}{\beta_2}$, or the effect of a unit increase in treatment effects on adoption of treatment. An implicit exclusion restriction has been made here, that W_i does not affect outcomes for agents who do not adopt treatment.

I consider estimation of β_2 by linear instrumental variables, using Z_i and W_i as instruments for D_i and $D_i W_i$. This yields the following IV estimand for β_2, the effect of an increase in W_i on treatment effects.

$$
\hat{\beta}_2 = \frac{\frac{\mathrm{Cov}(Y_i, W_i)}{\mathrm{Cov}(D_i, W_i)} - \frac{\mathrm{Cov}(Y_i, Z_i)}{\mathrm{Cov}(D_i, Z_i)}}{\frac{\mathrm{Cov}(D_i W_i, W_i)}{\mathrm{Cov}(D_i, W_i)} - \frac{\mathrm{Cov}(D_i W_i, Z_i)}{\mathrm{Cov}(D_i, Z_i)}}
$$

This estimator is the ratio of two terms. The denominator is nonzero when there is a first stage for the IV estimator (W_i and Z_i are correlated with $D_i W_i$ relative to D_i differentially). The numerator is the difference between two linear IV estimators. The first of these estimators, but not the second, violates the exclusion restriction for instrumental variables in the more general correlated random coefficients model $Y_i = \beta_0 + \beta_{1i} D_i + \epsilon_i$.[12]

What is this difference between IV estimators under this model? For expositional purposes, I assume that Z_i and W_i are each binary, that they are independent, and

[12] Note that this estimator I propose of β_2 is different from the natural estimator in the interacted model $Y_i = \beta_0 + \beta_1 D_i + \beta_2 D_i W_i + \beta_3 W_i + \epsilon_i$, using Z_i and $Z_i W_i$ as instruments for D_i and $D_i W_i$. When W_i is binary, one can show this $\hat{\beta}_2 = \frac{\mathrm{Cov}(Y_i, Z_i | W_i = 1)}{\mathrm{Cov}(D_i, Z_i | W_i = 1)} - \frac{\mathrm{Cov}(Y_i, Z_i | W_i = 0)}{\mathrm{Cov}(D_i, Z_i | W_i = 0)}$ (Hull, 2018). Under the more general econometric model presented in Section 3.2, even local versions of this estimator, and the one I propose under the exclusion restriction $\beta_3 = 0$, estimate different parameters. Loosely speaking, the estimator in the interacted model estimates the effect of W_i on the local average treatment effect, while the estimator in the model I propose estimates the effect of W_i on treatment on the treated.

that they are each 0 (1) with probability $\frac{1}{2}$ ($\frac{1}{2}$).[13]

$$\frac{\text{Cov}(Y_i, W_i)}{\text{Cov}(D_i, W_i)} - \frac{\text{Cov}(Y_i, Z_i)}{\text{Cov}(D_i, Z_i)} = \frac{\beta_2 \mathbf{E}[D_i]}{\gamma_2}$$

The difference between the two linear IV estimators is β_2, the change in treatment effects, times $\mathbf{E}[D_i]$, average adoption, divided by γ_2, the change in adoption. This is an inverse semielasticity of adoption to the treatment effect. The first IV estimator, $\frac{\text{Cov}(Y_i,W_i)}{\text{Cov}(D_i,W_i)}$, is the sum of two terms: $\beta_1 + \beta_2 \mathbf{E}[W_i]$, the local average treatment effect for agents induced to adopt treatment by W_i or Z_i, and an inverse semielasticity $\frac{\beta_2 \mathbf{E}[D_i]}{\gamma_2}$, the direct effect of W_i on outcomes per unit change in adoption of treatment.

The result is that the difference between two linear IV estimators, the first using an "instrument" for potential outcome under treatment, and the second using an instrument for treatment, estimates an inverse semielasticity of adoption of treatment to the treatment effect when the distribution of the "instrument" for potential outcome under treatment has no skew. However, it is not clear what this approach estimates when non-linearities or more flexible patterns of selection are permitted. With this motivation, I now ask if a similar approach can be used to estimate an inverse semielasticity of adoption in a generalized Roy model, where agents select into treatment on heterogeneous treatment effects and costs of adoption.[14]

3.2 Environment

Farmers ("agents") decide whether to adopt irrigation ("treatment") to maximize their profits ("surplus"), which is their gross revenue ("outcome") net of any costs, broadly defined. Let Y_{1i} be the gross revenue farmer i receives when they irrigate ("potential outcome under treatment"), and Y_{0i} be the gross revenue farmer i receives when they engage in rainfed agriculture ("potential outcome under control"). Let C_{1i} be farmer i's relative costs of adopting irrigation ("costs of adoption"). Let D_i be an indicator

[13] The latter two are without loss of generality as long as $(Z_i, W_i) = (z, w)$ with positive probability for all $(z, w) \in \{0, 1\}^2$, as this can be achieved by reweighting. A more general model that relaxes many of these assumptions is developed in Section 3.2.

[14] Wooldridge (2015) proposes control function approaches that allow for selection on unobservable treatment effect heterogeneity and that allow for multiple endogenous regressors. However, what linear estimators with multiple endogenous regressors estimate when the structural model is misspecified may not be useful (Kirkeboen et al., 2016; Hull, 2018; Mountjoy, 2018), while linear instrumental variables with a single endogenous regressor retains a LATE interpretation without any assumptions on functional forms (Heckman & Vytlacil, 2005). I ask if this robustness can be extended to linear instrumental variables with W_i.

for farmer i's decision to irrigate ("treatment indicator"). Farmers maximize profits, $\pi_i = D_i(Y_{1i} - C_{1i}) + (1 - D_i)Y_{0i}$ ("surplus"). I assume the researcher observes $Y_i = D_iY_{1i} + (1 - D_i)Y_{0i}$, farmer i's gross revenue ("outcome"), and D_i, farmer i's decision to irrigate ("adoption decision"), but does not observe profits, costs, or counterfactual revenue.

The surplus maximization assumption implies

$$D_i = \mathbf{1}\{Y_{1i} - C_{1i} - Y_{0i} > 0\} \tag{1}$$

Equation 1 is equivalent to the generalized Roy modeling framework discussed in Heckman & Vytlacil (2007a,b). Agents adopt treatment if their treatment effect $(Y_{1i} - Y_{0i})$ is greater than their costs of adoption (C_{1i}).

Next, I assume the presence of instruments z and w. z is a conventional instrument, in that it shifts agents' costs of adoption, C_{1i}, without affecting their potential outcomes, Y_{1i} and Y_{0i}. I refer to it as the "cost instrument". However, w is a nonstandard instrument: it shifts agents' potential outcome under treatment, Y_{1i}, without shifting their costs of adoption, C_{1i}, or their potential outcome under control, Y_{0i}. I refer to it as the "outcome instrument". Additional assumptions are explained below.

Assumption 1.

$$\begin{aligned} Y_{1i}(w) &= V_{\gamma i}\gamma_W(w) + V_{1i} \\ C_{1i}(z) &= V_{\gamma i}\gamma_Z(z) + V_{Ci} \\ Y_{0i} &= V_{0i} \end{aligned}$$

Assumption 2. *γ_W and γ_Z are each monotonic in their arguments, and $V_{\gamma i} > 0$ $\forall i$. The distribution of $V_i \equiv \frac{-V_{1i}+V_{Ci}+V_{0i}}{V_{\gamma i}}$ is continuous and has a strictly increasing cumulative distribution function F_V and smooth density f_V.*

Assumption 1 implicitly makes a number of assumptions. First, w and z each satisfy exclusion restrictions. Only Y_{1i} is structurally a function of w, and only C_{1i} is structurally a function of z. These exclusion restrictions are strong assumptions, and I discuss possible violations in my empirical context in Section 6. That only Y_{1i} is structurally a function of w is a novel exclusion restriction in generalized Roy models.[15]

[15] It is not novel in one-sided selection models, such as studying labor market participation, which two-sided models nest with a normalization of $Y_{0i} = 0$ (no earnings for non-participants). In these

It is most similar to Eisenhauer et al. (2015), who assume there is a regressor excluded from just C_{1i}, while I assume w is excluded from C_{1i} and Y_{0i}. That z is excluded from Y_{1i} and Y_{0i} is the standard exclusion restriction made to estimate a local average treatment effect.

Second, (z, w) are weakly separable from unobserved heterogeneity, through the index $(\gamma_W(w) - \gamma_Z(z))$. Combined with Assumption 2, this implies monotonicity in an index of (z, w). It also implies the more general weak separability assumption made in Willig (1978), Small & Rosen (1981), and Bhattacharya (2017), who assume weak separability of price and product quality to estimate welfare impacts of changes to product quality on consumers. Crucially, this assumption guarantees that z and w enter choices and surplus symmetrically, so impacts on choices are strictly increasing in impacts on potential surplus under treatment. However, although weak separability only requires that (z, w) enter jointly through a flexible index, the more restrictive functional form I use is the most general that satisfies weak separability, the exclusion restrictions, the monotonicity assumptions, and the additive generalized Roy structure.[16] Despite the restrictiveness of these assumptions, variability in $V_{\gamma i}$ flexibly captures, for example, that more productive farmers might be more responsive to shifts in the instruments, something that similar work does not allow.[17]

Assumption 2 makes all remaining technical assumptions. The assumptions on monotonicity of γ_Z and γ_W are standard for instrumental variables, and reasonable in my context.[18] That the distribution of V_i is continuous and strictly increasing is a standard technical assumption.

Additionally, define

$$U_i = F_V(V_i)$$

U_i is distributed Uniform[0,1], and orders agents from highest to lowest propensity to adopt treatment. Note that Equation 1, combined with Assumption 1 and the definition of V_i in Assumption 2, can now be rewritten as $D_i = \mathbf{1}\{U_i < F_V(\gamma_W(w) - \gamma_Z(z))\}$.

models, w is a wage shifter, D_i is the labor market participation decision, and z is an instrument for participation.

[16] The proof is in Appendix B.1.

[17] Specifically, Eisenhauer et al. (2015) and Adão (2016) require their instruments (z, w) are additively separable from unobserved heterogeneity, which implies that their instrument w has a homogeneous effect across agents conditional on observables. However, approaches in Das et al. (2003) and Eisenhauer et al. (2015) are straightforward to generalize to this environment.

[18] Specifically, in my context, I assume that potential revenue under irrigation is strictly increasing in potential irrigated crop yields, and that costs of irrigating are strictly decreasing in potential aquifer yield.

Therefore, the share of agents who adopt treatment $\mathbf{E}[D_i(z,w)] = F_V(\gamma_W(w) - \gamma_Z(z))$.

Lastly, let Z_i and W_i be agent i's realized value of the instruments z and w. I make an independence assumption that will be sufficient for identification.

Assumption 3.

$$(Z_i, W_i) \perp (V_{0i}, V_{Ci}, V_{1i}, V_{\gamma i})$$

3.3 Marginal surplus effects and marginal treatment effects

Within this structure, it is now possible to define the marginal treatment effect and the marginal surplus effect.

$$\text{MTE}(u; w) = \mathbf{E}[Y_{1i}(w) - Y_{0i} | U_i = u] \tag{2}$$

$$\text{MSE}(u) = \frac{u}{f_V(F_V^{-1}(u))}\mathbf{E}[V_{\gamma i} | U_i < u] \tag{3}$$

The definition of the marginal treatment effect in Equation 2 is standard and follows Heckman & Vytlacil (2005). The definition of the marginal surplus effect in Equation 3 is novel. To interpret this, note that the ratio $\frac{u}{f_V(F_V^{-1}(u))}$ is just a Mills ratio for the random variable V_i, evaluated at $v = F_V^{-1}(u)$. The numerator, u, is the share of agents adopting treatment. The denominator, $f_V(F_V^{-1}(u))$, is the density of agents on the margin, which is similar to an elasticity: when the density of marginal agents is large, small increases in potential surplus under treatment cause large movements of agents into treatment. The third term reflects the extent to which inframarginal adopters of treatment are relatively more affected by shifts to z and w than compliers.

Following this intuition, we can arrive at a key result.

$$\frac{d\mathbf{E}[Y_i(z,w)]/dz}{d\mathbf{E}[D_i(z,w)]/dz} = \text{MTE}(\mathbf{E}[D_i(z,w)]; w) \tag{4}$$

$$\frac{d\mathbf{E}[\pi_i(z,w)]/dz}{d\mathbf{E}[D_i(z,w)]/dz} = \frac{d\mathbf{E}[\pi_i(z,w)]/dw}{d\mathbf{E}[D_i(z,w)]/dw} = \text{MSE}(\mathbf{E}[D_i(z,w)]) \tag{5}$$

Equation 4 gives the standard result on marginal treatment effects: the marginal treatment effect is the change in average outcomes per unit change in adoption of treatment caused by a shift to z. Equation 5 gives a new result on the marginal surplus effect: the marginal surplus effect is the change in average surplus per unit change in adoption of treatment caused by a shift to z or w.[19]

[19] The derivations of Equation 4 and Equation 5 is in Appendix B.1.

Additionally, following Heckman & Vytlacil (2007a,b), it follows from Equation 4 that one can define impacts on outcomes of policies that shift z in terms of MTE and $\mathbf{E}[D_i]$ alone. Similarly, it follows from Equation 5 that one can define impacts on surplus of policies that shift z or w in terms of MSE and $\mathbf{E}[D_i]$ alone.

$$\frac{\mathbf{E}[Y_i(z',w)] - \mathbf{E}[Y_i(z,w)]}{\mathbf{E}[D_i(z',w)] - \mathbf{E}[D_i(z,w)]} = \underbrace{\frac{\int_{\mathbf{E}[D_i(z,w)]}^{\mathbf{E}[D_i(z',w)]} \mathrm{MTE}(u;w)du}{\mathbf{E}[D_i(z',w)] - \mathbf{E}[D_i(z,w)]}}_{\text{policy relevant treatment effect}} \tag{6}$$

$$\frac{\mathbf{E}[\pi_i(z',w')] - \mathbf{E}[\pi_i(z,w)]}{\mathbf{E}[D_i(z',w')] - \mathbf{E}[D_i(z,w)]} = \underbrace{\frac{\int_{\mathbf{E}[D_i(z,w)]}^{\mathbf{E}[D_i(z',w')]} \mathrm{MSE}(u)du}{\mathbf{E}[D_i(z',w')] - \mathbf{E}[D_i(z,w)]}}_{\text{policy relevant surplus effect}} \tag{7}$$

Equation 6 is the standard result from Heckman & Vytlacil (2007a,b) that the impact of a broad class of policies on average outcomes is equal to the product of a policy relevant treatment effect and the impact of the policy on adoption of treatment, where the policy relevant treatment effect is a weighted average of marginal treatment effects. Equation 7 is a new result that shows that the impact of a broad class of policies on average surplus is equal to the product of a policy relevant surplus effect and the impact of the policy on adoption of treatment, where the policy relevant surplus effect is a weighted average of marginal surplus effects.

Lastly, to interpret Equation 5, it is helpful to draw a comparison to consumer theory. There, a classic result is that the marginal surplus effect is price divided by the price elasticity of demand (Willig, 1978; Small & Rosen, 1981). Alternatively, one could phrase this as the price elasticity of demand is equal to the price divided by the marginal surplus effect. An equivalent result holds here. I define

$$\mathrm{TOT}(u;w) = \mathbf{E}[Y_{1i}(w) - Y_{0i}|U_i < u] \tag{8}$$

$$\epsilon^*(u;w) = \frac{\mathrm{TOT}(u;w)}{\mathrm{MSE}(u)} \tag{9}$$

Equation 8 gives the standard definition of treatment on the treated. Note that it has the standard interpretation, that $\mathrm{TOT}(\mathbf{E}[D_i(z,w)];w) = \mathbf{E}[Y_{1i}(w) - Y_{0i}|D_i(z,w) = 1]$. Given the analogy in consumer theory, one might hope that $\epsilon^*(u;w)$, as defined in Equation 9, is the treatment effect elasticity of demand. Equation 10 shows this result below.

$$\frac{\text{TOT}(\mathbf{E}[D_i(z,w)];w)}{\mathbf{E}[D_i(z,w)]}\frac{d\mathbf{E}[D_i(z,w)]/dw}{\partial\text{TOT}(\mathbf{E}[D_i(z,w)];w)/\partial w}=\epsilon^*(\mathbf{E}[D_i(z,w)];w) \tag{10}$$

Equation 10, combined with Equation 9, shows that the marginal surplus effect can be interpreted as the ratio of treatment on the treated to the treatment effect elasticity of demand for treatment.[20]

3.4 Identification

The identification of marginal surplus effects and marginal treatment effects follows from classic results on local instrumental variables from Heckman & Vytlacil (1999, 2005). I now assume that (Z_i, W_i) have a smooth density that is strictly positive at (z, w). Independence of the instruments and standard results on nonparametric identification imply the expectations $\mathbf{E}[Y_i(z,w)]$ and $\mathbf{E}[D_i(z,w)]$ and their derivatives with respect to z and w are identified (Matzkin, 2007).[21] As in Heckman & Vytlacil (2005), Equation 4 therefore establishes identification of marginal treatment effects from local instrumental variables using the cost instrument.

For identification of marginal surplus effects, the key result is what local instrumental variables using the outcome instrument estimates.

$$\frac{d\mathbf{E}[Y_i(z,w)]/dw}{d\mathbf{E}[D_i(z,w)]/dw}=\text{MTE}(\mathbf{E}[D_i(z,w)];w)+\text{MSE}(\mathbf{E}[D_i(z,w)]) \tag{11}$$

Local instrumental variables using the outcome instrument estimates the marginal treatment effect plus the marginal surplus effect.[22] This is the local version of the result for the linear model in Section 3.1.

Identification of marginal surplus effects follows simply from subtracting Equation 4 from Equation 11.

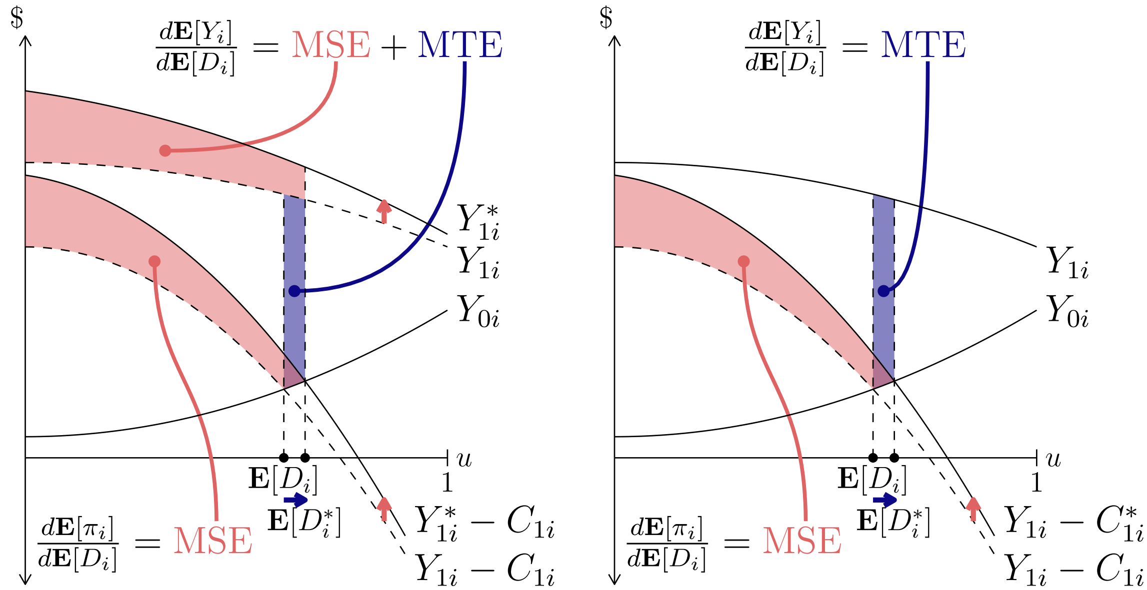
$$\text{MSE}(\mathbf{E}[D_i(z,w)])=\frac{d\mathbf{E}[Y_i(z,w)]/dw}{d\mathbf{E}[D_i(z,w)]/dw}-\frac{d\mathbf{E}[Y_i(z,w)]/dz}{d\mathbf{E}[D_i(z,w)]/dz} \tag{12}$$

[20] The derivation of Equation 10 is in Appendix B.1.

[21] Formally, $\mathbf{E}[Y_i(z,w)]=\mathbf{E}[Y_i|Z_i=z,W_i=w]$ and $\mathbf{E}[D_i(z,w)]=\mathbf{E}[D_i|Z_i=z,W_i=w]$.

[22] The derivation of Equation 11 is in Appendix B.1.

Figure 2: Model comparative statics



(a) Increased outcome under treatment

(b) Decreased costs of treatment

Notes: Panel (a) shows the effects of shifting w, the instrument for potential outcome under treatment (which shifts potential outcome under treatment Y_{1i} to Y_{1i}^*), while Panel (b) shows the effects of shifting z, the instrument for costs of adopting treatment (which shifts costs C_{1i} to C_{1i}^*). Changes in the share of agents adopting treatment, from $\mathbf{E}[D_i]$ to $\mathbf{E}[D_i^*]$, are displayed. Changes in average surplus $\mathbf{E}[\pi_i]$ or changes in average outcomes $\mathbf{E}[Y_i]$ are shaded. Marginal treatment effects are in purple, and are equal to the change in average outcomes per unit change in adoption of treatment caused by shifts to z. Marginal surplus effects are in pink, and are equal to the change in average surplus per unit change in adoption of treatment caused by shifts to either z or w. The change in average surplus caused by both z and w is proportional to the marginal surplus effect. However, the change in average outcomes caused by z is proportional to the marginal treatment effect, while the change in average outcomes caused by w is proportional to the marginal surplus effect plus the marginal treatment effect.

The intuition for this result is visible in Figure 2. Both the cost instrument z and the outcome instrument w affect agent adoption decisions and surplus through a common index, because of the weak separability assumption. Whether surplus under treatment increases from $Y_{1i} - C_{1i}$ to $Y_{1i}^* - C_{1i}$ (shock to w, as in Panel (a)) or to $Y_{1i} - C_{1i}^*$ (shock to z, as in Panel (b)), the effect on choices is a sufficient statistic for the effect on surplus; the marginal surplus effect is well defined. However, their effects on outcomes differ. In Panel (b), we can see that the cost instrument increases outcomes proportional to the marginal treatment effect: potential outcomes are unaffected by the cost instrument, but the induced increase in adoption $\mathbf{E}[D_i]$ causes agents' outcomes to increase by their treatment effect. However, in Panel (a), we can see that the outcome instrument has two effects on outcomes. The first effect is proportional to the marginal treatment effect: adoption $\mathbf{E}[D_i]$ increases because surplus under treatment increases, and this increase in adoption $\mathbf{E}[D_i]$ causes agents' outcomes to increase by their treatment effect. However, the second effect is proportional to the marginal surplus effect. This is the direct effect on outcomes caused by the increase in Y_{1i}; the increase in Y_{1i} and the increase in $Y_{1i}-C_{1i}$ are the same (because of the exclusion restriction), so this increase is exactly the same as the effect of the outcome instrument on surplus.

Note, however, that unlike marginal surplus effects and marginal treatment effects, treatment on the treated and the treatment effect elasticity of demand are not identified without either parametric assumptions or an identification at infinity argument. This contrasts with the standard consumer theory setting, where typically a price elasticity of demand is estimated, and marginal surplus effects can be calculated using that price elasticity. To allow comparison of results with price elasticities, I instead define the pseudo treatment effect elasticity of demand to be

$$\epsilon(u;w) = \frac{\text{MTE}(u;w)}{\text{MSE}(u)} \tag{13}$$

which, following the results above, is also identified. It is biased relative to the treatment effect elasticity of demand: $\epsilon^*(u;w) = \frac{\text{TOT}(u;w)}{\text{MTE}(u;w)}\epsilon(u;w)$, so the pseudo treatment effect elasticity of demand, which requires less restrictive assumptions for identification, will be too small (large) when treatment on the treated is large (small) relative to the marginal treatment effect.[23]

3.5 Estimation

For estimation, I now assume that a set of observable characteristics of each agent, X_i, are also observed. All assumptions above are now made conditional on $X_i = x$, and all results above now hold conditional on $X_i = x$. No additional assumptions are made

[23]Despite this, the pseudo treatment effect elasticity of demand is still useful. In some cases, instead of observing the outcome Y_i, the researcher might observe the outcome Y_i times an unknown constant (in agriculture, this could be yields measured using satellite data, as in Burke & Lobell (2017)) or costs D_iC_{1i} times an unknown constant (in my context, this is fixed infrastructure costs for irrigation). In both cases, the pseudo treatment effect elasticity of demand can still be consistently estimated. In my context, this permits an overidentification test. In other cases, one might estimate the pseudo treatment effect elasticity of demand in one context, and extrapolate to another where the marginal treatment effect is known but an instrument to estimate the marginal surplus effect is unobserved.

except where explicitly stated.

3.5.1 Instrumental variables

The nonparametric identification results suggest the application of local instrumental variable estimators. In practice, as discussed in Carneiro et al. (2011) and Eisenhauer et al. (2015), local instrumental variable estimators are difficult to implement in practice while conditioning on (Z_i, W_i, X_i) jointly. Frequently, their implementation relies on strong restrictions on how (W_i, X_i) can enter outcome equations. However, as Imbens & Angrist (1994) and Heckman & Vytlacil (2005) show, linear instrumental variables using a conventional instrument, such as Z_i, makes no such assumptions: instead, it only requires the researcher to estimate the expectation of Z_i conditional on all variables which are not excluded from outcome equations (in this case, (W_i, X_i)). Then, linear instrumental variables estimates a local average treatment effect, or a weighted average of marginal treatment effects. Flexibly controlling for observables in linear instrumental variables is well understood (for example, see Chernozhukov et al. (2016)), and does not require any assumptions on how non-excluded observables enter outcome equations, in contrast to how local instrumental variable methods are often implemented (Carneiro et al., 2011).

Just as linear instrumental variables with Z_i estimates a local average treatment effect, linear instrumental variables with W_i estimates the sum of a local average treatment effect and a local average surplus effect, where a local average surplus effect is a weighted average of marginal surplus effects. Formally,

$$\beta_Z^{IV} \equiv \frac{\text{Cov}(Y_i, Z_i - \mathbf{E}[Z_i|W_i, X_i])}{\text{Cov}(D_i, Z_i - \mathbf{E}[Z_i|W_i, X_i])} = \text{LATE}_Z \tag{14}$$

$$\text{LATE}_Z = \int \text{MTE}(u; w, x)\omega_Z(u; w, x)dudwdx \tag{15}$$

$$\beta_W^{IV} \equiv \frac{\text{Cov}(Y_i, W_i - \mathbf{E}[W_i|Z_i, X_i])}{\text{Cov}(D_i, W_i - \mathbf{E}[W_i|Z_i, X_i])} = \text{LATE}_W + \text{LASE}_W \tag{16}$$

$$\text{LATE}_W = \int \text{MTE}(u; w, x)\omega_W(u; w, x)dudwdx \tag{17}$$

$$\text{LASE}_W = \int \text{MSE}(u; x)\omega_W(u; w, x)dudwdx \tag{18}$$

Equation 14 and Equation 15 are the result from Heckman & Vytlacil (2005): linear instrumental variables using the cost instrument estimates a local average treatment effect, which is a weighted average of marginal treatment effects. As Heckman & Vytlacil (2005) show, these weights ω_Z are nonparametrically identified, positive, and integrate to 1. The new result is Equation 16: linear instrumental variables using the outcome instrument estimates a local average treatment effect plus a local average surplus effect. The local average surplus effect is a weighted average of marginal surplus effects. I show in Appendix B.2.1 that the LATE_W and LASE_W weights, ω_W, are nonparametrically identified, positive, and integrate to 1. This extends the result on the linear model from Section 3.1 to a generalized Roy model with nonlinearities and selection on heterogeneous treatment effects.

3.5.2 InterpoLATE-ing

There are multiple approaches in the literature to estimation of LATE_W. First, nonparametric bounds on LATE_W using LATE_Z are derived in Mogstad et al. (2017), by considering the largest and smallest possible values of LATE_W consistent with marginal treatment effects that would result in estimating LATE_Z. Second, if variation in treatment effects is explained by observables, Angrist & Fernandez-Val (2010) show weighted linear instrumental variables with the cost instrument can estimate LATE_W. Third, one could instead estimate marginal treatment effects directly using the cost instrument, and recover an estimate of LATE_W from the marginal treatment effects and an estimate of the LATE_W weights. Alternatively, Brinch et al. (2017) propose an approach to recovering marginal treatment effects from estimates of local average treatment effects, by imposing restrictions on outcome equations and flexibly modeling the distribution of unobservable heterogeneity.

I build on Angrist & Fernandez-Val (2010), and assume that variation in local average treatment effects is explained by observables. Specifically, I partition $X_i = (\tilde{X}_i, S_i)$, and assume that local average treatment effects conditional on S_i are homogeneous estimated using W_i or Z_i. Formally, define

$$\text{LATE}_{(\cdot)|s} = \frac{\int \text{MTE}(u; w, (\tilde{x}, s))\omega_{(\cdot)}(u; w, (\tilde{x}, s))dudwd\tilde{x}}{\int \omega_{(\cdot)}(u; w, (\tilde{x}, s))dudwd\tilde{x}}$$

to be the conditional local average treatment effect.[24] I assume

Assumption 5a. $LATE_{Z|s} = LATE_{W|s}\ \forall s \in Supp(S_i)$

[24] In my empirical context, S_i are a vector of state dummies; across state geographic heterogeneity and policies are likely to explain a significant share of treatment effect heterogeneity.

Although this is a strong assumption, I show in Appendix B.1 that this still potentially allows for arbitrary linear marginal treatment effects. This allows for "essential heterogeneity" (Heckman et al., 2006), substantially weakening the assumption made in Angrist & Fernandez-Val (2010), who assume these conditional local average treatment effects are also equal to a conditional average treatment effect. The difference is while their goal is to estimate the average treatment effect and other population moments, my goal is to estimate LATE_W, which requires a much weaker assumption.[25]

From the definition of the conditional local average treatment effect, it is clear that LATE_W is a weighted average of $\text{LATE}_{W|s}$, and therefore $\text{LATE}_{Z|s}$. It therefore follows that LATE_W can be estimated by weighted linear instrumental variables using Z_i. Letting $\overline{\omega}_{(\cdot)}(s) \equiv \int \omega_{(\cdot)}(u; w, (\tilde{x}, s)) du dw d\tilde{x}$, this yields the following estimator of LASE_W.[26]

$$\beta_W^{IV} - \beta_Z^{WIV} = \text{LASE}_W \tag{19}$$

$$\beta_Z^{WIV} \equiv \frac{\text{Cov}\left((\overline{\omega}_W(S_i)/\overline{\omega}_Z(S_i))Y_i, Z_i - \mathbf{E}[Z_i|W_i, X_i]\right)}{\text{Cov}\left((\overline{\omega}_W(S_i)/\overline{\omega}_Z(S_i))D_i, Z_i - \mathbf{E}[Z_i|W_i, X_i]\right)} \tag{20}$$

The difference between weighted linear instrumental variable estimators is a consistent estimator of LASE_W. Intuitively, the weights make the z compliers resemble the w compliers on the observable S_i.

Additionally, the ratio of the local average treatment effect to the local average surplus effect estimated using weighted instrumental variables estimates a weighted average of pseudo treatment effect elasticities of demand.

$$\frac{\beta_Z^{WIV}}{\beta_W^{IV} - \beta_Z^{WIV}} = \int \epsilon(u; w, x) \left(\frac{\omega_W(u; w, x)\text{MSE}(u; x)}{\int \omega_W(u; w, x)\text{MSE}(u; x) du dw dx} \right) du dw dx \tag{21}$$

This result follows straightforwardly from $\beta_Z^{WIV} = \text{LATE}_W$, and substituting the definition $\epsilon(u; w, x) = \frac{\text{MTE}(u; w, x)}{\text{MSE}(u; x)}$. The weights $\frac{\omega_W(u; w, x)\text{MSE}(u; x)}{\int \omega_W(u; w, x)\text{MSE}(u; x) du dw dx}$ are nonparametrically identified, positive, and integrate to 1.

This estimator of a local average surplus effect may be underpowered, if there are many w compliers but very few z compliers for some S_i, but there is balance for other

[25]Note that this is still much stronger than assumptions made by Brinch et al. (2017) and Mogstad et al. (2017). However, the estimator I propose is much simpler to implement. Additionally, in Section 5.2, I estimate a parametric version of the model from Section 3.2 that does not impose this assumption, and estimates of this model suggest bias from violations of this assumption is small in my context.

[26]The proof of Equation 19 is in Appendix B.1.

S_i. In Appendix B.2.2, I propose feasible reweighted instrumental variable estimators using both z and w to minimize the variance of the resulting estimator of a local average surplus effect; I refer to these estimators as β_W^{WIV} and β_Z^{WIV}. Additionally, estimating $\overline{\omega}_{(\cdot)}$, even under Assumption 5a, requires estimating the effect of w and z on adoption conditional on $S_i = s$, something I am underpowered for in my setting. Given this constraint, I calculate these weights under the assumption that the first stages for w and z (the derivatives of the propensity score conditional on $S_i = s$ with respect to w and z) are constant across $S_i = s$. However, the estimator is still consistent (although no longer efficient) if the first stage for w is a constant multiple of the first stage for z across $S_i = s$.

3.5.3 ExtrapoLASE-ing

Just as with a local average treatment effect, a single estimate of a local average surplus effect need not be policy relevant. I propose an approach similar to Brinch et al. (2017), who use estimates of outcomes for always takers, compliers, and never takers to recover the marginal treatment effect with a discrete instrument under parametric assumptions. Instead, I recover the marginal surplus effect from estimates of local average surplus effects. Recall that the local average surplus effect is a weighted average of marginal surplus effects, and the weights ω_W are identified. Furthermore, recall that $\text{MSE}(u;x) = \frac{u}{f_V(F_V^{-1}(u;x);x)}\mathbf{E}[V_{\gamma i}|U_i < u, X_i = x]$. Given this, with parametric restrictions on $\text{MSE}(u;x)$, implied by restrictions on the joint distribution of (V_{γ_i}, V_i) conditional on $X_i = x$, one can identify $\text{MSE}(u;x)$ from local average surplus effects and the weights they place on different marginal surplus effects.

In particular, I assume the marginal surplus effect is linear. Unlike a marginal treatment effect, for many distributions a marginal surplus effect will have a 0 intercept, and therefore a single parameter (the slope) is sufficient to characterize a linear marginal surplus effect.[27,28] A linear marginal surplus effect is therefore identified from a single estimate of a local average surplus effect, and the weights ω_W. Formally, I assume

Assumption 5b. $MSE(u) = ku$

Note that this assumption is neither necessary nor sufficient for linear marginal treatment effects conditional on $X_i = x$, and allows for flexible nonlinearities in the

[27] Specifically, bounded $V_{\gamma i}$ and the distribution of V_i not having fat tails are sufficient for the marginal surplus effect to have a 0 intercept; this is a standard property of a Mills ratio.

[28] One parametrization that yields a linear marginal surplus effect is $V_i \sim \text{Uniform}[a, a+k]|X_i = x$, and $V_{\gamma i} = 1 \ \forall i$.

effects of the cost and outcome instruments on costs and potential outcome under treatment, respectively, conditional on $X_i = x$. Under this assumption, estimation of the marginal surplus effect from an estimate of the local average surplus effect is straightforward.

$$k = \frac{\text{LASE}_W}{\int u\omega_W(u; w, x)dudwdx} \tag{22}$$

In general, estimation of $\omega_W(u; w, x)$ can be hard, even though it is nonparametrically identified. I simplify the problem by estimating $\omega_W(u; w, x)$ under the assumption that $\mathbf{E}[D_i(z, w; x)]$ is linear.

3.5.4 Parametric control function ("Heckit")

Past work has developed control function approaches that could be used to estimate a marginal surplus effect, including parametric (Heckman, 1979), semiparametric (Ahn & Powell, 1993), and nonparametric approaches (Das et al., 2003). In fact, the natural estimator of the marginal surplus effect building on the estimator of Das et al. (2003) is asymptotically equivalent to a local instrumental variables estimator suggested by Equation 12. However, the control function estimator is overidentified; this is because it requires observations of $\mathbf{E}[Y_i|D_i, W_i, Z_i, X_i]$ and $\mathbf{E}[D_i|W_i, Z_i, X_i]$, while the instrumental variable approach I propose only requires observations of $\mathbf{E}[Y_i|W_i, Z_i, X_i]$ and $\mathbf{E}[D_i|W_i, Z_i, X_i]$. Specifically, the exclusion restriction that Y_{0i} is not a function of w is more easily testable with more disaggregated data.

As an alternative to the instrumental variable approach to estimating a marginal surplus effect presented previously, I consider a two step parametric control function approach using a standard Heckman selection correction. As in Björklund & Moffitt (1987), I assume idiosyncratic variation in (Y_{1i}, C_{1i}, Y_{0i}) is jointly normally distributed. Although the normality assumption appears restrictive, Kline & Walters (2017) show that in many cases, parametric control function approaches exactly or closely match the same moments as linear IV estimators, and thus produce identical or similar estimates of local average treatment effects.

Assumption 5c.

$$\begin{pmatrix} Y_{1i} \\ C_{1i} \\ Y_{0i} \end{pmatrix} \sim N\left(\begin{pmatrix} (g_W + c_0)W_i + X_i'\mu_1 \\ g_Z Z_i + X_i'\mu_C \\ c_0 W_i + X_i'\mu_0 \end{pmatrix}, \begin{pmatrix} \Sigma_{11} & \Sigma_{1c} & \Sigma_{10} \\ \Sigma_{1c} & \Sigma_{cc} & \Sigma_{c0} \\ \Sigma_{10} & \Sigma_{c0} & \Sigma_{cc} \end{pmatrix}\right)$$

Details of the estimation are in Appendix Section B.3. From the estimated model, it is straightforward to calculate the marginal surplus effect; this calculation under normality is similar to the expression for the treatment effect elasticity of demand under normality in French & Taber (2011).

$$\text{MSE}(u; x) = \frac{\sigma_V u}{\phi(\Phi^{-1}(u))} \tag{23}$$

where $\sigma_V = \text{Var}(V_i)$, ϕ is the normal density function, and Φ is the normal cumulative distribution function.

This parametric control function approach is a useful benchmark for the instrumental variable approach I propose. It also allows enables two additional tests of the instrumental variable approach. First, it allows me to test the exclusion restriction that Y_{0i} is not a function of w. Second, it allows me to test the performance of the weighted instrumental variable estimator. Specifically, I follow Andrews et al. (2018) and calculate the informativeness of the weighted (and unweighted) instrumental variable estimators of LASE_W and LATE_Z for the control function estimators of LASE_W and LATE_Z, respectively.

4 Empirical strategy

4.1 Notation and context specific concerns

Following Section 3.5 and the end of Section 3.5.2, but adapting to my empirical context, I consider observations of $(Y_{ins}, D_{ins}, Z_{ns}, W_{ns}, (X_{ns}, S_s))$ for each plot i, located in district n in state s. Y_{ins} is plot i's realized gross revenue. D_{ins} is an indicator for whether plot i is irrigated. Z_{ns} is plot i's value of the cost instrument, its potential aquifer yield. W_{ns} is plot i's value of the outcome instrument, its log relative potential irrigated crop yield. X_{ns} is a vector of controls for plot i, which in my main specifications is log potential rainfed crop yield. S_s is a vector of state dummies.

The instruments, (Z_{ns}, W_{ns}), and controls (X_{ns}, S_s), are constant within district. All analysis reports robust standard errors clustered at the district level.

In regressions using district level data, I observe area weighted average outcomes for the district. I use Y_{ns} for average gross revenue per hectare, and D_{ns} for share of land irrigated at the district level. That Y_{ns} and D_{ns} might vary across districts with the same values of the instruments, even though we can treat Y_{ns} and D_{ns} as population averages within district, is consistent with the distribution of unobservables varying across districts. The independence assumption therefore implies that instruments are assigned across districts independent of this distribution.

In analysis using data from NSS '12, I observe plot level data.[29] Y_{ins} is now gross revenue per hectare for plot i, and D_{ins} is a dummy for irrigated. The sampling in the Agricultural NSS was stratified on village level irrigation status, which is endogenous; as a result, I use survey weights to recover unbiased estimates. To maintain comparability with regressions using district level data, I also weight by plot size, and normalize weights such that the sum of weights in each district is 1.

In analysis using Irr '07, I use the negative of average fixed costs of irrigation infrastructure per agricultural hectare as an outcome. This provides a useful check on results from other datasets, as I discuss in Section 4.2.

4.2 Instrumental variables

My objective is to construct 2SLS estimators of the form in Equation 14 and 16. With a large number of clusters, one could estimate the conditional expectations of Z_{ns} and W_{ns} nonparametrically. With the 222 districts I observe, I instead take a parametric approach and assume $\mathbf{E}[Z_{ns}|W_{ns}, X_{ns}, S_s]$ and $\mathbf{E}[W_{ns}|Z_{ns}, X_{ns}, S_s]$ are linear conditional on S_s. With this, I estimate by OLS

$$Y_{ins} = \beta_Z^{RF} Z_{ns} + \delta_{1s} W_{ns} + \delta_{2s} X_{ns} + \alpha_{1s} + \epsilon_{1,ins} \tag{24}$$

$$D_{ins} = \beta_Z^{FS} Z_{ns} + \delta_{3s} W_{ns} + \delta_{4s} X_{ns} + \alpha_{2s} + \epsilon_{2,ins} \tag{25}$$

$$Y_{ins} = \beta_W^{RF} W_{ns} + \delta_{5s} Z_{ns} + \delta_{6s} X_{ns} + \alpha_{3s} + \epsilon_{3,ins} \tag{26}$$

$$D_{ins} = \beta_W^{FS} W_{ns} + \delta_{7s} Z_{ns} + \delta_{8s} X_{ns} + \alpha_{4s} + \epsilon_{4,ins} \tag{27}$$

[29] To be more precise, observations are at the level of household-by-crop-by-irrigation adoption, which one can think of as aggregated across plots, proportional to area, on which households grow the same crop and make the same irrigation adoption decision.

Note that coefficients on controls are allowed to vary by state s in all specifications. Let $\beta_Z^{IV} = \beta_Z^{RF}/\beta_Z^{FS}$, and $\beta_W^{IV} = \beta_W^{RF}/\beta_W^{FS}$. I use $\beta_W^{IV} - \beta_Z^{IV}$ as an estimate of a local average surplus effect, and $\beta_Z^{IV}/(\beta_W^{IV} - \beta_Z^{IV})$ as an estimate of a pseudo treatment effect elasticity of demand.

These estimators may be inconsistent if $\text{LATE}_W \neq \text{LATE}_Z$. I therefore also implement the weighted instrumental variable estimator constructed in 3.5.2; this estimator will be consistent for a local average surplus effect and a pseudo treatment effect elasticity of demand under Assumption 5a.

To validate the approach, I also use the negative of average fixed costs of irrigation infrastructure per agricultural hectare as an outcome. This is consistent with the modeling framework; as Björklund & Moffitt (1987) and Eisenhauer et al. (2015) note, there is a duality between costs and benefits in the generalized Roy model; the difference is only which is treated as observable. To expand briefly, we are using $-qD_iC_{1i}$ as the outcome instead of Y_i, and $Y_{1i} - (1-q)C_{1i} - Y_{0i}$ as costs instead of C_{1i}, where q is the share of fixed costs in costs of irrigation times the discount rate (to convert infrastructure costs, which is a stock, into a flow); I assume q is constant. Instruments are now switched: W_i becomes the cost instrument, and Z_i becomes the outcome instrument. Estimated marginal treatment effects are $-q$ times marginal treatment effects, since $Y_{1i} - Y_{0i} = C_{1i}$ for marginal agents. Estimated marginal surplus effects are q times marginal surplus effects, since responses to increased surplus from decreased costs of irrigation and increased surplus from increased gross revenue under irrigation are the same. Therefore, the estimated pseudo treatment effect elasticity of demand (the ratio of the local average treatment effect to the local average surplus effect) when using negative fixed costs as an outcome should be the negative of the estimate using gross revenue as an outcome.[30]

[30]Note that imposing $C_{0i} = 0$ is no longer a normalization in order for these interpretations of results using fixed costs as an outcome to be valid. This creates two problems. First, it creates the potential for exclusion restriction violations due to Z_i affecting costs of rainfed agriculture. This is not a concern in my context, since Z_i affects the costs of extracting groundwater. Second, it affects the interpretation of q. Assumptions that would imply q is constant are very strong, and likely require all costs of irrigation to involve drilling for and pumping groundwater, ruling out irrigation reducing growing season labor costs for rice cultivation, for example. I therefore interpret these results as suggestive robustness.

4.3 Control function

To estimate the control function approach, I use NSS '12, in which I observe plot level data. This is crucial because this approach relies on observing average outcomes conditional both on the values of the instruments and on adoption of treatment, something the instrumental variables approach does not need. To separate differences in results coming from different methods and different data sets, I first estimate a local average surplus effect using linear instrumental variables in NSS '12. I follow Section 3.5.4 in estimating the control function approach. Controls include state fixed effects and their interaction with log potential rainfed crop yield, but the cost instrument z and outcome instrument w are not interacted with state fixed effects. Additional details of the approach are in Appendix B.3.

5 Results

5.1 Instrumental variables

Table 2: Instrumental variables estimates

	Share irrigated		Agricultural productivity ('000 Rs/ha)				
	First stage $\left(\beta^{FS}_{(\cdot)}\right)$		Reduced form $\left(\beta^{RF}_{(\cdot)}\right)$		OLS	IV $\left(\beta^{IV}_{(\cdot)} = \frac{\beta^{RF}_{(\cdot)}}{\beta^{FS}_{(\cdot)}}\right)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Z_n (cost instrument)	0.278***		6.3				
	(0.056)		(4.1)				
W_n (outcome instrument)		0.791***		42.9***			
		(0.188)		(10.2)			
D_n (share irrigated)					23.9***	22.6*	54.3***
					(2.8)	(13.1)	(14.5)
Instrument (IV only)	-	-	-	-	-	Z_n	W_n
State FE	X	X	X	X	X	X	X
State FE × X_n	X	X	X	X	X	X	X
State FE × Z_n	-	X	-	X	-	-	X
State FE × W_n	X	-	X	-	-	X	-
# of observations	884	884	884	884	884	884	884
# of clusters	222	222	222	222	222	222	222

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the district level are in parentheses. Regression table contains instrumental variable estimates from Ag '07-'11 using potential aquifer flow Z_n and log relative potential irrigated crop yield W_n as instruments. In each case, the effect of share irrigated on agricultural productivity per hectare is instrumented for. Controls in all specifications include state fixed effects and state fixed effects interacted with log potential rainfed crop yield X_n. The estimated local average surplus effect is the coefficient on share irrigated in Column 7 minus the coefficient on share irrigated in Column 6; estimates of local average surplus effects and pseudo treatment effect elasticities of demand are presented in Table 3.

Table 2 presents unweighted instrumental variable regressions in Ag ‘07-’11. Columns 1 and 2 show a strong first stage with the cost instrument and the outcome instrument, with t-statistics of 5.0 and 4.2, respectively. The instrumental variable coefficient in Column 6, which uses the cost instrument, is a local average treatment effect. Marginal irrigators increase their agricultural revenue by 22,600 Rs/ha when they adopt irrigation. For ease of interpretation, the same specification with log revenue per hectare as the outcome gives a coefficient of 0.95. This is similar to Duflo & Pande (2007), who estimate an elasticity of production with respect to dam induced irrigation of 0.61, which they note is in the lower range of existing estimates. The instrumental variable coefficient in Column 7, which uses the outcome instrument, is the sum of a local average treatment effect and a local average surplus effect.

Table 3: Local average surplus effect estimates

	Agricultural productivity		$(-)$ Infrastructure costs	
	Ag '07-'11		Irr '07	
	IV	WIV	IV	WIV
	(1)	(2)	(3)	(4)
Z_n				
β_Z^{FS} (first stage)	0.278***	0.245***	0.574***	0.575***
	(0.056)	(0.073)	(0.217)	(0.221)
$\beta_Z^{IV} = \frac{\beta_Z^{RF}}{\beta_Z^{FS}} = \text{LATE}_Z$	22.6*	32.9**	-59.1**	-86.9*
	(13.1)	(15.7)	(25.5)	(47.4)
State FE $\times$ W_n	X	X	X	X
W_n				
β_W^{FS} (first stage)	0.791***	0.654***	0.275***	0.258***
	(0.188)	(0.216)	(0.068)	(0.095)
$\beta_W^{IV} = \frac{\beta_W^{RF}}{\beta_W^{FS}} = \text{LASE}_W + \text{LATE}_W$	54.3***	82.7***	28.3	32.6
	(14.5)	(28.5)	(18.2)	(24.3)
State FE $\times$ Z_n	X	X	X	X
Surplus effects				
$\beta_W^{IV} - \beta_Z^{IV} \approx \text{LASE}_W$	31.7*	49.8	87.4***	119.6**
	(17.9)	(30.8)	(33.7)	(55.9)
$\frac{\beta_Z^{IV}}{\beta_W^{IV} - \beta_Z^{IV}} \approx$ Treatment effect elasticity of demand	0.715	0.660	-0.676***	-0.727***
	(0.733)	(0.607)	(0.156)	(0.172)
State FE	X	X	X	X
State FE $\times$ X_n	X	X	X	X
LASE: p-value [pairs bootstrap-c p-value]	0.077 [0.136]	0.106 [0.144]	0.010 [0.052]	0.033 [0.072]
$(Z_n, W_n) = (\text{Aquifer yield}_n, \text{Irr. crop yield}_n)$	X	X	-	-
$(Z_n, W_n) = (\text{Irr. crop yield}_n, \text{Aquifer yield}_n)$	-	-	X	X
# of observations	884	884	222	222
# of clusters	222	222	222	222

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the district level are in parentheses, and each cell reports a coefficient from a separate regression. Estimates from Columns 1 and 2 are directly comparable, while the relative interpretation of estimates from Columns 3 and 4 is discussed in Section 4.2 and 5.1. Rows 1 and 3 report first stage coefficients with irrigated share of agricultural land D_n as the dependent variable. Rows 2 and 4 report instrumental variable estimates with gross revenue (for Columns 1 and 2) or negative fixed costs of irrigation infrastructure (for Columns 3 and 4) as the dependent variable ('000 Rs/ha). Row 5 reports estimates of the local average surplus effect, and Row 6 reports estimates of a pseudo treatment effect elasticity of demand. Estimators in Columns 2 and 4 are weighted to balance the share of compliers in each state across β_Z^{IV} and β_W^{IV} as discussed in Section 3.5.2. All specifications include as controls state fixed effects and state fixed effects interacted with log potential rainfed crop yield X_n. The instrument Z_n is potential aquifer yield in Columns 1 and 2 and log relative potential irrigated crop yield in Columns 3 and 4, and the instrument W_n is log relative potential irrigated crop yield in Columns 1 and 2 and potential aquifer yield in Column 3 and 4. Pairs bootstrap-c p-values for estimates of local average surplus effects are calculated following Young (2018).

Table 3 presents instrumental variable and weighted instrumental variable estimates used to recover a local average surplus effect and pseudo treatment effect elasticity of demand; for compactness, each cell corresponds to a single regression. Columns correspond to a single set of estimates, while rows correspond to estimators. Column 1 presents the same results as are in Table 2. Row 5 of Column 1 is the difference between the IV estimator using the outcome instrument and the IV estimator using the cost instrument, which estimates a local average surplus effect if the two local average treatment effects (for cost instrument compliers and outcome instrument compliers) are the same. The estimated local average surplus effect is 31,700 Rs/ha. To facilitate interpretation, an estimate of the pseudo treatment effect elasticity of demand is presented in row 6: the resulting point estimate is 0.72, although it is imprecisely estimated.

Column 2 presents results with the weighted instrumental variable estimator, which corrects for potential bias from differences in shares of cost instrument and outcome instrument compliers in different states. The estimated local average surplus effect with this estimator, 49,800 Rs/ha, is larger (although not statistically significantly so), and the estimated pseudo treatment effect elasticity of demand is similar.

Columns 3 and 4 present results with negative infrastructure costs as the outcome using unweighted and weighted instrumental variables, respectively; as described in Section 4.2, the roles of the instruments are now switched. The local average treatment effect estimates imply marginal irrigation infrastructure costs of 59,100-86,900 Rs/ha. Unlike estimates with agricultural productivity as an outcome, these instrumental variable estimates are economically significantly different from OLS estimates, consistent with unobservable heterogeneity in costs of irrigation driving selection.[31] Although interpreting the local average surplus effect estimates is difficult, following the reasoning in Section 4.2, pseudo treatment effect elasticity of demand estimates should be the negative of estimates using agricultural productivity as an outcome. Estimates of this elasticity using infrastructure costs are statistically and economically indistinguishable from estimates using agricultural productivity, but are much more precisely estimated. The estimates imply a 1% increase in the gross returns to irrigation causes a 0.7% increase in adoption of irrigation, times a bias term equal to the ratio of gross returns for average irrigators to gross returns for marginal irrigators.

[31]The difference is not statistically significant (for the Hausman test, $p = 0.12$ for unweighted IV and $p = 0.13$ for weighted IV), so I interpret this difference as potentially suggestive of selection on unobservable heterogeneity in costs of irrigation.

5.2 Control function

Table 4: LASE robustness, NSS

	Agricultural productivity			Agricultural inputs
	Ag '07-'11	NSS '12		
	IV	IV	IV (CF predictions)	IV
	(1)	(2)	(3)	(4)
Z_n				
β_Z^{FS}	0.278***	0.289***	0.257	0.375***
	(0.056)	(0.073)	(0.056)	(0.078)
β_Z^{IV}	22.6*	37.5***	13.4	12.0*
	(13.1)	(13.9)	(13.5)	(6.6)
State FE × W_n	X	X	X	X
W_n				
β_W^{FS}	0.791***	0.834***	0.881	0.852***
	(0.188)	(0.226)	(0.218)	(0.214)
β_W^{IV}	54.3***	67.9***	10.1 + 54.3 + 4.6	8.6
	(14.5)	(23.9)	$\underbrace{(10.7)}_{\text{LATE}_W} + \underbrace{(20.0)}_{\text{LASE}_W} + \underbrace{(19.3)}_{\text{bias}_W}$	(7.3)
State FE × Z_n	X	X	X	X
Surplus effects				
$\beta_W^{IV} - \beta_Z^{IV}$	31.7*	30.4	55.5	-3.3
	(17.9)	(26.3)	(19.7)	(9.7)
State FE	X	X	X	X
State FE × X_n	X	X	X	X
# of observations	884	33,778	33,778	26,280
# of clusters	222	222	222	222

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the district level are in parentheses, and each cell reports a coefficient from a separate regression. Rows 1 and 3 report first stage coefficients with irrigated share of agricultural land D_n as the dependent variable. Rows 2 and 4 report instrumental variable estimates with gross revenue (for columns 1, 2, and 3) or expenditures on agricultural inputs net of irrigation (for column 4) as the dependent variable ('000 Rs/ha). Row 5 reports estimates of the local average surplus effect. Estimators in Columns 2, 3, and 4 are weighted using sample weights times plot area, with weights scaled so each district receives identical weight. Column 3 uses control function predicted outcomes and propensity scores as outcomes in the reduced form and first stage, respectively. This allows decomposition of β_W^{IV} into a LATE, a LASE, and bias from violations of the exclusion restriction $W_n \not\Rightarrow Y_{0i}$, which is identified using the control function approach. All specifications include as controls state fixed effects and state fixed effects interacted with log potential rainfed crop yield X_n. The instrument Z_n is potential aquifer yield, and the instrument W_n is log relative potential irrigated crop yield.

Before estimating key model parameters using a two step control function approach, I first compare instrumental variable estimates of the local average surplus effect in

NSS '12, on which the control function approach is implemented, to the estimates from Ag '07-'11. The estimate of the local average surplus effect in Column 1 on Table 4 is similar, but noisier; I interpret this to mean direct comparisons of control function estimates using NSS '12 to instrumental variable estimates using Ag '07-'11 are reasonable, although they should still be made with caution.

Table 5: Control function estimates

g_C	-34.1 (13.6)**
c_0	4.0 (17.0)
g_Y	78.6 (27.5)***
σ_V	25.8 (9.5)***
$\frac{\mathrm{Cov}(-V_{1i}, V_i - \mathbf{E}[V_i \mid X_i])}{\sigma_V^2}$	0.21 (0.44)
$\frac{\mathrm{Cov}(V_{0i}, V_i - \mathbf{E}[V_i \mid X_i])}{\sigma_V^2}$	0.11 (0.24)
$\frac{\mathrm{Cov}(V_{Ci}, V_i - \mathbf{E}[V_i \mid X_i])}{\sigma_V^2}$	0.68 (0.46)
# of observations	33778
# of clusters	222

Notes: Robust standard errors clustered at the district level are used to construct 95% confidence intervals in square brackets. Parameters are estimated by a two step control function approach as detailed in Section 3.5.4 and B.3, and standard errors are adjusted for the two step procedure. g_C is the effect of the cost instrument Z_{Cn} (potential aquifer yield) on cost per hectare of irrigation, g_Y and c_0 are the effects of the outcome instrument Z_{Yn} (log relative potential irrigated crop yield) on relative revenue per hectare from irrigation and revenue per hectare from rainfed agriculture, respectively. σ_V is the standard deviation of idiosyncratic relative profitability of irrigated agriculture. The three covariance terms decompose the variance of idiosyncratic relative profitability of irrigated agriculture into components from idiosyncratic revenue from irrigated agriculture, idiosyncratic revenue from rainfed agriculture, and idiosyncratic costs of irrigated agriculture, respectively.

I present the estimated coefficients from the control function approach in Table 5. A few things to note. First, the estimated effect of the outcome instrument on potential revenue under rainfed agriculture, c_0, is not significantly different from 0, so the overidentification test fails to reject. Second, the estimated standard deviation of idiosyncratic profitability of irrigation of 25,800 Rs/ha, σ_V, is large: as reference, the observed standard deviation of agricultural revenue per hectare is 26,100 Rs/ha, although these two measures need not be similar. Third, the selection terms are imprecisely estimated, although there is potentially suggestive evidence that there is selection on costs, consistent with the differences between instrumental variables and OLS estimators with fixed costs as the outcome in Section 5.1.

To compare the control function approach to the instrumental variable approach, Column 3 of Table 4 shows estimates of LATE_Z, LATE_W, and LASE_W from the control function approach, along with bias from violations of the exclusion restriction.[32] The local average surplus effect, 54,300 Rs/ha, is larger than estimates from either instrumental variable method and is more precisely estimated. The estimated bias from differences between local average treatment effects is small, at -3,300 Rs/ha. The estimated bias from violations of the exclusion restriction is also small, at 4,600 Rs/ha. These biases happen to offset, and the total bias in the instrumental variable estimator of the local average surplus effect is just 1,200 Rs/ha.

Table 6: Informativeness of IV estimators for CF predicted LATE and LASE

Descriptive Statistic (IV estimator)	Estimate of interest (CF prediction)	Informativeness
β_Z^{IV}	LATE_Z	0.506
$\beta_W^{IV} - \beta_Z^{IV}$	LASE_W	0.118
β_Z^{WIV}	LATE_Z^{WIV}	0.455
$\beta_W^{WIV} - \beta_Z^{WIV}$	LASE_W^{WIV}	0.504

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. The informativeness of 4 IV estimators for their target parameters estimated using a control function approach are presented here. Informativeness is calculated following Andrews et al. (2018), who note that it can be interpreted as the R^2 from the population regression of the target parameter on the corresponding IV estimator in their joint asymptotic distribution. IV estimators β_Z^{IV} and β_W^{IV} use Z (potential aquifer flow) and W (log relative potential irrigated crop yield) as instruments, respectively, for the effect of D (irrigation) on Y (gross revenue per hectare). CF predictions replace Y and D with their predictions using a two step control function approach following Kline & Walters (2017). LATE comparisons control for state FE, W (Z), and state FE interacted with X for $\beta_Z^{(\cdot)}$ ($\beta_W^{(\cdot)}$), and LASE comparisons control for state FE, state FE interacted with W (Z), and state FE interacted with X for $\beta_Z^{(\cdot)}$ ($\beta_W^{(\cdot)}$). WIV estimators use weights to balance compliers on state FE, with weights constructed as described in Section 3.5.2. Cluster robust variance covariance matrices are estimated clustered at the district level.

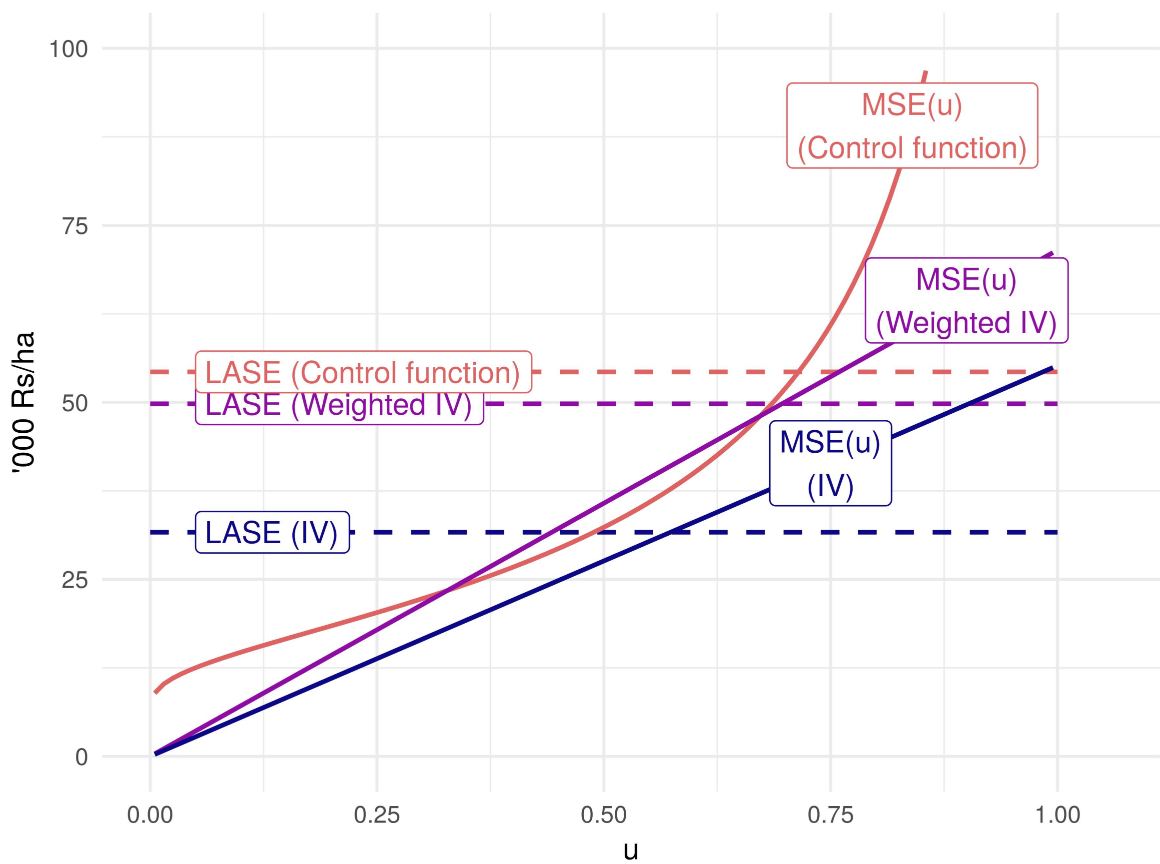
However, just because the control function estimates imply the linear IV estimator has a small bias in this case does not mean it is a good estimator of a local average surplus effect. To judge this, I follow Andrews et al. (2018) and calculate the informativeness of the IV and WIV estimators of LATE_Z and LASE_W for the equivalent control function estimates. This does not capture bias, which is small in this context but need not be in others, but does capture the extent to which structural estimates of LATE_Z and LASE_W are explained by IV estimators. Kline & Walters (2017) note that in many cases, IV and structural estimates of LATE_Z are numerically equivalent, which would yield an informativeness of 1; I therefore use the informativeness of IV estimates of

[32] I discuss the construction of these in Section B.3.

LATE_Z for structural estimates of LATE_Z as a benchmark. Table 6 shows these measures. The IV and weighted IV estimators of LATE_Z both have high informativeness of structural estimates (0.51 and 0.46, respectively). The IV estimator of LASE_W has a low informativeness of the structural estimator (0.12). However, the WIV estimator of LASE_W has an informativeness of the structural estimate that is similar to that of IV estimates of LATE_Z for structural estimates of LATE_Z (0.50). I interpret this as evidence that the instrumental variable approach is, at the least, a useful complement to traditional structural approaches one could use to estimate marginal surplus effects, as the two approaches should yield similar results.

5.3 MSE

Figure 3: Marginal surplus effect estimates



Notes: Solid lines present estimates of marginal surplus effects (the change in average surplus per unit change in adoption caused by shifts to either costs or outcomes under treatment), while dashed lines present estimates of local average surplus effects (a weighted average of marginal surplus effects). Dashed lines for IV and Weighted IV estimators are the estimates of local average surplus effects used to construct marginal surplus effects, following Section 3.5.3. The control function estimate of the local average surplus effect is constructed by replacing outcomes and treatment in the IV regression using w with control function estimates of predicted changes in surplus and changes in propensity scores.

Estimated marginal surplus effects and local average surplus effects for the instrumental variable estimator (in Ag '07-'11), the weighted instrumental variable estimator (in Ag '07-'11), and the control function estimator (in NSS '12) are presented in Figure 3. The instrumental variable estimates of marginal surplus effects are constructed from the local average surplus effect estimates as described in Section 3.5.3. The control function estimate of the local average surplus effect is constructed from the marginal surplus effect estimate as described in Section 3.5.4. First, note that although the weighted IV local average surplus effect is 57% larger than the IV estimate, the weighted IV marginal surplus effect is only 30% larger. This is because the weighted IV local average surplus effect places more weight on larger margins of adoption, where marginal surplus effects will typically be larger (and are by assumption with the functional forms I use). Second, the control function estimate of the marginal surplus effect is larger than the IV estimate, but it is close to the WIV estimate over empirically relevant margins of adoption. As a result, for counterfactual exercises, I pick the "median" of the three estimates and use the WIV estimate of the marginal surplus effect. Third, note that distributional assumptions can have a large impact on estimates of the marginal surplus effect when extrapolating outside of frequently observed margins of adoption.

5.4 Groundwater depletion and rural surplus

Table 7: Calibrated parameters

	Value [Low, High]	Source
Calibrated parameters		
$\epsilon_{A,p}$, $\epsilon_{M,p}$	-0.18	Badiani & Jessoe (2017)
r, upper bound (rural credit interest rate)	0.20	Hussam et al. (2017)
r, lower bound (India 30 year bond yield)	0.08	
m (energy/m^3 of water/m)	6.8 Wh/m^3/m	Shah (2009)
$d\mathbf{E}[D_i]/db$	-.0024/m	Fishman et al. (2017)
Calibrated parameters (Rajasthan)		
p	1.21 Rs/kWh	Fishman et al. (2016)
c	3.30 Rs/kWh	Fishman et al. (2016)
b (depth to water table)	[5m, 66m]	Well '95-'17
α (specific yield)	[0.015, 0.068]	Narain et al. (2006)
$\mathbf{E}[D_i]L/\overline{L}$ (aquifer share irrigated)	[0.015, 0.492]	Ag '07-'11
$A/\mathbf{E}[D_i]L$ (groundwater use/irrigated ha)	[0.065, 0.650] m ha/ha	Ag '07-'11
Rajasthan 2008 agricultural electricity use	9,791 GWh	Rajasthan DES (2011)
India statistics		
$\mathbf{E}[D_i]L$ (irrigated ha)	60 million ha	Ag '07-'11
$A/\mathbf{E}[D_i]L$ (avg. groundwater use/irrigated ha)	0.43 m ha/ha	Shah (2009), Ag '07-'11
p	1.05 Rs/kWh	Fishman et al. (2016)
$pM/\mathbf{E}[D_i]L$ (avg. elec. exp./irrigated ha)	1,470 Rs/ha	Fishman et al. (2016), Ag '07-'11
Estimates		
MSE(u)	71,500u Rs/ha	Section 5.3
$\epsilon_{A,p}$, $\epsilon_{M,p}$ (lower bound)	-0.045	Section 7.2

Notes: This table contains the calibrated parameters for the counterfactual exercises in Section 5.4 and Section 7. Values are provided as points when a single estimate is used, and as a range when the value used is allowed to vary across districts. Ranges for specific yield, depth to water table, aquifer share irrigated, and groundwater use/irrigated ha are specific to Rajasthan. Depth to water table is estimated as the median post monsoon Kharif reading from the network of monitoring tube wells, bottom winsorized at 5m.

With an estimate of the marginal surplus effect, we can calculate the effects of declining water tables on surplus. To do so, with the marginal surplus effect it is sufficient to have an estimate of the impact of declining water tables on adoption of irrigation. Let b be the depth to water table in meters. I calibrate $d\mathbf{E}[D_i]/db = -.0024/\text{m}$ based on estimates from Fishman et al. (2017), which I assume to be constant.[33] This yields

$$\frac{d\mathbf{E}[\pi_i]}{db} = \text{MSE}(\mathbf{E}[D_i])\frac{d\mathbf{E}[D_i]}{db}$$

Table 8: Lost surplus from groundwater depletion

	1m decline Rs/irrigated ha (1)	3.3m decline, NW India Rs/ha [% of productivity/ha] (2)
IV		
LASE		251 [0.80%]
MSE	132	282 [0.90%]
Weighted IV		
LASE		394 [1.26%]
MSE	172	365 [1.16%]
Control Function		
LASE		430 [1.37%]
Back of envelope		
3x Electricity costs	93	197 [0.63%]
6x Electricity costs	186	395 [1.26%]

Notes: This table presents estimates of the lost surplus from groundwater depletion using estimates of local average surplus effects and marginal surplus effects from Section 5.1 and 5.3, and calibrated parameters from Table 7. Column 1 presents the impact of a 1m decline in the water table on costs per irrigated hectare. Column 1 IV and WIV estimates are calculated using the estimated marginal surplus effect, and the calibrated effect of a 1m decline in water tables on adoption of irrigation. Column 1 back of the envelope approaches calculate the increased electricity costs farmers would have to pay to pump groundwater one additional meter, exclusively using calibrated parameters from Table 7. Column 2 presents the impact of a 3.3m decline in water tables in Northwestern India (Haryana, Punjab, and Rajasthan), the estimate of 2000's water table declines from Rodell et al. (2009).

I use this approach to calculate the impact of declining water tables on economic

[33]This, and all other calibrated parameters used in counterfactual exercises, are in Table 7.

surplus, and report estimates in Table 8. Column 1 reports estimates of the impact of a 1m decline in water tables on economic surplus in Rs/ha. The WIV marginal surplus effect implies a 1m decline in water tables reduces surplus per irrigated hectare by 172 Rs, or 0.7% of agricultural productivity per hectare in India in 2009. Across monitoring wells in India, one standard deviation of depth to water table is 15.4m, implying a one standard deviation increase in depth to water table would cause a loss of surplus per irrigated hectare equal to 10.8% of 2009 Indian agricultural productivity per hectare.

To assess the plausibility of this estimate, I do an alternative calculation. Instead, I ask how much farmers' private electricity costs of pumping groundwater would increase if depth to water table fell by 1m; an appeal to the envelope theorem suggests this is a direct loss of surplus for farmers. I then scale this up by the inverse share of electricity costs in costs of declining water tables; I consider values of 3 and 6 for this.[34] The IV and weighted IV estimates of the marginal surplus effect are 4.3 and 5.5 times larger than the increase in farmers' private electricity costs of pumping groundwater from a 1m decline in water tables, respectively. I interpret this as validation of that these estimates are reasonable to use for the remaining counterfactuals.

Next, I use the estimated marginal surplus effects, or local average surplus effects, to calculate the lost surplus from declining water tables in Haryana, Punjab, and Rajasthan, from 2000-2010, as estimated by Rodell et al. (2009). My preferred estimate, using the WIV marginal surplus effect, finds lost surplus of 365 Rs/ha, or 1.16% of agricultural productivity per hectare in northwest India. Other estimates range from 251 to 430 Rs/ha, while back of the envelope calculations scaling increased electricity costs are 197 and 395 Rs/ha.

[34] I calculate this share in two ways. For the first approach, I begin by noting that, on the margin, costs of adopting irrigation should equal benefits. I therefore use the IV LATE for the cost instrument on agricultural productivity as a measure of the costs of adopting irrigation. Next, I assume that the share of electricity costs in costs of declining water tables equals one minus the share of irrigation infrastructure in costs of adopting irrigation. Lastly, I use the IV LATE on fixed costs as a measure of fixed costs of adopting irrigation. To convert this to a flow, I multiply by 0.2, a common interest rate on credit in India (Hussam et al., 2017). This calculation yields an electricity cost share of 0.5. Alternatively, I assume that only fixed costs and electricity costs increase when water tables decline, and I assume they do so in proportion to their aggregate shares. I calculate the share of fixed costs using the approach above, and I calibrate electricity expenditures per irrigated hectare at 1,470 Rs/ha. This calculation yields an electricity cost share of 0.12. These yield a range of 2 to 8.

6 Robustness

I present an analysis of robustness of the estimated local average surplus effect here. Sections 6.1, 6.2, and 6.3 discuss the exclusion restrictions that the outcome instrument does not affect costs, that the outcome instrument does not affect potential revenue under rainfed agriculture, and that the cost instrument does not affect potential revenue, respectively. Section 6.4 discusses potential violations of the weak separability assumption. Section 6.5 discusses endogenous attrition, or that the instruments may increase gross cultivated area.

6.1 $W_n \not\Rightarrow C_{1i}$

The outcome instrument W_n might affect costs of agriculture if farmers reoptimize in response to increases in potential revenue under irrigation, and increase expenditures on inputs conditional on irrigating. If this is the case, direct effects on potential revenue driven by W_n may be the sum of increases in surplus and increases in costs; any such increases in costs are an exclusion restriction violation. To test this, in Column 4 of Table 4, I use household level data on agricultural input expenditures from NSS '12 as the outcome, and I compare instrumental variable estimates using the cost instrument Z_n and the outcome instrument W_n of the effect of irrigation D_n. Additionally, the cost instrument Z_n should have a direct effect on input expenditures related to pumping groundwater, so I exclude these.[35] This is a standard overidentification test: both Z_n and W_n should be valid instruments for the effect of irrigation on agricultural inputs excluding direct expenditures on irrigation if farmers do not reoptimize. Row 5 shows I fail to reject this overidentification test, and the estimate is a precise 0.

[35] Specifically, I drop the categories "Diesel", "Electricity", and "Irrigation". While one might be tempted to use these categories to construct a measure of agricultural profits, they crucially do not include depreciation of irrigation infrastructure.

Table 9: Irrigation technology

	Irr '07					Well '95-'17	Well '07-'11
	Groundwater ha/ha	Surface water ha/ha	Deep tubwell/ha	Shallow tubewell/ha	Dugwell/ha	Depletion (mbgl/year)	Depth to water table (mbgl)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D_n (share irrigated)	0.718***	0.282	0.091*	0.067	-0.019	2.14	18.1
	(0.222)	(0.222)	(0.053)	(0.078)	(0.127)	(1.39)	(19.1)
Instrument	W_n	W_n	W_n	W_n	W_n	W_n	W_n
State FE	X	X	X	X	X	X	X
State FE $\times X_n$	X	X	X	X	X	X	X
State FE $\times Z_n$	X	X	X	X	X	X	X
# of observations	222	222	222	222	222	85,804	28,169
# of clusters	222	222	222	222	222	198	176

	Irr '07					Well '95-'17	Well '07-'11
	Groundwater ha/ha	Surface water ha/ha	Deep tubwell/ha	Shallow tubewell/ha	Dugwell/ha	Depletion (mbgl/year)	Depth to water table (mbgl)
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
D_n (share irrigated)	1.000***	0.000	-0.002	0.325***	-0.395**	3.75	67.5
	(0.207)	(0.207)	(0.031)	(0.096)	(0.155)	(2.59)	(41.4)
Instrument	Z_n	Z_n	Z_n	Z_n	Z_n	Z_n	Z_n
State FE	X	X	X	X	X	X	X
State FE $\times X_n$	X	X	X	X	X	X	X
State FE $\times W_n$	X	X	X	X	X	X	X
# of observations	222	222	222	222	222	85,804	28,169
# of clusters	222	222	222	222	222	198	176

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the district level are in parentheses. In the first subtable, coefficients on share irrigated are estimated using W_n, log relative potential irrigated crop yield, as an instrument. In the second subtable, coefficients on share irrigated are estimated using Z_n, potential aquifer flow, as an instrument. Controls X_n are log potential rainfed crop yield.

Alternatively, the outcome instrument may affect direct costs of irrigating through falling water tables. The outcome instrument should cause increases in extraction of groundwater, which would cause water tables to fall, which in turn will increase costs of irrigation. I test for this in Table 9. In Columns 6 and 7 of the first subtable, I fail to reject the null of no depletion caused by increases in irrigation caused by W_n. However, the coefficients are not small: they suggest a fully irrigated district has water tables that are 18m deeper than a district with no irrigation (1.2 standard deviations of depth to water table across monitoring wells), and depletion is 2m/year faster. However, this will not meaningfully bias my estimates: multiplying 18m by the 172 Rs/ha cost increase caused by a 1m fall in water tables, this implies that costs increased by 3,110 Rs/ha, which is less than 10% of my estimates of the local average surplus effect.

6.2 $W_n \not\Rightarrow Y_{0i}$

Table 10: LASE robustness, controls

	Agricultural productivity (Y_n)					
	Ag '07-'11					
	IV (1)	IV (2)	IV (3)	IV (4)	IV (5)	IV (6)
Z_n						
β_Z^{FS}	0.278***	0.465***	0.229***	0.239***	0.310***	0.394***
	(0.056)	(0.035)	(0.053)	(0.058)	(0.060)	(0.072)
β_Z^{IV}	22.6*	22.3***	26.3**	17.7	34.8***	36.1***
	(13.1)	(4.6)	(12.4)	(15.1)	(11.3)	(10.0)
W_n	X	-	X	X	X	X
State FE × W_n	X	-	-	-	X	X
State FE × X_nW_n	-	-	-	-	-	X
State FE × W_n^2	-	-	-	-	-	X
W_n						
β_W^{FS}	0.791***	0.302***	0.522***	0.756***	0.502**	0.400*
	(0.188)	(0.101)	(0.187)	(0.187)	(0.220)	(0.222)
β_W^{IV}	54.3***	26.3***	83.2***	57.4***	76.6**	84.3*
	(14.5)	(8.6)	(27.1)	(15.5)	(33.7)	(45.4)
Z_n	X	-	X	X	X	X
State FE × Z_n	X	-	-	-	X	X
State FE × X_nZ_n	-	-	-	-	-	X
State FE × Z_n^2	-	-	-	-	-	X
Surplus effects						
$\beta_W^{IV} - \beta_Z^{IV}$	31.7*	4.0	56.9**	39.6*	41.9	48.2
	(17.9)	(9.6)	(28.3)	(20.6)	(35.1)	(47.0)
X_n	X	-	X	X	X	X
State FE	X	-	X	X	X	X
State FE × X_n	X	-	-	X	X	X
State FE × X_n^2	-	-	-	-	X	X
# of observations	884	884	884	884	884	884
# of clusters	222	222	222	222	222	222

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the district level are in parentheses, and each cell reports a coefficient from a separate regression. Rows 1 and 3 report first stage coefficients with irrigated share of agricultural land D_n as the dependent variable. Rows 2 and 4 report instrumental variable estimates with gross revenue as the dependent variable ('000 Rs/ha). The control X_n is log potential rainfed crop yield, the instrument Z_n is potential aquifer yield, and the instrument W_n is log relative potential irrigated crop yield.

The outcome instrument W_n might affect potential revenue under rainfed agriculture; it is constructed using FAO GAEZ data on predicted relative yields under irrigated agriculture. This is negatively correlated with predicted yields under rainfed agriculture, as places with high returns to irrigation typically have low yields under rainfed agriculture. I address this in two ways. First, I consider including more or less flexible controls for FAO GAEZ potential rainfed crop yield. All primary specifications include controls for state fixed effects interacted with potential rainfed crop yield, I compare this baseline specification to specifications with alternative controls in Table 10. First, Column 2 shows a specification with no controls. The estimated local average surplus effect is biased downward, as relative potential irrigated yields are negatively correlated with rainfed yields. Columns 3, 4, 5, and 6 include progressively more flexible controls, with controls in my preferred specification (in Column 1) falling between Column 4 and Column 5. Estimates of the local average surplus effect range from 39,600 Rs/ha to 56,900 Rs/ha, compared to 31,700 Rs/ha with unweighted instrumental variables, although the precision begins to decrease as more controls are added.

Alternatively, the effect of the outcome instrument on rainfed yields is identified. Flexible models which allow for this in Ag '07-'11 are underpowered, but the control function approach I implement in NSS '12 is sufficiently powered to test this under more parametric restrictions. I implement this overidentification test in Row 2 of Table 5; I fail to reject the outcome instrument has no effect on rainfed yields, and the 0 is small and precise. I assess the magnitude of bias from exclusion restriction violations in Table 4, Column 3: the bias in instrumental variables from violations of the exclusion restriction is estimated to be 4,600 Rs/ha, less than 10% of the control function estimate of the local average surplus effect.

6.3 $Z_n \not\Rightarrow (Y_{0i}, Y_{1i})$

Table 11: Placebo before Green Revolution

	D_{nt} (share irrigated)	$\log Y_{nt}$ (log agricultural productivity)
	(1)	(2)
Z_n	0.050	0.028
	(0.063)	(0.103)
$1\{t > 1966\} Z_n$	0.116***	0.120*
	(0.042)	(0.067)
W_n	0.182	0.755*
	(0.144)	(0.411)
$1\{t > 1966\} W_n$	0.335***	0.781***
	(0.114)	(0.240)
$\log \text{RF yield}_n$	0.144*	1.150***
	(0.085)	(0.260)
$1\{t > 1966\} \log \text{RF yield}_n$	0.193***	0.200
	(0.074)	(0.154)
State-by-year FE	X	X
# of observations	11,799	11,799
# of clusters	222	222

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the district level are in parentheses. Z_n is potential aquifer yield, W_n is log relative potential irrigated crop yield, and RF yield$_n$ is log potential rainfed crop yield. Outcomes are from Ag '56-'11.

The cost instrument Z_n decreases costs of groundwater irrigation by enabling lower cost tubewell irrigation. In India, prior to the Green Revolution, almost no agricultural land was irrigated using tubewells, so the cost instrument should have no effect on irrigation or agricultural revenue before the start of the Green Revolution. I estimate a difference in difference specification in Table 11, comparing coefficients on the cost instrument Z_n, the outcome instrument W_n, and the rainfed yield control $\log \text{RF yield}_n$, along with their interactions with a post Green Revolution start dummy.[36] To facilitate comparison across years, I use log agricultural productivity instead of its level. The cost instrument has no significant effects on irrigation or agricultural productivity before the Green Revolution, when tubewells are not available as a technology. In contrast, the outcome instrument increases revenue even before the Green Revolution, as other forms of irrigation were already available as a technology. However, the outcome instrument

[36] I follow Sekhri (2014) and define 1966 to be the start of the Green Revolution.

has limited effects on adoption of irrigation: increases in the returns to irrigation have a small effect on adoption of irrigation when there is large variation in the costs of irrigation, as was the case before the expansion of tubewell irrigation.

Table 12: Irrigation and crop choice

		$D_i 1\{\text{Crop}_i = (.)\}$												
	D_i (irrigated)	Wheat	Rice	Cotton	Soya	Bajra	Gram	Maize	Jowar	Sugar	RM	Tur	Groundnut	Potato
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Z_n	0.289***													
	(0.073)													
D_i (irrigated)		0.314	0.983***	-0.160	0.094	0.001	-0.249**	0.039	0.012	-0.060	0.028	0.009	-0.028	0.016
		(0.219)	(0.297)	(0.108)	(0.083)	(0.143)	(0.119)	(0.116)	(0.030)	(0.107)	(0.070)	(0.012)	(0.024)	(0.045)
Instrument (IV only)	-	Z_n	Z_n	Z_n	Z_n	Z_n	Z_n	Z_n	Z_n	Z_n	Z_n	Z_n	Z_n	Z_n
BH q-value	-	0.495	0.012	0.495	0.558	0.996	0.236	0.796	0.796	0.796	0.796	0.796	0.558	0.796
State FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
State FE $\times X_n$	X	X	X	X	X	X	X	X	X	X	X	X	X	X
State FE $\times W_n$	X	X	X	X	X	X	X	X	X	X	X	X	X	X
# of observations	33,778	33,778	33,778	33,778	33,778	33,778	33,778	33,778	33,778	33,778	33,778	33,778	33,778	33,778
# of clusters	222	222	222	222	222	222	222	222	222	222	222	222	222	222

		$(1 - D_i) 1\{\text{Crop}_i = (.)\}$												
	D_i (irrigated)	Wheat	Rice	Cotton	Soya	Bajra	Gram	Maize	Jowar	Sugar	RM	Tur	Groundnut	Potato
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Z_n	0.289***													
	(0.073)													
D_i (irrigated)		-0.087**	-0.513***	-0.053	-0.220**	0.158	-0.081	-0.187***	-0.027	0.000	-0.021	0.058	-0.027	0.000
		(0.038)	(0.148)	(0.096)	(0.107)	(0.097)	(0.057)	(0.072)	(0.045)	(0.000)	(0.027)	(0.083)	(0.054)	(0.000)
Instrument (IV only)	-	Z_n	Z_n	Z_n	Z_n	Z_n	Z_n	Z_n	Z_n	Z_n	Z_n	Z_n	Z_n	Z_n
BH q-value	-	0.096	0.007	0.674	0.127	0.269	0.347	0.060	0.674	0.871	0.674	0.674	0.674	0.419
State FE	X	X	X	X	X	X	X	X	X	X	X	X	X	X
State FE $\times X_n$	X	X	X	X	X	X	X	X	X	X	X	X	X	X
State FE $\times W_n$	X	X	X	X	X	X	X	X	X	X	X	X	X	X
# of observations	33,778	33,778	33,778	33,778	33,778	33,778	33,778	33,778	33,778	33,778	33,778	33,778	33,778	33,778
# of clusters	222	222	222	222	222	222	222	222	222	222	222	222	222	222

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the district level are in parentheses. Coefficients on share irrigated are estimated using Z_n, potential aquifer yield, as an instrument. D_i is an irrigation indicator for plot i, and Crop_i is the crop cultivated on plot i. Controls X_n are log potential rainfed crop yield, and W_n is log relative potential irrigated crop yield. D_i and Crop_i are from NSS '12. Following Benjamini & Hochberg (1995) and Anderson (2008), BH p-value are multiple inference adjusted p-values (adjusted within table).

Alternatively, the cost instrument Z_n might affect potential revenue directly if farmers reoptimize in response to decreases in costs of irrigation, and increase expenditures on inputs conditional on irrigating. To some extent, Column 4 of Table 4 should alleviate those concerns, as effects of the cost instrument on input expenditures are small. However, I explicitly excluded any expenditures specific to irrigation, as the cost instrument should have direct negative effects on these. Additionally, that the magnitudes of the LATE estimates in Columns 1 and 2 of Table 3 are reasonable should alleviate concerns of large bias, but given the limited precision with which they are estimated, this is also insufficient. To construct a test for reoptimization, I argue that if falling costs of irrigation cause farmers to reoptimize, we should see shifting of crop choice under irrigation towards water intensive crops; this appears as a violation of monotonicity, where the instrument decreases area irrigated under crops with low water intensity. I test for this in Table 12. Because I test for effects on every crop in the data, I adjust inference for multiple hypothesis testing; after this adjustment, no monotonicity violations are detected. Decreases in costs of irrigation cause shifts away from rainfed rice, maize, and wheat, and into irrigated rice.

6.4 Weak separability

In general, monotonicity with multiple instruments is a much stronger assumption than monotonicity with a single instrument. This is equally true here: through the lens of the model, it requires farmers can only differ in their responsiveness to the instruments through $V_{\gamma i}$. This is violated if some farmers' surplus under irrigation is relatively more responsive to the cost instrument. I consider likely violations of this in this section.

Table 13: LASE robustness, surface water and endogenous cultivation

	Agricultural productivity (Y_n)		$Y_n L_n / \overline{L}_n$	$(Y_n L_n + 20(\overline{L}_n - L_n))/\overline{L}_n$
	Ag '07-'11			
	IV	IV	IV	IV
	(1)	(2)	(3)	(4)
Z_n				
β_Z^{FS}	0.278***	0.279***	0.456***	0.456***
	(0.056)	(0.054)	(0.075)	(0.075)
β_Z^{IV}	22.6*	15.1	34.5***	17.2***
	(13.1)	(12.9)	(5.6)	(5.7)
State FE × W_n	X	X	X	X
W_n				
β_W^{FS}	0.791***	0.777***	0.559**	0.559**
	(0.188)	(0.227)	(0.241)	(0.241)
β_W^{IV}	54.3***	64.3***	55.9***	39.5**
	(14.5)	(19.3)	(17.5)	(18.4)
State FE × Z_n	X	X	X	X
Surplus effects				
$\beta_W^{IV} - \beta_Z^{IV}$	31.7*	49.2**	21.4	22.4
	(17.9)	(20.7)	(17.4)	(18.0)
State FE	X	X	X	X
State FE × X_n	X	X	X	X
GJ, HA+PJ, MH, RJ, UP	-	X	-	-
Endog. $D_n L_n / \overline{L}_n$	-	-	X	X
# of observations	884	447	884	884
# of clusters	222	133	222	222

Notes: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$. Robust standard errors clustered at the district level are in parentheses, and each cell reports a coefficient from a separate regression. Rows 1 and 3 report first stage coefficients with irrigated share of agricultural land D_n as the dependent variable. Rows 2 and 4 report instrumental variable estimates with gross revenue as the dependent variable ('000 Rs/ha). The control X_n is log potential rainfed crop yield, the instrument Z_n is potential aquifer yield, and the instrument W_n is log relative potential irrigated crop yield. Column 2 restricts observations to districts in the five 1961 states with the smallest shares of surface water irrigation. Columns 3 and 4 use share of district land irrigated, instead of share of district agricultural land irrigated, as treatment D_n. Columns 3 and 4 use agricultural production plus a reservation rent for uncultivated land (0 in Column 7 and 20,000 Rs/ha in Column 8) per hectare of district land as the outcome, instead of agricultural revenue per cultivated hectare.

The clearest violation of monotonicity is the presence of surface water. Farmers with access to surface water will not have their costs of irrigation respond to the cost instrument, since they will irrigate using surface water even if their costs of pumping groundwater fall. However, these farmers will still respond to the outcome instrument, since their revenue under irrigation will still shift up. Let Surface$_i$ be a dummy for access to surface water. To see how this violates monotonicity, one can write this modified model as

$$
\begin{aligned}
Y_{1i}(w) &= V_{\gamma i}\gamma_W(w) + V_{1i} \\
C_{1i}(z) &= (1 - \text{Surface}_i)V_{\gamma i}\gamma_Z(z) + V_{Ci} \\
Y_{0i} &= V_{0i}
\end{aligned}
$$

I take two approaches to handling this. First, I drop states where more than one third of irrigation is surface water, and present results in Column 2 of Table 13. States with large shares of surface water may bias up estimation of a local average surplus effect, if the outcome instrument increases revenues in those states but does not affect adoption of irrigation. The estimated local average surplus effect restricted to states with low shares of surface water is in fact slightly larger, suggesting such bias is not large in this context.

Second, I take a more model driven approach. I make the additional assumption that $\text{Surface}_i \perp (W_i, Z_i, V_{1i}, V_{Ci}, V_{0i}, V_{\gamma i})|X_i$, or that access to surface water for irrigation is exogenous conditional on the controls X_i. Additionally, I assume that everyone with access to surface water irrigates. This latter assumption I test: I show in Columns 1 and 2 of Table 9 that the outcome instrument (in the first subtable) and the cost instrument (in the second subtable) cause significant increases in groundwater irrigation, but not surface water irrigation. Under these assumptions, all results on estimation still hold, but when conducting counterfactuals using the local average surplus effect that affect only groundwater, it must be scaled down by the share of groundwater in irrigation. When I applied the local average surplus effect to estimation of the welfare losses from falling water tables in Section 5.4, the estimate of the effect of falling water tables on groundwater irrigation I use was from communities without access to surface water irrigation. On the other hand, when I use the local average surplus effect to recover an estimate of the elasticity of irrigation to the price of electricity, I must account for having estimated the local average surplus effect nationally, where the groundwater share of irrigation is 0.66.

6.5 Attrition

An addition concern is attrition: when costs of irrigation fall, some farmers will shift from rainfed agriculture to irrigated agriculture, but land that was fallow will also become irrigated, and farmers may begin to multiple crop. This constitutes endogenous selection into the sample. To account for this, I allow land to shift from either rainfed agriculture or fallow into irrigated agriculture in response to the instruments. Instead of looking at the share of agricultural land that is irrigated, I look at the share of district land that is irrigated. However, I do not observe the reservation rent on fallow land, or the gross revenue under rainfed agriculture that land would need to yield in order to be cultivated. However, an extended model implies that selection out of fallow should be the same in response to the outcome instrument and the cost instrument, so I test robustness of the results to imputation of a range of reservation rents; I use both 0 Rs/ha and 20,000 Rs/ha (just under the average revenue per hectare on rainfed plots in NSS '12). The results of this exercise are in Columns 3 and 4 of Table 13. The estimated local average surplus effect is smaller, but not significantly different, and does not depend on the choice of reservation rent.

7 Optimal policy

In Section 5.4, I calculated the lost surplus per hectare from a one meter decline in the water table. I now apply this estimate to optimal policy for groundwater subsidies. As discussed in Section 2.1, irrigation is implicitly subsidized in India through subsidies for electricity for pumping groundwater. Although there is not volumetric electricity pricing, pump capacity fees implicitly price electricity at an average of one third of marginal cost (Fishman et al., 2016; Badiani & Jessoe, 2017). Following Allcott et al. (2014), I consider a policy maker maximizing social surplus in choosing how to set pump capacity fees. Despite deadweight loss, subsidies may be optimal because the policy maker has a preference for redistribution, and is willing to spend $\lambda > 1$ Rs to transfer 1 Rs to farmers, a stated motive behind electricity subsidies (Dubash, 2007).[37] However, the impacts of marginal pumping induced by the subsidy on depth to water table of other farmers are not internalized by farmers increasing their pumping. This negative externality, and the deadweight loss from the subsidies, must be traded off by the social planner against the value of the subsidies as a transfer.

In Section 7.1, I model the planner's problem, and in Section 7.2, I discuss calibration of key parameters, including the marginal surplus effect. In Section 7.3, I use the

[37]Whether the policy maker is justified in acting as if $\lambda > 1$ is a question beyond the scope of this paper, but for electricity subsidies $\lambda > 1$ may be efficient if other transfers to farmers create greater deadweight loss (Hendren, 2014) or have high leakage (Niehaus & Sukhtankar, 2013).

model to calculate the gains from decentralizing the setting of pump capacity fees in Rajasthan. Rajasthan is in northwestern India, where I estimated the lost surplus from declining water tables in Section 5.4, and relative to other states in the region has greater heterogeneity of aquifer characteristics, and therefore in the magnitude of the negative externality. I quantify potential gains from reducing relative subsidies in districts with large negative pumping externalities.

7.1 Planner's problem

I model groundwater irrigation closely following Shah et al. (1995). In period t, farmers have access to an available stock of groundwater, S_t, from which they can pump groundwater for irrigation. If farmer i irrigates ($D_{it} = 1$), they receive revenue $Y_{1i}(a_{it})$ and incur costs $C_{1i}(a_{it}; S_t)$, where a_{it} is quantity of water farmer i would extract to maximize surplus conditional on irrigating in period t. If farmer i does not irrigate, they receive revenue Y_{0i}. Costs $C_{1i}(a_{it}; S_t)$ include fixed costs $k_i(S_t)$, linear electricity costs $m_i(S_t)p_t a_{it}$, where p_t is the price per kWh in period t, and other linear variable costs $c_i(S_t)a_{it}$. Farmers are atomistic, in that farmers do not internalize any impact their extraction a_{it} has on the available stock of groundwater S_t. Farmers maximize surplus π_i by solving

$$\pi_i = \int_0^T e^{-rt} \max_{a_{it}, D_{it}} \left[D_{it} Y_{1i}(a_{it}) - D_{it} \underbrace{\left((c_i(S_t) + m_i(S_t)p_t)a_{it} + k_i(S_t)\right)}_{C_{1i}(a_{it};S_t)} + (1 - D_{it})Y_{0i} \right] dt \tag{28}$$

I make a few additional realistic assumptions on electricity use and groundwater extraction. I model the evolution of the stock of groundwater simply; it falls by one unit per unit of extraction, so $\dot{S}_t = A_t \equiv \int D_{it} a_{it} di$. To extract a unit of water, the electricity required $m_i(S_t) = (h_i + b(S_t))m$, where $h_i + b(S_t)$ is the depth to groundwater for farmer i. The electricity requirement per unit of water per meter of depth to groundwater, m, is simply the energy required to lift one unit of water by one meter divided by the pump efficiency. The global component of depth to groundwater, $b(S_t) = S_t/\alpha\overline{L}$, where α is the specific yield of the aquifer (the fall in the water table per unit of groundwater extracted), and $\overline{L}$ is the area of the aquifer in hectares; as a result, when one meter hectare of groundwater is extracted, farmers experience an increase in depth to groundwater of $1/\alpha\overline{L}$ meters.

The social planner chooses p_t, the price of electricity charged to farmers, to maximize social surplus. Social surplus is total farmer surplus times λ plus profits from the electricity sector. Total agricultural electricity use in period t is $M_t \equiv \int D_{it} m_i(S_t) a_{it} di$, and the cost of producing a unit of electricity is c_t. The social planner solves

$$\max_p V(p) \equiv \lambda \int \pi_i di + \int e^{-rt}(p_t - c_t) M_t dt \tag{29}$$

I make three additional simplifications. First, I ignore rebound effects, where increases in the price of electricity today, by reducing extraction of groundwater, increase the available stock of groundwater, which reduces future costs of extraction and in turn increases future extraction. I further assume that current extraction is a good approximation of future extraction. In fact, extraction is growing (Rodell et al., 2018). These two simplifications have offsetting effects: rebound implies externalities are smaller than I estimate, while growing extraction implies externalities are larger than I estimate. I anticipate that these biases are small, as my calibrated elasticity is low (which reduces the bias from ignoring rebound) and my calibrated discount rate is high (which reduces the bias from ignoring rebound and growth in extraction). Third, I assume that current costs of electricity generation and electricity subsidies are a good approximation of future costs and subsidies. This is difficult to know, but I consider it a natural starting point for analysis.

I consider the social planner's first order condition for social surplus maximization with respect to the period 0 price of electricity. When writing the social planner's first order condition, I normalize by total electricity use M_0, and multiply by -1; this normalized first order condition can be interpreted as changes in social welfare per rupee of surplus transferred to farmers. I follow the public economics literature and express this first order condition in terms of reduced form sufficient statistics (Chetty, 2009). I define $\epsilon_{M,p}$ to be the elasticity of electricity use to the price of electricity, and $\epsilon_{A,p}$ to be the elasticity of groundwater extraction to the price of electricity.

$$-\frac{1}{M_0}\frac{dV(p)}{dp_0} = \underbrace{\lambda - 1}_{\text{Transfer value}} \underbrace{- \epsilon_{M,p}\frac{p_0 - c_0}{p_0}}_{\text{DWL}}$$

$$\underbrace{- \frac{\lambda}{r}\epsilon_{A,p}\frac{(L/\alpha\overline{L})\ \overbrace{(\partial \mathbf{E}[D_{i0}]/\partial b_0)\mathrm{MSE}(\mathbf{E}[D_{i0}])}^{\text{Farmer cost of 1m fall in water table/ha}}}{p_0 M_0/A_0}}_{\text{Pumping externality (farmer)}} \underbrace{- \frac{1}{r}\epsilon_{A,p}\frac{(L/\alpha\overline{L})\overbrace{(p_0 - c_0)(mA_0/L)}^{\text{Utility cost of 1m fall in water table/ha}}}{p_0 M_0/A_0}}_{\text{Pumping externality (utility)}} \quad (30)$$

I consider each term in Equation 30. The first term, $\lambda - 1$, is the value the social planner places on shifting one rupee from public funds to farmers. The second term, $-\epsilon_{M,p}\frac{p_0-c_0}{p_0}$, is the standard deadweight loss term. It is the elasticity of electricity use to the price of electricity times a term that captures the distortion from subsidies.

The third term, $\frac{\lambda}{r}\epsilon_{A,p}\frac{(L/\alpha\overline{L})(\partial\mathbf{E}[D_{i0}]/\partial b_0)\mathrm{MSE}(\mathbf{E}[D_{i0}])}{p_0 M_0/A_0}$, is the pumping externality experienced by farmers per Rs of transfer. It is scaled by λ, because changes in farmer surplus, whether from transfers or increased pumping costs from externalities, are valued the same by the social planner. It is scaled by $\frac{1}{r}$, because while transfers are experienced immediately, and deadweight loss is based on the farmer's static optimization, the externality from a unit fall in the water table is experienced indefinitely by all farmers. It is scaled by $\epsilon_{A,p}$ because the externality caused per rupee of transfer is proportional to the extraction caused per rupee of transfer. The remainder $\frac{(L/\alpha\overline{L})\frac{\partial\mathbf{E}[D_{i0}]}{\partial b_0}\mathrm{MSE}(\mathbf{E}[D_{i0}])}{p_0 M_0/A_0}$ captures the distortion. The numerator is the externality per unit of water extracted, and equals the fall in water table experienced by farmers per unit of water extracted $L/\alpha\overline{L}$ times the lost farmer surplus per unit fall in the water table $\frac{\partial\mathbf{E}[D_{i0}]}{\partial b_0}\mathrm{MSE}(\mathbf{E}[D_{i0}])$. The denominator is the electricity cost per unit of water extracted, $p_0 M_0/A_0$. The full term $\frac{1}{r}\epsilon_{A,p}\frac{(L/\alpha\overline{L})\frac{\partial\mathbf{E}[D_{i0}]}{\partial b_0}\mathrm{MSE}(\mathbf{E}[D_{i0}])}{p_0 M_0/A_0}$, is the externality ratio, or the Rs of externality created per Rs of surplus transferred to farmers.

The fourth term, $\frac{1}{r}\epsilon_{A,p}\frac{(L/\alpha\overline{L})(p_0-c_0)(mA_0/L)}{p_0 M_0/A_0}$, is the pumping externality experienced by the utility per Rs of transfer. The utility experiences the externality because of the wedge between the price farmers pay for electricity and the marginal cost of generation. It is scaled by $\frac{1}{r}$, $\epsilon_{A,p}$, and inversely proportional to $p_0 M_0/A_0$ for the same reasons the pumping externality experienced by farmers is. The numerator, $(L/\alpha\overline{L})(p_0 - c_0)(mA_0/L)$, is lost profits experienced by the utility per unit of water extracted caused by the increase in electricity required to pump groundwater caused by falls in the water table. The wedge $p_0 - c_0$ is the future difference between the price of electricity and the marginal cost of generation, as the increased electricity use caused by the externality occurs indefinitely.

7.2 Calibration

I discuss a few key aspects of the calibration. Note that all parameters used in the calibration are in Table 7.

First, I take two approaches to calibrating $\epsilon_{A,p}$ and $\epsilon_{M,p}$. In both cases, I assume electricity use for extracting groundwater is a constant proportion of extraction, so $\epsilon_{A,p} = \epsilon_{M,p}$. This need not hold in the model above, in the presence of heterogeneity in responsiveness to the price of electricity that is correlated with idiosyncratic depth to groundwater h_i. For the first approach, I use an estimate from Badiani & Jessoe (2017), $\epsilon_{A,p} = -0.18$. For the second approach, I use my preferred estimate of a local average surplus effect to calculate this elasticity; the inverse of a local average surplus effect is a semielasticity of irrigation to its gross returns. I calculate $\epsilon_{A,p} = -0.045$.[38] This estimate is likely to be biased downwards, since it ignores intensive margin responses of extraction to changes in the subsidy. I therefore interpret it as a lower bound, and I show estimates using both $\epsilon_{A,p} = -0.18$ and $\epsilon_{A,p} = -0.045$.

Second, the numerator of the externality ratio, $(L/\alpha\overline{L})(\partial\mathbf{E}[D_{i0}]/\partial b_0)\text{MSE}(\mathbf{E}[D_{i0}])$ can be decomposed into the product of three terms. The first, $1/\alpha$, is the inverse specific yield of the aquifer, or the total fall in the water table per unit of water extracted. The second, $L\mathbf{E}[D_{i0}]/\overline{L}$ is the share of the aquifer that is irrigated; this captures the fraction of a fall in the water table experienced by farmers. These first two terms will vary across aquifers, which may fall within district or cross district boundaries. For this exercise I assume each district is a single, contiguous aquifer; however, with more granular data, this exercise is straightforward at the aquifer level. The third, $(\partial\mathbf{E}[D_{i0}]/\partial b_0)(\text{MSE}(\mathbf{E}[D_{i0}])/\mathbf{E}[D_{i0}])$, is the lost surplus per irrigated hectare per unit fall in the depth to groundwater. My preferred estimate of this is 172 Rs/ha/m in Table 8, which I use for this exercise.

Third, calculating m, the electricity needed to pump one unit of groundwater one meter, is a simple physics problem which depends only on the depth to water table and

[38] Specifically, I approximate $\epsilon_{A,p} \approx \frac{p_0 M_0/\mathbf{E}[D_{i0}]L}{0.66\text{LASE}}$, where 0.66 is the groundwater share of irrigated land. I use LASE = 49,800 Rs/ha, and electricity expenditures per irrigated hectare by farmers of $p_0 M_0/\mathbf{E}[D_{i0}]L = 1{,}470$ Rs/ha.

the efficiency of extraction. Shah (2009) suggests 40% is a reasonable efficiency in the Indian context. Further, I assume that $M_0 = A_0 b_0 m$, or that electricity use for irrigation is groundwater extraction times depth to groundwater times the electricity needed to pump one unit of groundwater one meter.[39] This calculation yields total agricultural electricity use that is 36% of reported electricity use. I assume this difference is driven by depth to water table in farmers' wells being significantly deeper than the depths to water table in India's monitoring wells. I scale up my estimates of electricity use M_0 by a constant proportion across districts to match this total.

Fourth, a key decision is which parameters I allow to vary across districts. In this exercise, I focus on heterogeneity in optimal subsidies that stems from variation in the magnitude of the pumping externality. I therefore allow the key parameters which determine the pumping externality to vary: the average specific yield, the depth to water table, and the irrigated share of land. The externality ratio is inversely proportional, inversely proportional, and proportional to each of these parameters, respectively. I do a variance decomposition of the log externality ratio across districts: 11% of the variation is attributed to specific yield, 52% is attributed to irrigated share of land, and 37% is attributed to depth to water table.[40]

Fifth, for counterfactuals, a necessary decision is to determine which parameters are permitted to respond endogenously to changes in the policy, and which are not. The only parameters I allow to vary in response to changes in p are A_0, the total extraction of groundwater in the current period, and $\mathbf{E}[D_i]$, the irrigated share of the aquifer. For both, I use $\epsilon_{A,p}$ as the relevant elasticity. As mentioned previously, I ignore rebound; equivalently stated, I do not allow farmers to respond to changes in depth to water table b_t, but I do calculate the changes in rates of depletion implied by the changes in A_0. Additionally, I undertake the analysis as if the policy change were permanent; future decreases in $\mathbf{E}[D_i]$ caused by increases in electricity prices reduce negative externalities, and future increases in $p_t - c_t$ caused by increases in electricity prices reduce the negative externality on the utility. Both of these effects reduce the magnitude of optimal variation in subsidies relative to ignoring these responses. In sum, this represents a compromise between a full numerical simulation of the model, as would be standard in the optimal control literature, and the simpler sufficient statistics

[39] Depth to groundwater is measured using the median depth to groundwater by district across monitoring tubewells in Well '95-'17

[40] The externality experienced by the utility varies with the extraction of groundwater per irrigated hectare by district, which I also allow to vary. Setting this to the average extraction across districts does not meaningfully change any results, so I do not emphasize it.

approach I undertake, and I leave I comparison of my approach to a full numerical simulation to future work.

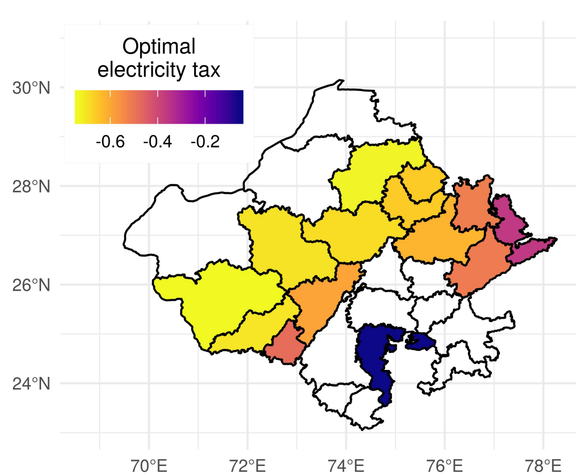
Sixth, for aggregating across districts, it is necessary to know district specific levels of extraction A_0 at baseline subsidy levels; I collect this data from district groundwater brochures from the Central Ground Water Board, which estimate groundwater withdrawals in each district in an idiosyncratic year ranging from 2004 to 2011, with a modal year of 2008.

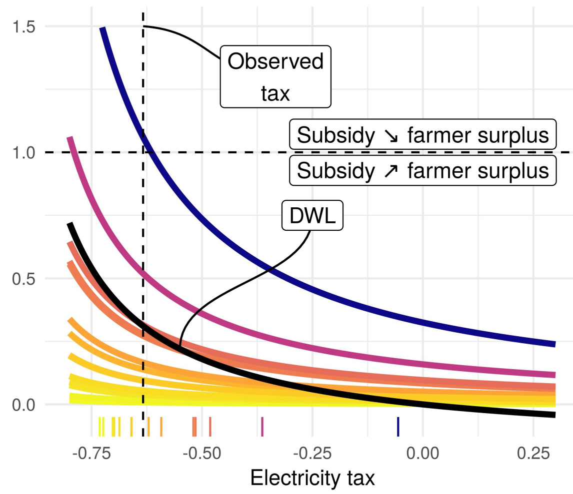
Seventh, I make two sample restrictions for districts for the counterfactual exercise. First, I only use districts for which depth to water table, district irrigated land share, and average aquifer specific yield are available; this brings me from 24 districts in the main analysis to 22. Second, I drop districts where more than 7% of irrigation uses surface water. In districts with high levels of surface water irrigation, optimal policy requires a different set of considerations: surface water irrigation has positive externalities, as it causes recharge of groundwater, and surface water and groundwater irrigation may be substitutes. This reduces the set of districts from 22 to 14.

7.3 Results

Figure 4: Optimal electricity taxes in Rajasthan

(a) Optimal tax, by district (b) Externality ratios and DWL, by district





Notes: This figure presents the results of the optimal policy exercise. In Panel (a), I plot the optimal electricity tax by district in Rajasthan, dropping districts with missing data or high levels of surface water irrigation. In Panel (b) I plot farmer externality ratios (the negative externality on farmers created by induced marginal groundwater extraction per unit of transfer to farmers, which varies across districts) and deadweight loss (DWL) as a function of the electricity tax. The optimal electricity tax solves

$$\lambda - 1 = (\text{DWL}) + \lambda(\text{Farmer externality ratio}) + (\text{Utility externality ratio})$$

λ is the willingness to pay of the social planner to increase farmer surplus by 1 unit. I use $\lambda = 1.56$ for values reported in this figure, which implies current subsidies are optimal if the planner is constrained to a single state level subsidy. I assume a constant elasticity of demand for electricity and water to the price of electricity. Both deadweight loss and externality ratios vary with the tax as electricity use and groundwater extraction respond. Farmer externality ratios by district are plotted in Panel (b). These externality ratios drive variation across districts in the optimal tax, and are the product of the inverse specific yield, inverse depth to water table, and the share of aquifer irrigated. The vertical dotted line in Panel (b) is the observed tax in Rajasthan (Fishman et al., 2016), while the horizontal dotted line is at 1: as discussed in Section 7.1, when the farmer externality ratio is above 1, any subsidy decreases farmer surplus, while when the farmer externality ratio is below 1, any subsidy increases farmer surplus (although subsidies are still costly to the social planner, due to increased net fiscal outlays, deadweight loss, and negative externalities on utilities). A tick is added to the bottom of the graph for the optimal tax in each district.

Figure 4 presents the optimal district specific electricity taxes in Rajasthan. To calculate optimal taxes, I first calibrate the social planners willingness to pay to increase farmer surplus by 1 unit, λ, under the assumption current policy is optimal subject to the constraint that there is a single subsidy at the state level, which yields $\lambda = 1.56$. Note that this λ is just the inverse marginal value of public funds; as a reference, this is similar to the inverse marginal value of public funds for SNAP, a public assistance program in the United States, as calculated in Hendren (2016).

Panel (a) presents the optimal tax by district. The optimal tax is relatively low in districts in northwestern Rajasthan, which tend to have lower land shares of irrigation, cultivating bajra instead of more water intensive wheat and maize, lower depths to water table, and higher specific yields, and therefore relatively small pumping externalities. Panel (b) presents the externality ratio and deadweight loss in each district as a function of the electricity tax. First, note that negative externalities are almost triple deadweight loss in the highest externality district, but close to 0 in other districts. Second, current subsidy levels reduce farmer surplus on the margin in the district with the largest pumping externalities, as the marginal pumping induced by current levels of subsidies in that district reduces farmer surplus by more than their value as a transfer.

Table 14: Optimal electricity taxes in Rajasthan

	$\epsilon = 0.18$, $r = 0.2$		$\epsilon = 0.045$, $r = 0.2$		$\epsilon = 0.18$, $r = 0.08$	
	Status quo (1)	Optimal (2)	Status quo (3)	Optimal (4)	Status quo (5)	Optimal (6)
λ (implied by status quo)	1.56	1.56	1.12	1.12	2.13	2.13
	Billion Rs [% of agricultural production]					
Total subsidy	10.32 [6.59%]	10.32 [6.59%]	10.32 [6.59%]	10.32 [6.59%]	10.32 [6.59%]	10.32 [6.59%]
Deadweight loss	1.02 [0.65%]	1.09 [0.69%]	0.27 [0.17%]	0.29 [0.18%]	1.02 [0.65%]	1.20 [0.76%]
Externality (utility)	0.10 [0.06%]	0.07 [0.05%]	0.03 [0.02%]	0.02 [0.01%]	0.25 [0.16%]	0.17 [0.11%]
Farmer surplus						
Subsidy	9.31 [5.94%]	9.24 [5.90%]	10.06 [6.42%]	10.04 [6.41%]	9.31 [5.94%]	9.13 [5.83%]
Externality (farmer)	0.70 [0.45%]	0.52 [0.33%]	0.20 [0.13%]	0.16 [0.10%]	1.75 [1.12%]	1.12 [0.71%]
Total	8.61 [5.50%]	8.72 [5.57%]	9.86 [6.30%]	9.88 [6.31%]	7.56 [4.83%]	8.01 [5.12%]
	m/decade [% of 2000-2010 decline]					
Water table decline	1.51 [45.7%]	1.26 [38.3%]	0.40 [12.2%]	0.34 [10.4%]	1.51 [45.7%]	1.19 [36.1%]

Notes: This table presents the results of the optimal policy exercise. Columns 1, 3, and 5 present results from maintaining the status quo ($p =$ 1.21 Rs/ha in all districts, with marginal cost $c = 3.30$ Rs/ha). Columns 2, 4, and 6 present results from optimal subsidies holding fixed total subsidies. ϵ is the calibrated elasticity of groundwater extraction/electricity use to the price of electricity, and r is the calibrated discount rate. λ is the inverse marginal value of public funds for a marginal change to state level subsidies under the status quo. All cells report impacts of the policy relative to no subsidies.

Table 14 presents results for total subsidies, deadweight loss, farmer surplus, and groundwater depletion, all relative to a no subsidy policy, under three scenarios. Column 1 presents the status quo. Total subsidies equal 6.6% of agricultural production, but deadweight loss from the subsidies is 0.65% of agricultural production, despite the high subsidy level. This follows from the low estimate of the price elasticity of electricity demand in agriculture I use from Badiani & Jessoe (2017). Externalities experienced by the utility are small relative to externalities experienced by farmers, as despite the high subsidies, electricity for pumping groundwater is a low share of costs of falling water tables. Negative pumping externalities induced by subsidies are meaningful, at 0.45% of agricultural production, but smaller than deadweight loss; however, this masks substantial heterogeneity. Additionally, subsidies were responsible for declines in water tables of 1.51m from 2000-2010, 46% of the observed decline in northwestern India.

Column 2 of Table 14 presents a scenario where the social planner chooses district specific subsidies to maximize social welfare under the same λ that implies the policy in Column 1 is the optimal state level policy, while holding total subsidies fixed. This policy involves increasing subsidies in districts with small pumping externalities, while decreasing subsidies in districts with large pumping externalities. First, note that this policy increases deadweight loss: this follows from the constant elasticity assumption, which implies a constant subsidy across locations minimizes deadweight loss holding fixed total subsidy payments. However, the increased deadweight loss is smaller than the decrease in negative pumping externalities. Negative externalities relative to the no subsidy policy fall by 25%, the total distortion relative to no subsidy falls by 7%, and the effect of subsidies on depth to groundwater decreases by 16%. However, total farmer surplus increases by only 0.07% of agricultural production.

Columns 4 and 6 present equivalent exercises, but using a lower calibrated elasticity (0.045) and a lower calibrated discount rate (0.08), respectively. Focusing on Column 4, the lower elasticity implies the inefficiency from subsidies is small: the λ which implies current policy is the optimal state level policy is 1.12. As a result, potential gains from spatially explicit policy are small. This highlights the importance of having a more precise estimate of this elasticity. Focusing on Column 6, the lower discount rate magnifies externalities, which in turn increases the potential gains from spatially explicit policy from 0.07% of agricultural production to 0.29% of agricultural production. It also implies that subsidies are very inefficient as transfers due to large negative externalities.

In this exercise, although "optimal" district specific subsidies increase total surplus, for high calibrations of the discount rate they do reduce farmer surplus in high externality districts, as relatively inefficient subsidies are reduced in those districts. As a result, this "optimal" policy may not be politically feasible. However, alternative more feasible policies can replicate the proposed optimal electricity tariff, while generating potentially larger gains. First, Badiani & Jessoe (2017) and Fishman et al. (2017) find that responses to changes in the cost of groundwater extraction tend to be on the extensive margin (in reduced area under irrigation) and not intensive margin (through reduced pumping). As a result, impacts of changing electricity tariffs can be replicated through other policies that change incentives to irrigate.[41] Additionally, Chatterjee et al. (2017) document that output subsidies for water intensive crops create incentives to increase groundwater extraction. Therefore, policies which reduce input subsidies complementary to irrigation or output subsidies for water intensive crops while increasing subsidies for inputs complementary to rainfed agriculture could increase the efficiency of farmer subsidies, especially in districts with large pumping externalities.

8 Conclusion

This analysis suggests that groundwater depletion in India from 2000-2010 permanently reduced economic surplus by 1.2% of gross agricultural revenue. This is similar to anticipated losses in India due to climate change of 1.8%/decade under the 4°C warming scenario (Government of India (2018)), and is especially concerning given accelerating rates of depletion (Jacoby (2017)). Policy solutions without economic tradeoffs may not be easy to come by: without reducing total electricity subsidies, the spatially explicit subsides I study can only increase surplus by a magnitude equal to losses from less than 1 year of groundwater depletion. Moreover, this policy reduces farmer surplus in districts with large externalities, and therefore may be politically infeasible. However, understanding the magnitudes of these externalities and the losses from depletion enables quantifying the potential efficiency gains from investments in surface water irrigation, or subsidies for inputs complementary to rainfed agriculture.

To undertake this analysis, I have expanded on tools from the program evaluation literature and microeconomic theory to define the marginal surplus effect. While marginal treatment effects capture the impact of policies or shocks which increase adoption of some treatment (such as college attendance) on observable outcomes, marginal

[41] Note that implementation of volumetric pricing could have a very different set of impacts on electricity use, especially with respect to efficiency, than the changes to electricity pricing as implemented through pump capacity fees that I consider.

surplus effects capture the direct impact of these policies or shocks on the economic surplus of inframarginal adopters. This is an important metric for policy across a range of contexts, such as health and safety regulations for workers, environmental regulations for firms, or, in this study, groundwater depletion in agriculture.

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A Data appendix

A.1 Construction of W_{ns}

I construct two variables using potential crop yield: log relative potential irrigated crop yield, and log potential rainfed crop yield. Define A^I_{nsc} and A^R_{nsc} to be the FAO GAEZ potential crop yield in district n in state s for crop c under the intermediate irrigated and rainfed scenarios, respectively, which I calculate by averaging the values across FAO GAEZ 5 arc-minute cells to the district level. Let L_{nsct} be the land allocated to crop c in district n in state s in year t, observed in Ag '56-'11. Let $L_{sc} = \sum_{n,t} L_{nsct}$ be the total area, across all years in Ag '56-'11, allocated to crop c in state s. I define

$$W_{ns} \equiv \log \frac{\sum_c L_{sc} \min\{A^I_{nsc}, 10A^R_{nsc}\}}{\sum_c L_{sc} A^R_{nsc}}$$
$$\log \text{RF yield}_{ns} \equiv \log \frac{\sum_c L_{sc} A^R_{nsc}}{\sum_c L_{sc}}$$

where W_{ns} is the log relative potential irrigated crop yield, and RF yield$_{ns}$ is the log potential rainfed crop yield. A few notes on the construction. First, the weights L_{sc} are constant within state; this ensures that variation in W_n is caused by variation across districts in the potential yield increase from irrigation, and not variation across districts in weights. Since these weights vary across states, I control flexibly for state in all analysis. It is important to allow the weights to vary across states; there is large variation across states in crop choice. Second, applying $\min\{A^I_{nsc}, 10A^R_{nsc}\}$ is similar to winsorizing W_{ns} at $\log 10$ for each crop. This is almost exclusively necessary for a few desert districts in Rajasthan and Gujarat; dropping these districts does not meaningfully change results, and the weighted instrumental variables estimator already places very little weight on these districts. However, not implementing this winsorization puts very high weight on these districts in estimation of the coefficient on W_{ns}, since these districts' predicted rainfed yield is close to 0. Since these districts are very dependent on irrigation and have relatively high yields, this increases the first stage and reduced form coefficients on W_{ns}. Third, controlling for $\log \text{RF yield}_{ns}$ and a state fixed effect, the coefficient on W_{ns} would be the same if instead $W_{ns} = \log \frac{\sum_c L_{sc} \min\{A^I_{nsc}, 10A^R_{nsc}\}}{\sum_c L_{sc}}$, or log potential irrigated crop yield.

B Model appendix

B.1 Proofs and derivations appendix

Proof of generality of functional form. Under weak separability of unobserved heterogeneity, and imposing the exclusion restrictions, agent surplus under treatment $Y_{1i}(w) - C_{1i}(z) = U(h(w,z), \tilde{V}_i)$, following Bhattacharya (2017) in defining weak separability. Taking derivatives with respect to w and z yields

$$\frac{\partial Y_{1i}}{\partial w} = \frac{\partial U(h(z,w);\tilde{V}_i)}{\partial h} \frac{\partial h(z,w)}{\partial w}$$
$$\frac{\partial C_{1i}}{\partial z} = \frac{\partial U(h(z,w);\tilde{V}_i)}{\partial h} \frac{\partial h(z,w)}{\partial z}$$
$$\frac{\partial^2 Y_{1i}}{\partial w \partial z} = \frac{\partial^2 U(h(z,w);\tilde{V}_i)}{\partial h^2} \frac{\partial h(z,w)}{\partial w} \frac{\partial h(z,w)}{\partial z} + \frac{\partial U(h(z,w);\tilde{V}_i)}{\partial h} \frac{\partial^2 h(z,w)}{\partial w \partial z}$$

A few restrictions appear here. First, $\frac{\partial^2 Y_{1i}}{\partial w \partial z} = 0$ (exclusion restriction). Second, $\frac{\partial h(z,w)}{\partial z} > 0$ and $\frac{\partial h(z,w)}{\partial w} > 0$ (monotonicity). Third, $\frac{\partial U(h(z,w);\tilde{V}_i)}{\partial h} > 0$ (monotonicity). Therefore, excluding edge cases, $\frac{\partial^2 U(h(z,w);\tilde{V}_i)}{\partial h^2} = 0$ and $\frac{\partial^2 h(z,w)}{\partial w \partial z} = 0$. The latter implies $h(z,w) = h_W(w) + h_Z(z) + V_{hi}$. The former implies $\frac{\partial U(h(z,w);\tilde{V}_i)}{\partial h} = V_{\gamma i}$ for some constant which is a function of $\tilde{V}_i$. Making these substitutions implies

$$Y_{1i}(w) - C_{1i}(z) = V_{\gamma i}(h_W(w) + h_Z(z) + V_{hi}) + \tilde{v}_i$$

which is equivalent to

$$Y_{1i}(w) = V_{\gamma i}\gamma_W(w) + V_{1i}$$
$$C_{1i}(z) = V_{\gamma i}\gamma_Z(z) + V_{Ci}$$

□

Derivation of Equation 4 and 5. Calculating each derivative,

$$\frac{d\mathbf{E}[Y_i(z,w)]}{dz} = f_V(F_V^{-1}(\mathbf{E}[D_i(z,w)]))\frac{d\gamma_Z(z)}{dz}\mathbf{E}[Y_{1i}(w) - Y_{0i}|U_i = \mathbf{E}[D_i(z,w)]]$$
$$\frac{d\mathbf{E}[\pi_i(z,w)]}{dz} = -\mathbf{E}[D_i(z,w)]\mathbf{E}[V_{\gamma i}|U_i < \mathbf{E}[D_i(z,w)]]\frac{d\gamma_Z(z)}{dz}$$
$$\frac{d\mathbf{E}[\pi_i(z,w)]}{dw} = -\mathbf{E}[D_i(z,w)]\mathbf{E}[V_{\gamma i}|U_i < \mathbf{E}[D_i(z,w)]]\frac{d\gamma_W(w)}{dw}$$
$$\frac{d\mathbf{E}[D_i(z,w)]}{dz} = f_V(F_V^{-1}(\mathbf{E}[D_i(z,w)]))\frac{d\gamma_Z(z)}{dz}$$
$$\frac{d\mathbf{E}[D_i(z,w)]}{dw} = f_V(F_V^{-1}(\mathbf{E}[D_i(z,w)]))\frac{d\gamma_W(w)}{dw}$$

Some algebra then yields the desired result. □

Derivation of Equation 10. Calculating the derivative of TOT$(u;w)$ yields

$$\frac{d\mathrm{TOT}(u;w)}{dw} = \mathbf{E}[V_{\gamma i}|U_i < u]\frac{d\gamma_W(w)}{dw}$$

Some algebra, and results from the proof of Equation 4 and 5, yields the desired result.
□

Derivation of Equation 11. Calculating each derivative,

$$\frac{d\mathbf{E}[Y_i(z,w)]}{dw} = f_V(F_V^{-1}(\mathbf{E}[D_i(z,w)]))\frac{d\gamma_W(w)}{dw}\mathbf{E}[Y_{1i}(w) - Y_{0i}|U_i = \mathbf{E}[D_i(z,w)]]+$$
$$\mathbf{E}[D_i(z,w)]\mathbf{E}[V_{\gamma i}|U_i < \mathbf{E}[D_i(z,w)]]\frac{d\gamma_W(w)}{dw}$$

Some algebra, and results from the proof of Equation 4 and 5, yields the desired result.
□

Proof of Equation 19. It suffices to show that $\beta_Z^{WIV} + \mathrm{LASE}_W = \beta_W^{IV}$. Let $Z_i^\perp \equiv Z_i - \mathbf{E}[Z_i|W_i, X_i]$, and $W_i^\perp \equiv W_i - \mathbf{E}[W_i|Z_i, X_i]$. Note that

$$\beta_Z^{WIV} = \sum_s \frac{\mathbf{E}[Y_i Z_i^\perp|S_i = s]}{\mathbf{E}[D_i Z_i^\perp|S_i = s]}\frac{\mathbf{E}[1\{S_i = s\}(\overline{\omega}_W(S_i)/\overline{\omega}_Z(S_i))D_i Z_i^\perp]}{\mathbf{E}[(\overline{\omega}_W(S_i)/\overline{\omega}_Z(S_i))D_i Z_i^\perp]}$$

I then proceed in two steps. First, I show that

$$\frac{\mathbf{E}[1\{S_i = s\}(\overline{\omega}_W(S_i)/\overline{\omega}_Z(S_i))D_i Z_i^\perp]}{\mathbf{E}[(\overline{\omega}_W(S_i)/\overline{\omega}_Z(S_i))D_i Z_i^\perp]} = \frac{\mathbf{E}[1\{S_i = s\}D_i W_i^\perp]}{\mathbf{E}[D_i W_i^\perp]}$$

Second, I consider conditions under which Assumption 5a holds. Written in terms of the natural estimators of $\text{LATE}_{Z|s}$ and $\text{LATE}_{W|s} + \text{LASE}_{W|s}$, with $\text{LASE}_{W|s}$ defined similarly,

$$\frac{\mathbf{E}[Y_i Z_i^{\perp}|S_i = s]}{\mathbf{E}[D_i Z_i^{\perp}|S_i = s]} = \frac{\mathbf{E}[Y_i W_i^{\perp}|S_i = s]}{\mathbf{E}[D_i W_i^{\perp}|S_i = s]} - \text{LASE}_{W|s}$$

Substituting each of these expressions into the original equation yields

$$\beta_Z^{WIV} + \text{LASE}_W = \sum_s \frac{\mathbf{E}[Y_i W_i^{\perp}|S_i = s]}{\mathbf{E}[D_i W_i^{\perp}|S_i = s]} \frac{\mathbf{E}[1\{S_i = s\} D_i W_i^{\perp}]}{\mathbf{E}[D_i W_i^{\perp}]} = \beta_W^{IV}$$

which completes the proof.

For the first step, I use the result that $\overline{\omega}_W(s) = \frac{\mathbf{E}[1\{S_i=s\}D_i W_i^{\perp}]}{\mathbf{E}[D_i W_i^{\perp}]}$ and $\overline{\omega}_Z(s) = \frac{\mathbf{E}[1\{S_i=s\}D_i Z_i^{\perp}]}{\mathbf{E}[D_i Z_i^{\perp}]}$, which can be shown by rewriting the IV estimator as a weighted average of IV estimators conditional on $S_i = s$. Substituting these expressions in immediately completes the first step.

For the second step, I impose some additional assumptions. First, $Z_i^{\perp} \perp (W_i, \tilde{X}_i)$ and $W_i^{\perp} \perp (Z_i, \tilde{X}_i)$ conditional on $S_i = s$. These are strong assumptions, but can be achieved by reweighting. Second, I assume marginal treatment effects and the propensity score are linear conditional on $S_i = s$. Third, I assume $\mathbf{E}[(Z_i^{\perp})^3|S_i = s] = 0$ and $\mathbf{E}[(W_i^{\perp})^3|S_i = s] = 0$. Again, these are strong assumptions, but can be achieved by reweighting.

I then proceed using

$$\frac{\mathbf{E}[Y_i Z_i^{\perp}|S_i = s]}{\mathbf{E}[D_i Z_i^{\perp}|S_i = s]} = \frac{\mathbf{E}[(\mathbf{E}[Y_i|Z_i^{\perp}, W_i, X_i] - \mathbf{E}[Y_i|Z_i = \mathbf{E}[Z_i|W_i, X_i], W_i, X_i]) Z_i^{\perp}|S_i = s]}{\mathbf{E}[(\mathbf{E}[D_i|Z_i^{\perp}, W_i, X_i] - \mathbf{E}[D_i|Z_i = \mathbf{E}[Z_i|W_i, X_i], W_i, X_i]) Z_i^{\perp}|S_i = s]}$$

This requires a few steps. I focus on the numerator; the approach is the same for the denominator. First, I project Y_i onto $Z_i^{\perp}$, yielding $\mathbf{E}[Y_i Z_i^{\perp}|S_i = s] = \mathbf{E}[\mathbf{E}[Y_i|Z_i^{\perp}, S_i] Z_i^{\perp}|S_i = s]$. Second, I apply the law of iterated expectations. Since $Z_i^{\perp} \perp (W_i, \tilde{X}_i)$ conditional on $S_i = s$, $\mathbf{E}[\mathbf{E}[Y_i|Z_i^{\perp}, S_i] Z_i^{\perp}|S_i = s] = \mathbf{E}[\mathbf{E}[Y_i|Z_i^{\perp}, W_i, X_i] Z_i^{\perp}|S_i = s]$. Lastly, using $Z_i^{\perp} \perp (W_i, \tilde{X}_i)$, and $\mathbf{E}[Z_i^{\perp}|S_i = s] = 0$, we complete the equality.

Next, I substitute these differences with integrals over marginal treatment effects and the propensity score. Here, I use the linearization of both. Let $\text{MTE}(u; w, \tilde{x}, s) = m_{1s} u + m_{2s} w + \tilde{x}' m_{3s}$ and $\mathbf{E}[D_i(z, w; \tilde{x}, s)] = d_{1s} z + d_{2s} w + \tilde{x}' d_{3s}$. Then, some calculus yields

$$\frac{\mathbf{E}[Y_i Z_i^{\perp}|S_i = s]}{\mathbf{E}[D_i Z_i^{\perp}|S_i = s]} = \frac{\mathbf{E}[d_{1s}(Z_i^{\perp})^2(m_{1s}\mathbf{E}[D_i|W_i, X_i] + m_{2s}W_i + \tilde{X}_i' m_{3s}) + \frac{1}{2}d_{1s}m_{1s}(Z_i^{\perp})^3|S_i = s]}{\mathbf{E}[d_{1s}(Z_i^{\perp})^2|S_i = s]}$$

Two simplifications can be made here. First, I use $\mathbf{E}[(Z_i^{\perp})^3|S_i = s] = 0$. Second, I use $Z_i^{\perp} \perp (W_i, \tilde{X}_i)$. Together, these yield

$$\frac{\mathbf{E}[Y_i Z_i^{\perp}|S_i = s]}{\mathbf{E}[D_i Z_i^{\perp}|S_i = s]} = m_{1s}\mathbf{E}[D_i|S_i = s] + m_{2s}\mathbf{E}[W_i|S_i = s] + \mathbf{E}[\tilde{X}_i'|S_i = s]m_{3s}$$

A symmetric proof shows the same result holds for $\frac{\mathbf{E}[Y_i W_i^{\perp}|S_i=s]}{\mathbf{E}[D_i W_i^{\perp}|S_i=s]} - \text{LASE}_{W|s}$, which completes the proof.

□

B.2 Weights

B.2.1 LATE and LASE weights

I start with the result from Heckman & Vytlacil (2005) on OLS.

$$\frac{\text{Cov}(Q, T - \mathbf{E}[T|X])}{\text{Var}(T - \mathbf{E}[T|X])} = \int\int \frac{\partial \mathbf{E}[Q|T = t, X = x]}{\partial t}\omega(t, x)dtdx$$

$$\omega(t, x) = \frac{\Pr[T > t, X = x]\mathbf{E}[T - \mathbf{E}[T|X]|T > t, X = x]}{\int\int \Pr[T > t', X = x']\mathbf{E}[T - \mathbf{E}[T|X]|T > t', X = x]dt'dx'}$$

The first expression shows that the coefficient on T, controlling for X, estimates a weighted average of derivatives of the conditional expectation function of Q given $T = t$ and $X = x$ with respect to t. The second expression shows that the weights $\omega(t, x)$ are the partial expectation, conditional on $X = x$, of $T - \mathbf{E}[T|X]$ given $T > t$, times the probability that $X = x$. Note this partial expectation approaches 0 at the edges of the conditional support of T conditional on $X = x$, which is consistent with our intuition that OLS estimates should not depend on derivatives of the conditional expectation function outside the support of the covariates. Additionally, it is helpful to note that

$$\int \omega(t, x)dt = \frac{\Pr[X = x]\text{Var}(T|X = x)}{\int \Pr[X = x']\text{Var}(T|X = x')dx'}$$

The weights placed on each x depend on the probability $X = x$ and the conditional variance of T given $X = x$.

Still following Heckman & Vytlacil (2005), we can now apply this to the IV estimator $\beta_Z^{IV} = \frac{\text{Cov}(Y_i, Z_i - \mathbf{E}[Z_i|W_i,X_i])}{\text{Cov}(D_i, Z_i - \mathbf{E}[Z_i|W_i,X_i])} = \text{LATE}_Z$. For the definition of these weights, it will be useful to define the propensity score $P(z, w; x) = \mathbf{E}[D_i|Z_i = z, W_i = w, X_i = x]$. Note that just identified linear instrumental variables is just a ratio of OLS estimators, so we can simply apply the formula above. Additionally, we make the substitution that $\frac{\partial \mathbf{E}[Y_i(z,w;x)]}{\partial z} = \frac{\partial P(z,w;x)}{\partial z}\text{MTE}(P(z, w; x); w, x)$. Applying these results yields

$$
\begin{aligned}
\text{LATE}_Z &= \int \text{MTE}(u; w, x)\omega_Z(u; w, x)dudwdx \\
\omega_Z(u; w, x) &= (\Pr[P(Z_i, W_i; X_i) > u, W_i = w, X_i = x]\cdot \\
&\quad \mathbf{E}[Z_i - \mathbf{E}[Z_i|W_i, X_i]|P(Z_i, W_i; X_i) > u, W_i = w, X_i = x]) \,/ \\
&\quad \left(\int\int\int \Pr[P(Z_i, W_i; X_i) > u', W_i = w', X_i = x']\cdot\right. \\
&\quad \left.\mathbf{E}[Z_i - \mathbf{E}[Z_i|W_i, X_i]|P(Z_i, W_i; X_i) > u', W_i = w', X_i = x']du'dw'dx'\right)
\end{aligned}
$$

Once again, the weights on MTE are in terms of partial expectation functions; weight is placed on latent propensities to adopt u within the support of the propensity score $P(Z_i, W_i; X_i)$. Again, for interpretation it is helpful to integrate over u to estimate the weight placed on observations with $(W_i, X_i) = (w, x)$. When the propensity score is linear in z conditional on (W_i, X_i), one can show

$$
\int \omega_Z(u; w, x)du = \frac{\text{Var}(P(Z_i, W_i; X_i)|W_i = w, X_i = x)\Pr[W_i = w, X_i = x]}{\int\int \text{Var}(P(Z_i, W_i; X_i)|W_i = w', X_i = x')\Pr[W_i = w', X_i = x']dw'dx'}
$$

The most weight is placed on values of (W_i, X_i) which have the highest conditional variance of the propensity score and which are observed the most frequently.

Finally, we can apply this to instrumental variables using W_i as an instrument, $\beta_W^{IV} = \frac{\text{Cov}(Y_i, W_i - \mathbf{E}[W_i|Z_i,X_i])}{\text{Cov}(D_i, W_i - \mathbf{E}[W_i|Z_i,X_i])} = \text{LASE}_W + \text{LATE}_W$. Once again, we represent this as the ratio of OLS estimators, and we apply the result above for OLS. Here, we make use of the fact that $\frac{\partial \mathbf{E}[Y_i(z,w;x)]}{\partial w} = \frac{\partial P(z,w;x)}{\partial w}(\text{MSE}(P(z, w; x); x) + \text{MTE}(P(z, w; x); w, x))$. It will also be necessary to define implicitly define $\check{Z}(u; w, x)$ by $u = P(\check{Z}(u; w, x), w; x)$; $\check{Z}$ inverts the propensity score to recover the value of z that will set the propensity score equal to u given $(W_i, X_i) = (w, x)$. Then,

$$
\begin{aligned}
\text{LATE}_W &= \int \text{MTE}(u; w, x)\omega_W(u; w, x)dudwdx \\
\text{LASE}_W &= \int \text{MSE}(u; x)\omega_W(u; w, x)dudwdx \\
\omega_W(u; w, x) &= \Bigg(\frac{\partial P(\check{Z}(u; w, x), w; x)/\partial w}{\partial P(\check{Z}(u; w, x), w; x)/\partial z} \cdot \\
&\qquad \Pr[W_i > w, P(Z_i, W_i; X_i) = u, X_i = x] \cdot \\
&\qquad \mathbf{E}[W_i - \mathbf{E}[W_i|Z_i, X_i]|W_i > w, P(Z_i, W_i; X_i) = u, X_i = x]\Bigg) / \\
&\qquad \Bigg(\int\int\int \frac{\partial P(\check{Z}(u'; w', x'), w'; x')/\partial w}{\partial P(\check{Z}(u'; w', x'), w'; x')/\partial z} \cdot \\
&\qquad \Pr[W_i > w', P(Z_i, W_i; X_i) = u', X_i = x'] \cdot \\
&\qquad \mathbf{E}[W_i - \mathbf{E}[W_i|Z_i, X_i]|W_i > w', P(Z_i, W_i; X_i) = u', X_i = x']du'dw'dx'\Bigg)
\end{aligned}
$$

Although these expressions appear more complicated, integrating over u and w, once again we can interpret them roughly as variances of the propensity score conditional on the controls Z_i and X_i; this is exact when the propensity score is linear in z and w conditional on $X_i = x$.

Finally, these expressions are all functions of $P(z, w; x)$ and the joint distribution of (Z_i, W_i, X_i), all of which are nonparametrically identified, so the weights are nonparametrically identified. In practice, estimation of the weights may involve placing parametric restrictions on $P(z, w; x)$.

B.2.2 Efficient reweighting

Define

$$\beta_Z^{WIV}(w_Z) = \frac{\text{Cov}(w_Z(S_i)Y_i, Z_i - \mathbf{E}[Z_i|W_i, (X_i, S_i)])}{\text{Cov}(w_Z(S_i)D_i, Z_i - \mathbf{E}[Z_i|W_i, (X_i, S_i)])}$$

and $\beta_W^{WIV}(w_W)$ analagously. Let $\overline{\omega}_W(s) = \int \omega_W(u; w, (x, s))dudwdx$ and $\overline{\omega}_Z(s) = \int \omega_Z(u; w, (x, s))dudwdx$. Given this, for $\beta_W^{WIV}(w_W)$ and $\beta_Z^{WIV}(w_Z)$ to place the same weight on compliers with $S_i = s$, it must be the case that

$$w_Z(s)\overline{\omega}_Z(s) = w_W(s)\overline{\omega}_W(s)$$

Efficient weights solve

$$w = \arg\min_{m} \operatorname{Var}\left[\hat{\beta}_W^{WIV}(w_W) - \hat{\beta}_Z^{WIV}(w_Z)\right]$$
$$\text{s.t. } w_Z(s)\overline{\omega}_Z(s) = w_W(s)\overline{\omega}_W(s)$$

I assume the propensity score is linear in (z, w). Under this assumption, $\overline{\omega}_W$ and $\overline{\omega}_Z$ simplify to

$$\overline{\omega}_W(s) = \frac{\operatorname{Var}(W_i - \mathbf{E}[W_i|Z_i,(X_i,S_i)]|S_i = s)\Pr[S_i = s]}{\operatorname{Var}(W_i - \mathbf{E}[W_i|Z_i,(X_i,S_i)])}$$
$$\overline{\omega}_Z(s) = \frac{\operatorname{Var}(Z_i - \mathbf{E}[Z_i|W_i,(X_i,S_i)]|S_i = s)\Pr[S_i = s]}{\operatorname{Var}(Z_i - \mathbf{E}[Z_i|W_i,(X_i,S_i)])}$$

Define $g_Z \equiv \frac{\operatorname{Cov}(D_i, Z_i - \mathbf{E}[Z_i|W_i,X_i])}{\operatorname{Var}(Z_i - \mathbf{E}[Z_i|W_i,X_i])}$ and $g_W \equiv \frac{\operatorname{Cov}(D_i, W_i - \mathbf{E}[W_i|Z_i,X_i])}{\operatorname{Var}(W_i - \mathbf{E}[W_i|Z_i,X_i])}$; that g_Z and g_W are constants follows from the assumption that the propensity score is linear in (z, w). Suppose further that the structural errors in the outcome equation are homoskedastic. Then the optimal weights satisfy

$$w_Z(s) = \frac{g_W^2 \operatorname{Var}(W_i - \mathbf{E}[W_i|Z_i,(X_i,S_i)])\overline{\omega}_W(s)}{g_Z^2 \operatorname{Var}(Z_i - \mathbf{E}[Z_i|W_i,(X_i,S_i)])\overline{\omega}_Z(s) + g_W^2 \operatorname{Var}(W_i - \mathbf{E}[W_i|Z_i,(X_i,S_i)])\overline{\omega}_W(s)}$$
$$w_W(s) = \frac{g_Z^2 \operatorname{Var}(Z_i - \mathbf{E}[Z_i|W_i,(X_i,S_i)])\overline{\omega}_Z(s)}{g_Z^2 \operatorname{Var}(Z_i - \mathbf{E}[Z_i|W_i,(X_i,S_i)])\overline{\omega}_Z(s) + g_W^2 \operatorname{Var}(W_i - \mathbf{E}[W_i|Z_i,(X_i,S_i)])\overline{\omega}_W(s)}$$

To interpret this expression, note that the realized equivalent of $\frac{g_Z^2 \operatorname{Var}(Z_i|W_i,(X_i,S_i))}{g_W^2 \operatorname{Var}(W_i|Z_i,(X_i,S_i))}$ is just the ratio of the first stage F-stats. As one F-stat grows arbitrarily large relative to the other, the weights essentially reweight observations in the regression with the larger F-stat so that the weights on observables in that regression are the same as the weights on observables in the unweighted regression with the smaller F-stat.

B.3 Control function

The control function approach is predicated on the normality assumption

$$\begin{pmatrix} Y_{1i} \\ C_{1i} \\ Y_{0i} \end{pmatrix} \sim N\left(\begin{pmatrix} (g_W + c_0)W_i + X_i'\mu_1 \\ g_Z Z_i + X_i'\mu_C \\ c_0 W_i + X_i'\mu_0 \end{pmatrix}, \begin{pmatrix} \Sigma_{11} & \Sigma_{1c} & \Sigma_{10} \\ \Sigma_{1c} & \Sigma_{cc} & \Sigma_{c0} \\ \Sigma_{10} & \Sigma_{c0} & \Sigma_{cc} \end{pmatrix}\right)$$

Under this model,

$$\mathbf{E}[D_i(z,w;x)] = \Phi\left(\frac{-x'\mu_V + g_W w - g_Z z}{\sigma_V}\right)$$

where Φ is the normal CDF, $\mu_V = -\mu_1 + \mu_C + \mu_0$,[42] and $\sigma_V^2 = \mathrm{Var}[V_i|X_i]$. I estimate this with a first step probit; conventionally, σ_V would not be identified. However, as noted by Björklund & Moffitt (1987), the generalized Roy structure allows it to be identified here, since we can estimate the direct effect of w on treatment effects. I do this in the second step, using the identity

$$\mathbf{E}\left[Y_{di}|D_i = d, Z_i = z, W_i = w, X_i = x\right] = X_i'\mu_d + c_d w + b_d \lambda_d(\mathbf{E}[D_i(z,w;x)])$$

where $c_0 = 0$, $c_1 - c_0 = g_W$, $b_0 = \frac{\mathrm{Cov}(V_{0i},V_i|X_i)}{\sigma_V}$, $b_1 = -\frac{\mathrm{Cov}(V_{1i},V_i|X_i)}{\sigma_V}$, $\lambda_0(u) = \frac{\phi(\Phi^{-1}(u))}{1-u}$, and $\lambda_1(u) = \frac{\phi(\Phi^{-1}(u))}{u}$. I estimate this conditional expectation function by OLS. Note the exclusion restriction that Z_i does not directly enter the conditional expectation function for Y_{di}. Although this is not required to estimate the model under normality, without this exclusion restriction identification depends strongly on functional form assumptions.

In Table 4 and Table 6, I construct control function estimates of local average treatment effects and local average surplus effects. Let $Z_i^{\perp} = Z_i - \mathbf{E}[Z_i|W_i, X_i]$ For a local average treatment effect, I use

$$\begin{aligned}
\frac{\mathbf{E}[Y_i Z_i^{\perp}]}{\mathbf{E}[D_i Z_i^{\perp}]} &= \frac{\mathbf{E}[(Y_i - \mathbf{E}[Y_i|Z_i = \mathbf{E}[Z_i|W_i,X_i],W_i,X_i])Z_i^{\perp}]}{\mathbf{E}[(D_i - \mathbf{E}[D_i|Z_i = \mathbf{E}[Z_i|W_i,X_i],W_i,X_i])Z_i^{\perp}]} \\
&= \frac{\mathbf{E}[(\mathbf{E}[Y_i|Z_i,W_i,X_i] - \mathbf{E}[Y_i|Z_i = \mathbf{E}[Z_i|W_i,X_i],W_i,X_i])Z_i^{\perp}]}{\mathbf{E}[(D_i - \mathbf{E}[D_i|Z_i = \mathbf{E}[Z_i|W_i,X_i],W_i,X_i])Z_i^{\perp}]} \\
&= \frac{\mathbf{E}\left[\int_{\mathbf{E}[D_i|Z_i = \mathbf{E}[Z_i|W_i,X_i],W_i,X_i]}^{\mathbf{E}[D_i|Z_i,W_i,X_i]} \mathrm{MTE}(u;W_i,X_i)du Z_i^{\perp}\right]}{\mathbf{E}[(D_i - \mathbf{E}[D_i|Z_i = \mathbf{E}[Z_i|W_i,X_i],W_i,X_i])Z_i^{\perp}]}
\end{aligned}$$

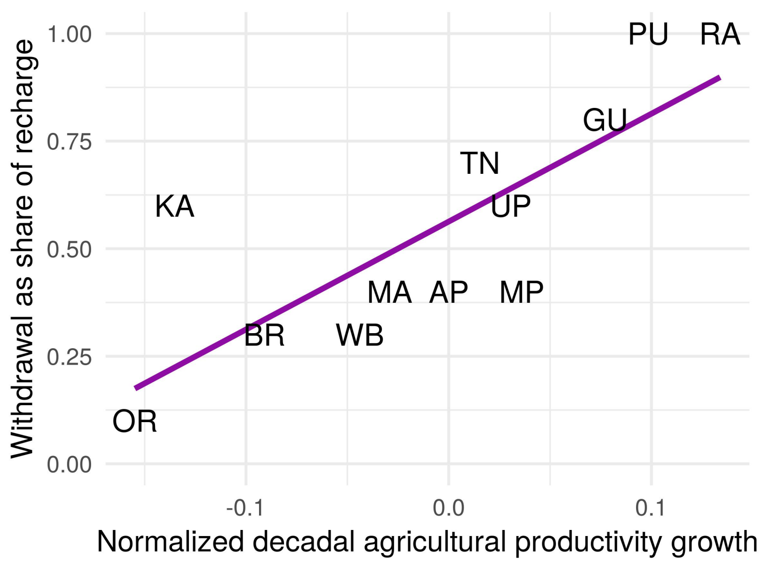
Focusing on the numerator in each expression. The first step follows from $\mathbf{E}[\mathbf{E}[Y_i|Z_i = \mathbf{E}[Z_i|W_i,X_i],W_i,X_i]Z_i^{\perp}] = 0$, which follows from an application of the law of iterated expectations conditioning on (W_i, X_i). The second step follows from $\mathbf{E}[Y_i Z_i^{\perp}] = \mathbf{E}[\mathbf{E}[Y_i|Z_i,W_i,X_i]Z_i^{\perp}]$. This again follows from an application of the law of iterated expectations conditioning on (Z_i, W_i, X_i). The third step is just the fundamental theorem

[42] This implies $\mathbf{E}[V_i|X_i] = X_i'\mu_V$.

of calculus, and that the marginal treatment effect equals the derivative of the conditional expectation of Y_i with respect to z. I therefore use the plug-in estimator of this as my control function estimate of the local average treatment effect. Nearly identical calculations hold for the local average surplus effect, and bias from exclusion restriction violations. Standard errors are calculated using the delta method, and derivatives with respect to control function parameters are estimated numerically.

C Figures

Figure A.1: Productivity growth and groundwater withdrawals



Notes: This figure plots, for each state, the lower bound estimate of its groundwater withdrawals as a share of recharge rate, as reported in Rodell et al. (2009), against its normalized decadal agricultural productivity growth, calculated in a regression of log agricultural productivity on state fixed effects interacted with year dummies, relative to Andhra Pradesh (AP). The purple line is the line of best fit, with a slope of 2.5 and $R^2 = 0.63$.