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

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Abstract

I estimate the elasticity of demand for irrigation to its effect on crop yields in rural India. Conventional approaches to estimating this elasticity fail when agents select into adopting irrigation on heterogeneous yield effects and costs. I develop a novel approach to correct for selection that works with aggregated data on yields and adoption. I use climate and soil characteristics as a yield shifter, and I use hydrogeology as an instrument for irrigation to correct for selection. I estimate a 1% increase in the effect of irrigation on yields causes a 0.7% increase in adoption of irrigation. I then use this estimated elasticity to conduct welfare counterfactuals. Groundwater depletion from 2000-2010 in northwestern India permanently reduced economic surplus by 1.2% of gross agricultural revenue.

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1 Introduction

Much of Indian agriculture is dependent on pumping groundwater for irrigation. Since 1960, just before the start of India's Green Revolution, the irrigated share of agricultural land has grown from 18% to 54%, largely from the expansion of tubewells, with an associated doubling of crop yields for major water intensive staples. However, the availability of groundwater, a common pool resource, has declined sharply over this period, with the greatest rates of decline in states with the highest gains in agricultural productivity during the Green Revolution.[1] Declining water tables caused by extraction have been shown to cause increased poverty Sekhri (2014), decreased land values Jacoby (2017), and outmigration Fishman et al. (2017), through increased costs of irrigation, and the rate of decline is projected to increase in the future. Moreover, much of this decline is believed to be driven by socially superoptimal groundwater extraction: farmers do not internalize the increase in pumping costs their extraction causes for neighboring farmers (Jacoby (2017)), and the government of India implicitly subsidizes groundwater extraction through electricity subsidies for pumping groundwater (Badiani & Jessoe (2017)) and output subsidies for water intensive crops (Chatterjee et al. (2017)). Formulating optimal policy responses to this decline is therefore an important challenge.

To date, formulating optimal policy responses has been difficult because empirical estimates of the impacts of declining water tables on agricultural profits are not available. Existing estimates in the literature of impacts on welfare proxies such as poverty are insufficient, because there is no agreed upon convention for converting these estimates into the same units as fiscal costs of or deadweight loss from policy. Estimating impacts on agricultural profits is a hard problem because agricultural profits in developing countries are notoriously difficult to measure reliably.[2] However, estimating the impact of declining water tables on adoption of irrigation is much simpler, as adoption of irrigation is easy to observe; this suggests a revealed preference approach. Although on its own, an estimate of the impact of declining water tables on adoption of irrigation could be consistent with large decreases in profits and inelastic demand for irrigation,

[1]The $R^2 = 0.63$ from a regression of state level groundwater withdrawals as a share of recharge on agricultural productivity growth, see Appendix Figure A.1 for details.

[2]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.

or small decreases in profits and elastic demand for irrigation, this estimate combined with an estimate of the elasticity of demand for irrigation is sufficient to recover the impact of declining water tables on agricultural profits.

I take this revealed preference approach, and estimate an elasticity of demand for irrigation to its effect on yields. However, conventional approaches to estimate this elasticity with an irrigated yield shifter fail when agents select into adopting irrigation on idiosyncratic yield effects and costs. I build a generalized Roy (1951) model that allows a nonparametric joint distribution of comparative advantage in irrigation, absolute advantage in agriculture, and costs of irrigation; farmers adopt irrigation if their increased yields from irrigation are greater than their costs of adoption. However, I relax the assumption in Eisenhauer et al. (2015) and Adão (2016) that there is no idiosyncratic responsiveness to the irrigated yield shifter that is correlated with selection into irrigation. Under this model, I show that linear instrumental variables, using the irrigated yield shifter instead of an instrument for the effect of irrigation on yields, estimates the sum of a weighted average of effects of irrigation on yields (a "local average treatment effect") and a weighted average of inverse semielasticities of demand for irrigation. This simplifies estimating the demand elasticity to correcting for selection by estimating this weighted average of effects of irrigation on yields. I show that this weighted average of effects of irrigation on yields is nonparametrically identified with an instrument for irrigation. Under stronger assumptions, which still allow sorting on unobserved heterogeneity in both yield effects and costs, I show that one can estimate this weighted average using weighted linear instrumental variables with this instrument for irrigation; the weights adjust the compliers to the instrument to resemble the compliers to the yield shifter.

I estimate that a 1% increase in the effect of irrigation on yields causes a 0.7% increase in the irrigated share of agricultural land. 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 the 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' cost share of electricity in irrigation.[3]

In providing these estimates, I build on a rich 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, hedonic estimates of the value of access to groundwater in India (Jacoby (2017)) and in the US (Schlenker et al. (2007)). Relative to them, I estimate sufficient parameters for many optimal policy calculations: the economic losses from a 1m decline in the water table, and the elasticity of demand for irrigation to its impact on yields. 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)). With this estimate, It takes an alternative approach to conducting optimal policy than the optimal control literature; a large body of work has used complicated, calibrated dynamic models of management of aquifers to characterize optimal policy. 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 (2004) argue their findings are driven by functional form assumptions, while Brozović et al. (2010) argue they are driven by the characteristics of the aquifer they study. Relative 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.

I also build on a large literature studying the economics and econometrics of the generalized Roy model, where agents adopt a binary treatment if the effect of adoption on their observed outcome ("treatment effect") is greater than their costs of adoption; Heckman & Vytlacil (2007a,b) provide an in depth review of these models. Common examples include sectoral choice or education and wages (Roy (1951), Willis & Rosen (1979)), or technology adoption and yields in agriculture (Suri (2011)). Theoretically, I build most closely on Eisenhauer et al. (2015), who establish nonparametric identification of agents' willingness to pay for adoption from a conventional instrument for adoption, which affects costs of adoption but not outcomes, and a regressor which affects outcomes but not costs. I instead assume the existence of a regressor which

[3]This calculation multiplies the increased electricity needed to pump typical water use per irrigated hectare one additional meter by the mean implicit price of electricity and the irrigated share of agricultural land in northwestern India. I calculate the share of private electricity costs in costs of irrigation at average electricity prices is between one eighth and one half under a range of approaches. Details of these calculations are in Section 5.4.

only affects outcomes conditional on adoption, an "outcome shifter", in addition to a conventional instrument for adoption, and establish nonparametric identification of the inverse semielasticity of adoption to outcomes under weaker conditions. Moreover, I show these weaker conditions are the union of the assumptions of standard LATE framework (Imbens & Angrist (1994)) and the assumptions needed for point identification of economic surplus from a change in costs when there is independence of outcomes conditional on observables (Willig (1978), Small & Rosen (1981)). I show that linear instrumental variables using an outcome shifter estimates a local average treatment effect plus a weighted average of inverse semielasticities of adoption; this builds on work from Angrist et al. (1996) who provide formulas for instrumental variables bias when the exclusion restriction is violated. Like Heckman & Vytlacil (2005), I show the weights this estimator places on marginal treatment effects and inverse semielasticities of adoption are nonparametrically identified; therefore, this local average treatment effect is nonparametrically identified from an instrument for treatment. Angrist & Fernandez-Val (2010) show this (or any) local average treatment effect can be estimated by weighted linear instrumental variables when treatment effects are constant conditional on observables, by reweighting the instrument compliers to resemble the outcome shifter compliers on observables. I show their result holds for linear marginal treatment effects under some assumptions on the joint distribution of the outcome shifter and the instrument conditional on observables. More broadly, this builds on the many papers that test differences between instrumental variable estimators by making some assumption to ensure compliers for each instrument are comparable: Hausman (1978) assume treatment effects are constant, Angrist & Fernandez-Val (2010) and Bhuller et al. (2018) assume treatment effects are constant conditional on observables, Mogstad et al. (2017) bound differences under weaker assumptions, and Kowalski (2016), Arnold et al. (2018), and Mountjoy (2018) estimate marginal treatment effects and compare agents on the same margin of adoption. Lastly, as an alternative approach, Berry et al. (2018) estimate the elasticity of adoption to outcomes by directly eliciting willingness to pay (the equivalent of observing profits in my context), and estimating treatment effects conditional on willingness to pay, under the assumption that treatment effects are independent of costs of adoption.

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. Section

?? considers optimal subsidies for electricity for groundwater irrigation, building on results from Section 5. Section **??** 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 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.

In India, groundwater for agriculture is typically extracted using tubewells. Drilling tubewells is costly: according to the 2007 Minor Irrigation Census, the fixed cost of infrastructure for groundwater irrigation in the median district was approximately 25,000 Rs/ha, just over 1 year of agricultural revenue per hectare.[4] This cost varies substantially across districts, with a coefficient of variation of 0.5. This variation is partially driven by the accessibility of groundwater. At lower 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 are depleted, the rate at which the water table falls, and the number of wells required per unit of water extracted (Fishman et al. (2017)).

[4] This was calculated using agricultural revenue per hectare in the median district in 2007.

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 (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. Although these fees partially substitute for volumetric pricing, since many farmers pump groundwater whenever electricity is available during the growing seasons, 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 caused by 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 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 (Brozović et al. (2010)) 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)). This is largely a solved physics problem, which depends primarily on characteristics of the aquifer.

Second, these declines in the water table, largely experienced by farmers other than the farmer pumping the unit of water, will cause decreases in the profitability of irrigated agriculture, as the cost of groundwater extraction increases. 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. 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 1 cubic meter decline in water tables, an estimate which is unavailable in the literature.

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.

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 the "Agricultural Panel". 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. I construct an imbalanced panel of the 222 districts in 11 states I observe from 1956-2011 of agricultural revenue per hectare and irrigated share of agricultural land.[5]

I supplement this with the 2012 Agricultural National Sample Survey, which included questions on household level agricultural production by crop, crucially both on irrigated and rainfed land. I refer to this dataset as the "Agricultural NSS". 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 the agricultural panel, I reweight districts so each district receives the same weight as in the agricultural panel.

For data on irrigation technologies, I use the 2007 Minor Irrigation Census. I refer to this dataset as the "Irrigation Census". In this, I observe district level counts of 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[6].

I use potential aquifer yield as my instrument for costs of irrigation, a measure of the flow rate of water 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.[7] 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.

[5]More districts are observed in this data set, but for comparability across specifications I restrict to districts which appear in all data sets used for analysis.

[6]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. However, the median fixed cost of groundwater irrigation infrastructure per irrigated hectare across districts that I estimate, 23,000 Rs/ha, is within the range of conventional estimates; results are similar across codings that hold this average fixed.

[7]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).

I use a measure of log relative potential irrigated crop yield, controlling for log potential rainfed crop yield, as my instrument for potential 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 relative potential irrigated crop yield as a weighted average of potential yields under the intermediate irrigated scenario, divided by a weighted average of potential yields under the intermediate rainfed scenario; this is similar to how Bustos et al. (2016) construct their measure of potential gains from improved soybean varieties. I plot variation in this measure across districts in Panel (b) of Figure 1.[8] I discuss the construction of the relative potential irrigated crop yield and potential rainfed crop yield variables in more detail in Appendix A.

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 relative costs of irrigating is greater than their gross revenue under rainfed agriculture. 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 effect of irrigation on gross revenue), and instruments for both costs and treatment effects (Eisenhauer et al. (2015)).[9]

In Section 3.1, I setup a generalized Roy model building on this work. 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

[8]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 high input scenario on the intermediate input scenario yields R^2 ranging from 0.87 to 1, while regressing potential yields from the irrigated intermediate input scenario on the 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).

[9]A comparison of this approach to existing approaches is presented in Table 1.

revenue under rainfed agriculture (potential outcome under control). In Section 3.2, 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 captures 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 3.3, 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 3.4, 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. Lastly, In Section 3.5, I discuss settings under which key identifying assumptions may not hold exactly, and propose microeconomic theory based approaches to correct for bias from certain forms of exclusion restriction violations.

3.1 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 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 costs or counterfactual revenue.

The surplus maximization assumption implies

Assumption 1.

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

Assumption 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_C and z_Y. z_C 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, z_Y is a non-standard 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 2.

$$\begin{aligned} Y_{1i}(z_Y) &= V_{\gamma i}\gamma_Y(z_Y) + V_{1i} \\ C_{1i}(z_C) &= V_{\gamma i}\gamma_C(z_C) + V_{Ci} \\ Y_{0i} &= V_{0i} \end{aligned}$$

Assumption 3. *γ_Y and γ_C 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 2 implicitly makes a number of assumptions. First, z_Y and z_C each satisfy exclusion restrictions. Only Y_{1i} is structurally a function of z_Y, and only C_{1i} is structurally a function of z_C. These exclusion restrictions are strong assumptions, and I discuss possible violations in Section 3.5. That only Y_{1i} is structurally a function of z_Y is a novel exclusion restriction in the program evaluation literature. It is most similar to Eisenhauer et al. (2015), who assume there is a regressor excluded from just C_{1i}, while I assume z_Y is excluded from C_{1i} and Y_{0i}. That z_C is excluded from Y_{1i} and Y_{0i} is the standard exclusion restriction made for instrumental variables.

Second, (z_C, z_Y) are weakly separable from unobserved heterogeneity, through the index $(\gamma_Y(z_Y) - \gamma_C(z_C))$. This 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_C and z_Y enter choices and surplus symmetrically, so impacts on surplus are locally proportional to impacts on choices. However, although weak separability only requires that (z_C, z_Y) enter jointly through a flexible index, the more restrictive functional form I use is the most general that satisfies weak separability, the exclusion restrictions, and the additive generalized Roy structure. Despite that, 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.[10]

Assumption 3 makes all remaining technical assumptions. The monotonicity assumptions are standard in the IV literature, and reasonable in my context. That the distribution of V_i is continuous and strictly increasing is a standard technical assumption.

Next, I define one particular population expectation of interest. Let

$$P(z_C, z_Y) = \mathbf{E}[D_i(z_C, z_Y)]$$

or the proportion of agents who adopt treatment at given values of the instruments. As previously, outcomes Y_i and treatment status D_i are observable to the researcher, but surplus π_i is not.

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 Assumption 1, combined with Assumption 2 and the definition of V_i in Assumption 3, can now be rewritten as $D_i = \mathbf{1}\{U_i < F_V(\gamma_Y(z_Y) - \gamma_C(z_C))\}$, and therefore $P(z_C, z_Y) = F_V(\gamma_Y(z_Y) - \gamma_C(z_C))$.

Lastly, let Z_{Ci} and Z_{Yi} be agent i's realized value of the instruments z_C and z_Y. I make an independence assumption that will be necessary for identification.

Assumption 4.

$$(Z_{Ci}, Z_{Yi}) \perp (V_{0i}, V_{Ci}, V_{1i}, V_{\gamma i})$$

[10]Specifically, Eisenhauer et al. (2015) and Adão (2016) require their instrument for treatment effects has a homogeneous effect across agents conditional on observables, equivalent to an additive separability assumption.

3.2 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.

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

$$\text{MSE}(u) = \frac{u}{f_V(F_V^{-1}(u))} \mathbf{E}[V_{\gamma i} | U_i < u] \tag{2}$$

The definition of the marginal treatment effect in Equation 1 is standard. The definition of the marginal surplus effect in Equation 2 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_C and z_Y than compliers.

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

$$\frac{d\mathbf{E}[Y_i(z_C, z_Y)]/dz_C}{dP(z_C, z_Y)/dz_C} = \text{MTE}(P(z_C, z_Y); z_Y) \tag{3}$$

$$\frac{d\mathbf{E}[\pi_i(z_C, z_Y)]/dz_C}{dP(z_C, z_Y)/dz_C} = \frac{d\mathbf{E}[\pi_i(z_C, z_Y)]/dz_Y}{dP(z_C, z_Y)/dz_Y} = \text{MSE}(P(z_C, z_Y)) \tag{4}$$

Equation 3 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_C. Equation 4 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_C or z_Y.[11]

Additionally, following Heckman & Vytlacil (2007a,b), it follows from Equation 3 that one can define impacts on outcomes of policies that shift z_C in terms of MTE and P alone. Similarly, it follows from Equation 4 that one can define impacts on surplus

[11] The proof of Equation 3 and Equation 4 is in Appendix B.1.

of policies that shift z_C or z_Y in terms of MSE and P alone.

$$\frac{\mathbf{E}[Y_i(z'_C, z_Y)] - \mathbf{E}[Y_i(z_C, z_Y)]}{P(z'_C, z_Y) - P(z_C, z_Y)} = \underbrace{\frac{\int_{P(z_C,z_Y)}^{P(z'_C,z_Y)} \mathrm{MTE}(u; z_Y)du}{P(z'_C, z_Y) - P(z_C, z_Y)}}_{\text{policy relevant treatment effect}} \tag{5}$$

$$\frac{\mathbf{E}[\pi_i(z'_C, z'_Y)] - \mathbf{E}[\pi_i(z_C, z_Y)]}{P(z'_C, z'_Y) - P(z_C, z_Y)} = \underbrace{\frac{\int_{P(z_C,z_Y)}^{P(z'_C,z'_Y)} \mathrm{MSE}(u)du}{P(z'_C, z'_Y) - P(z_C, z_Y)}}_{\text{policy relevant surplus effect}} \tag{6}$$

Equation 5 shows 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 6 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 4, 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. 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

$$\mathrm{TOT}(u; z_Y) = \mathbf{E}[Y_{1i}(z_Y) - Y_{0i}|U_i < u] \tag{7}$$

$$\epsilon^*(u; z_Y) = \frac{\mathrm{TOT}(u; z_Y)}{\mathrm{MSE}(u)} \tag{8}$$

Equation 7 gives the standard definition of treatment on the treated. Note that it has the standard interpretation, that $\mathrm{TOT}(P(z_C, z_Y); z_Y) = \mathbf{E}[Y_{1i}(z_Y) - Y_{0i}|D_i(z_C, z_Y) = 1]$. Given the analogy in consumer theory, one might hope that $\epsilon^*(u; z_Y)$, as defined in Equation 8, is the treatment effect elasticity of demand. Equation 9 shows this result below.

$$\frac{\mathrm{TOT}(P(z_C, z_Y); z_Y)}{P(z_C, z_Y)} \frac{dP(z_C, z_Y)/dz_Y}{\partial \mathrm{TOT}(P(z_C, z_Y); z_Y)/\partial z_Y} = \epsilon^*(P(z_C, z_Y); z_Y) \tag{9}$$

Equation 9, combined with Equation 8, 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.[12]

3.3 Identification

Proving the identification of marginal surplus effects and marginal treatment effects follows from classic results on local instrumental variables from Heckman & Vytlacil (1999, 2005). For the results below, I also make the assumption that (Z_{Ci}, Z_{Yi}) has a smooth density that is strictly positive at (z_C, z_Y). First, from the independence assumption on the instruments,

$$\mathbf{E}[Y_i(z_C, z_Y)] = \mathbf{E}[Y_i | Z_{Ci} = z_C, Z_{Yi} = z_Y] \tag{10}$$

$$P(z_C, z_Y) = \mathbf{E}[D_i | Z_{Ci} = z_C, Z_{Yi} = z_Y] \tag{11}$$

Equation 10 and 11 show identification of $\mathbf{E}[Y_i(z_C, z_Y)]$ and $P(z_C, z_Y)$ from identified conditional expectation functions, which follows from the independence assumption. As a result, derivatives of $\mathbf{E}[Y_i(z_C, z_Y)]$ and $P(z_C, z_Y)$ are also identified (Matzkin (2007)). Equation 3 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.

$$\frac{d\mathbf{E}[Y_i(z_C, z_Y)]/dz_Y}{dP(z_C, z_Y)/dz_Y} = \mathrm{MTE}(P(z_C, z_Y); z_Y) + \mathrm{MSE}(P(z_C, z_Y)) \tag{12}$$

Local instrumental variables using the outcome instrument estimates the marginal treatment effect plus the marginal surplus effect.[13] Identification of marginal surplus effects follows simply from subtracting Equation 3 from Equation 12.

$$\mathrm{MSE}(P(z_C, z_Y)) = \frac{d\mathbf{E}[Y_i(z_C, z_Y)]/dz_Y}{dP(z_C, z_Y)/dz_Y} - \frac{d\mathbf{E}[Y_i(z_C, z_Y)]/dz_C}{dP(z_C, z_Y)/dz_C} \tag{13}$$

The intuition for this result is visible in Figure 2. Both the cost instrument and the outcome instrument 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 $Y_{1i}^* - C_{1i}$ (as in Panel (a)) or to $Y_{1i} - C_{1i}^*$ (as in Panel (b)), the

[12] The proof of Equation 9 is in Appendix B.1.
[13] The proof of Equation 12 is in Appendix B.1.

effect on choices and surplus is the same. As a result, they share a common marginal surplus effect. 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 increase in P caused by the increase in surplus under treatment 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: P increases because surplus under treatment increases, and this increase in P 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}. However, 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

$$\epsilon(u; z_Y) = \frac{\text{MTE}(u; z_Y)}{\text{MSE}(u)} \tag{14}$$

which, following the results above, is also identified. It is biased relative to the treatment effect elasticity of demand: $\epsilon^*(u; z_Y) = \frac{\text{TOT}(u;z_Y)}{\text{MTE}(u;z_Y)}\epsilon(u; z_Y)$, 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.

3.4 Estimation

For purposes of 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 except where explicitly stated.

3.4.1 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_{Ci}, Z_{Yi}, X_i) jointly. Frequently, their implementation relies on strong restrictions on how (Z_{Yi}, 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_{Ci}, makes no such assumptions: instead, it only requires the researcher to estimate the expectation of Z_{Ci} conditional on all variables which are not excluded from outcome equations (in this case, (Z_{Yi}, 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_{Ci} estimates a local average treatment effect, linear instrumental variables with Z_{Yi} 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,

$$\beta_C^{IV} \equiv \frac{\text{Cov}(Y_i, Z_{Ci} - \mathbf{E}[Z_{Ci}|Z_{Yi}, X_i])}{\text{Cov}(D_i, Z_{Ci} - \mathbf{E}[Z_{Ci}|Z_{Yi}, X_i])} = \text{LATE}_C \tag{15}$$

$$\text{LATE}_C = \int \text{MTE}(u; z_Y, x)\omega_C(u; z_Y, x)du dz_Y dx \tag{16}$$

$$\beta_Y^{IV} \equiv \frac{\text{Cov}(Y_i, Z_{Yi} - \mathbf{E}[Z_{Yi}|Z_{Ci}, X_i])}{\text{Cov}(D_i, Z_{Yi} - \mathbf{E}[Z_{Yi}|Z_{Ci}, X_i])} = \text{LATE}_Y + \text{LASE}_Y \tag{17}$$

$$\text{LATE}_Y = \int \text{MTE}(u; z_Y, x)\omega_Y(u; z_Y, x)du dz_Y dx \tag{18}$$

$$\text{LASE}_Y = \int \text{MSE}(u; x)\omega_Y^*(u; x)du dx \tag{19}$$

Equation 15 and Equation 16 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_C are nonparametrically identified, positive, and integrate to 1. The new result is Equation 17: 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 then show in Appendix B.2.1 that the LATE_Y and LASE_Y weights, ω_Y and ω_Y^* respectively, are nonparametrically identified, positive, and integrate to 1.

With these results on local average treatment effect weights, other results in the literature on bounding arbitrary functions of $\text{MTE}(u; z_Y, x)$ from estimates of local average treatment effects can be applied (Brinch et al. (2017), Mogstad et al. (2017)). With the results on local average surplus effect weights, these results can also be applied to bounding arbitrary functions of $\text{MSE}(u; x)$ with an estimate of a local average surplus effect. I discuss these considerations in Section 3.4.2. Given this, I consider the problem of estimating any local average surplus effect.

Additionally, for comparison to estimates of price elasticities, I focus on estimating any pseudo treatment effect elasticity of demand. If (Z_{Ci}, Z_{Yi}, X_i) has a smooth density with convex support, then there exists (u', z'_Y, x') such that $\omega_Y(u'; z'_Y, x') > 0$ and[14]

$$\epsilon(u'; z'_Y, x') = \frac{\text{LATE}_Y}{\text{LASE}_Y} \tag{20}$$

Together, these results suggest the following approximate estimators of a local average surplus effect and a pseudo treatment effect elasticity of demand.

$$\widehat{\text{LASE}}_Y \equiv \beta_Y^{IV} - \beta_C^{IV} = \text{LASE}_Y + \underbrace{(\text{LATE}_Y - \text{LATE}_C)}_{\text{bias}} \tag{21}$$

$$\hat{\epsilon} \equiv \frac{\beta_C^{IV}}{\beta_Y^{IV} - \beta_C^{IV}} = \frac{\text{LATE}_Y}{\text{LASE}_Y} \underbrace{\frac{\text{LATE}_C}{\text{LATE}_Y} \frac{\text{LASE}_Y}{\text{LASE}_Y + (\text{LATE}_Y - \text{LATE}_C)}}_{\text{bias}} \tag{22}$$

Note that these estimators recover a local average surplus effect and a pseudo treatment effect elasticity of demand whenever $\text{LATE}_Y = \text{LATE}_C$. Alternatively phrased, whenever one has an estimator of LATE_Y, one can use that estimator in place of β_C^{IV} and recover a consistent estimator of LASE_Y and $\epsilon(u'; z'_Y, x')$. Therefore, this reduces the bias problem to constructing an estimator of LATE_Y.

[14] A proof of Equation 20 is in Appendix B.1.

3.4.2 Weighted instrumental variables

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

To understand the bias from $\text{LATE}_Y \neq \text{LATE}_C$, I consider difference in the weights each estimator places on different marginal treatment effects. I decompose this difference in weights into a term that depends on the difference in average weights on observable controls x, and a term that depends on the difference in weights on (u, z_Y) conditional on $X_i = x$.

$$\begin{aligned}\text{LATE}_Y - \text{LATE}_C = &\int\int \text{MTE}(u; z_Y, x)\left(\frac{\omega_Y(u; z_Y, x)}{\overline{\omega}_Y(x)} - \frac{\omega_C(u; z_Y, x)}{\overline{\omega}_C(x)}\right) du dz_Y \overline{\omega}_Y(x) dx \\ &+ \int\int \text{MTE}(u; z_Y, x)\frac{\omega_C(u; z_Y, x)}{\overline{\omega}_C(x)} du dz_Y (\overline{\omega}_Y(x) - \overline{\omega}_C(x)) dx\end{aligned} \tag{23}$$

$$\textit{where } \overline{\omega}_{(\cdot)}(x) = \int \omega_{(\cdot)}(u; z_Y, x) du dz_Y \tag{24}$$

The term in the first line of Equation 23 captures the difference between LATE_Y and LATE_C that comes from differences in weights conditional on observables. The term in the second line of Equation 23 captures the difference between LATE_Y and LATE_C that comes from weights on different observables. We can now consider each source of bias independently.

The bias in the first line, $\int \text{MTE}(u; z_Y, x)\left(\frac{\omega_Y(u; z_Y, x)}{\overline{\omega}_Y(x)} - \frac{\omega_C(u; z_Y, x)}{\overline{\omega}_C(x)}\right) du dz_Y$, comes exclusively from nonlinearities in $\text{MTE}(u; z_Y, x)$ and $P(z_C, z_Y; x)$ conditional on $X_i = x$. There are two main sources of intuition for this result. First, when $\text{MTE}(u; z_Y, x)$ is linear conditional on $X_i = x$, this integral depends only on the average weight placed on u and z_Y conditional on $X_i = x$. However, when $P(z_C, z_Y; x)$ is linear, then $\omega_C(u; z_Y, x)$

and $\omega_Y(u; z_Y, x)$ each place the same average weight on u and z_Y conditional on $X_i = x$. Therefore, this integral is 0. Second, linear instrumental variables conditional on $X_i = x$ can be seen as a local instrumental variable estimator, as long as X_i includes sufficiently flexible controls for Z_{Ci} and Z_{Yi}. This works because it ensures that $\text{MTE}(u; z_Y, x)$ and $P(z_C, z_Y; x)$ are linear, as long as they are differentiable, which our assumptions guarantee. In this case, both local instrumental variable estimators must return the same estimate. Therefore, as long as X_i explains a sufficiently large share of the variation in (z_C, z_Y), we might expect this bias to be small relative to the bias in the second line. Formally, I assume this bias is 0 for the remainder of this section (Section 3.4.2).

The bias in the second line comes from $\overline{\omega}_Y(x) - \overline{\omega}_C(x) \neq 0$. However, one can correct this bias with estimators that reweight observations by $X_i = x$; I therefore consider weighted linear instrumental variable estimators that implement this reweighting.[15] Define

$$\beta_C^{WIV}(w_C) = \frac{\text{Cov}(w_C(X_i)Y_i, Z_{Ci} - \mathbf{E}[Z_{Ci}|Z_{Yi}, X_i])}{\text{Cov}(w_C(X_i)D_i, Z_{Ci} - \mathbf{E}[Z_{Ci}|Z_{Yi}, X_i])} \tag{25}$$

$$\beta_Y^{WIV}(w_Y) = \frac{\text{Cov}(w_Y(X_i)Y_i, Z_{Yi} - \mathbf{E}[Z_{Yi}|Z_{Ci}, X_i])}{\text{Cov}(w_Y(X_i)D_i, Z_{Yi} - \mathbf{E}[Z_{Yi}|Z_{Ci}, X_i])} \tag{26}$$

for weighting functions w_C, w_Y such that $\frac{w_C(x)}{w_Y(x)} = \frac{\overline{\omega}_Y(x)}{\overline{\omega}_C(x)}$. For this class of estimators, the reweighting eliminates this bias.

With these two results on bias in estimating local average surplus effects and pseudo treatment effect elasticities of demand, I therefore consider optimal weighted instrumental variable estimators of local average surplus effects, where the weights solve

$$\begin{gathered}(w_C^*, w_Y^*) = \arg\min_{w_C, w_Y} \text{Var}\left[\beta_Y^{WIV}(w_Y) - \beta_C^{WIV}(w_C)\right] \\ \textit{subject to } \frac{w_C(x)}{w_Y(x)} = \frac{\overline{\omega}_Y(x)}{\overline{\omega}_C(x)}\end{gathered} \tag{27}$$

Although in general this is a complicated high dimensional problem, I make two sets of assumptions to simplify it. First, I assume $P(z_C, z_Y; x)$ is linear conditional on $X_i = x$, X_i is discrete, and the controls in the estimated linear model are fully saturated in X_i:

[15] Bhuller et al. (2016) and Dobbie et al. (2018) both implement estimators similar to this to isolate differences between OLS and IV estimators that come from selection on unobservables instead of heterogeneous effects conditional on observables. Angrist & Fernandez-Val (2010) propose a test of the existence of treatment effect heterogeneity that is unexplained by observable characteristics that generalizes the infeasible test of whether the LATE estimated by $\beta_Y^{WIV}(w_Y^*)$ is the same as the LATE estimated by $\beta_C^{WIV}(w_Y^*)$ (infeasible because $\beta_Y^{WIV}(w_Y^*)$ estimates a LATE plus a LASE).

these assumptions ensure estimation of $\frac{\overline{\omega}_Y(x)}{\overline{\omega}_C(x)}$ is straightforward and that estimators satisfying $\frac{w_C(x)}{w_Y(x)} = \frac{\overline{\omega}_Y(x)}{\overline{\omega}_C(x)}$ are consistent. Second, I assume errors are homoskedastic in the outcome equation, and $P(z_C, z_Y; x)$ is linear in (z_C, z_Y). This second set of assumptions almost certainly does not hold, and in fact they are invalidated by the very features of the model that require the estimation procedures developed in this paper. However, under these assumptions the optimal weights have an intuitive closed form solution, and depend only on the joint distribution of (Z_{Ci}, Z_{Yi}, X_i), which simplifies both estimation of the optimal weights and inference, but sacrifices efficiency if these assumptions do not hold. Finally, when reweighting in practice, as is true in my context, it may only be tractable to reweight based on a subset of the variables in X_i, which I call S_i. In this case, one now needs to assume linearity of $P(z_C, z_Y; (x, s))$ condtional on $S_i = s$ and $\text{MTE}(u; z_Y, (x, s))$ conditional on $S_i = s$. Optimal weights when $P(z_C, z_Y; (x, s))$ is unconditionally linear in (z_C, z_Y), homoskedasticity is satisfied, and both $P(z_C, z_Y; (x, s))$ and $\text{MTE}(u; z_Y, (x, s))$ are linear conditional on $S_i = s$ are derived in Appendix B.2.2.

With this procedure completed, and under the assumptions discussed above, it is now the case that

$$\beta_Y^{WIV} - \beta_C^{WIV} = \text{LASE}_Y^{WIV} \tag{28}$$

$$\frac{\beta_C^{WIV}}{\beta_Y^{WIV} - \beta_C^{WIV}} = \frac{\text{LATE}_Y^{WIV}}{\text{LASE}_Y^{WIV}} \tag{29}$$

where LATE_Y^{WIV} is a local average treatment effect, LASE_Y^{WIV} is a local average surplus effect, and $\frac{\text{LATE}_Y^{WIV}}{\text{LASE}_Y^{WIV}}$ is a pseudo treatment effect elasticity of demand.

3.4.3 From LASE to MSE

With an estimate of a local average surplus effect, following an approach similar to Brinch et al. (2017) it is possible to recover a marginal surplus effect. Recall that the local average surplus effect is a weighted average of marginal surplus effects, and the weights $\omega_Y^*(u; x)$ are nonparametrically 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 this paper, I implement the simplest case, where the researcher has a single estimate of the local average surplus effect, LASE. I assume

Assumption 5a. $V_i \sim Uniform[a, a+k] | X_i = x$, *and* $V_{\gamma i} = 1 \; \forall i$.

Assumption 5a yields a linear marginal surplus effect, with $\text{MSE}(u; x) = ku$. This assumption is neither necessary nor sufficient for linear marginal treatment effects conditional on $X_i = x$, and allows for arbitrary nonlinearities in the effects of the cost and outcome instruments on costs and potential outcome under treatment, respectively, conditional on $X_i = x$ (maintaining monotonicity). It is similar to the approach taken to recovering parameters of a linear marginal treatment effect using a discrete instrument in Brinch et al. (2017). Under this assumption, estimation of the marginal surplus effect from an estimate of the local average surplus effect is straightforward.

$$\text{MSE}(u; x) = ku \tag{30}$$

$$k = \frac{\text{LASE}_Y}{\int u \omega_Y^*(u; x) du dx} \tag{31}$$

For implementation, in general estimation of $\omega_Y^*(u; x)$ can be hard, even though it is nonparametrically identified. I simplify the problem by specifying a restrictive functional form for $P(z_C, z_Y; x)$, which I discuss in Appendix Section B.2.3.

3.4.4 Control function

Alternatively, I consider a fully parametric specification of the model. Björklund & Moffitt (1987) and Eisenhauer et al. (2015) implement similar approaches, which they estimate by maximum likelihood. I follow their work and assume linear outcome and cost equations and normally distributed additively separable heterogeneity, but instead estimate the model by a two step control function approach.

Assumption 5b.

$$\begin{pmatrix} Y_{1i} \\ C_{1i} \\ Y_{0i} \end{pmatrix} \sim N \left(\begin{pmatrix} (g_Y + c_0) Z_{Yi} + X_i' \mu_1 \\ g_C Z_{Ci} + X_i' \mu_C \\ c_0 Z_{Yi} + X_i' \mu_0 \end{pmatrix}, \begin{pmatrix} \Sigma_{11} & \Sigma_{1c} & \Sigma_{10} \\ \Sigma_{1c} & \Sigma_{cc} & \Sigma_{c0} \\ \Sigma_{10} & \Sigma_{c0} & \Sigma_{cc} \end{pmatrix} \right)$$

As Eisenhauer et al. (2015) show, identification of this model does not depend on the assumption that Z_{Yi} is excluded from the outcome equation for Y_{i0}, but instead follows from the assumption of additively separable heterogeneity. Because of the stronger exclusion restriction I make, additive separability enables an overidentification test of the exclusion restriction, namely that Z_{Yi} is excluded from the outcome equation for Y_{i0}.

This is simple to implement in the control function approach: it is just a test of whether $c_0 = 0$. Details of the two step control function approach are in Appendix Section B.3. In brief, the first stage is a probit regression of the decision to irrigate on the cost instrument, the outcome instrument, and controls. The second stage is a regression of gross revenue on the decision to irrigate interacted with the outcome instrument and controls, and the appropriate control function conditional on the decision to irrigate.

On the interpretation of the control function approach, under this normality assumption it follows that

$$\text{MSE}(u;x) = \frac{\sigma_V u}{\phi(\Phi^{-1}(u))} \tag{32}$$

where σ_V is the standard deviation of V_i, ϕ is the normal density function, and Φ is the normal cumulative distribution function. One can show that σ_V is the ratio of the second stage coefficient on the outcome instrument interacted with the decision to irrigate to the first stage coefficient on the outcome instrument. Loosely speaking, this implies that $\frac{1}{\sigma_V}$ equals the effect of the treatment effect of irrigation on gross revenue on adoption of irrigation, instrumented with the outcome instrument. In this sense, the control function approach is similar to estimating the treatment effect elasticity of demand by instrumenting for the effect of increased treatment effects on adoption on treatment, and then recovering the marginal surplus effect from this estimate. In contrast, the IV approach directly estimates the marginal surplus effect, from which it can be used to recover a pseudo treatment effect elasticity of demand.

Finally, as a test of the IV method, it is useful to compare the IV estimate for both the marginal surplus effect, estimated using the method in Section 3.4.3, and the local average surplus effect, estimated as described in Section 3.4.1, to estimates from the control function approach. For the former, I plot IV and control function estimates of the marginal surplus effect against each other in Section 5.3. For the latter, following Kline & Walters (2017), a useful comparison is the estimate of the local average surplus effect from the control function approach, which is simply

$$\text{LASE}_{\text{CF}} = \int \omega_Y^*(u;x) \frac{\sigma_V u}{\phi(\Phi^{-1}(u))} dudx \tag{33}$$

Lastly, I measure the informativeness of the linear instrumental variable LASE for the control function parameter σ_V, following Andrews et al. (2018). The econometric model suggests we should expect a relatively high informativeness, since the two approaches are estimating a similar parameter.

3.5 Model robustness

In standard linear instrumental variable models, a common concern is violations of the exclusion restriction and monotonicity assumptions. Recent work has developed methods to conduct inference in the presence of likely violations of the exclusion restriction (Conley et al. (2012)), to correct for violations of exclusion restrictions generated by endogenous reoptimization by agents (Jones (2015)), and to test for violations of monotonicity (Heckman & Vytlacil (2005), Kitagawa (2015)). This approach requires additional assumptions that may fail to hold exactly in many contexts where it is potentially useful: that the instruments (z_C, z_Y) are weakly separable from unobserved heterogeneity, and the exclusion restrictions that z_Y is excluded from costs and potential outcome under control.[16] In this section, I discuss the most likely violations of these assumptions in my context: failures of weak separability, failure of the restriction that z_C is excluded from potential outcome under treatment, and failure of the restriction that z_Y is excluded from costs. I derive general bias formulas for each violation, and following Jones (2015) derive bias formulas for the exclusion restriction violations in terms of economic primitives under stronger assumptions. However, I only calculate these bias formulas for the local instrumental variable estimator without controls; a similar exercise to that undertaken in Appendix Section B.2 would allow calculation of these biases for the linear instrumental variable estimator with controls as well.

First, consider the nonseparable model in which the exclusion restrictions and monotonicity assumptions hold, where potential outcome under treatment is $Y_{1i}(z_Y)$, costs are $C_{1i}(z_C)$, and potential outcome under control is Y_{0i}. With the failure of weak separability, the marginal surplus effect is no longer well defined, as the set of agents adopting treatment may differ conditional on $P(z_C, z_Y) = u$. Instead, for now define the marginal surplus effect in terms of the local instrumental variables estimand, using a tilde to denote the alternative definition.

$$\tilde{\text{MSE}}(z_C, z_Y) \equiv \frac{d\mathbf{E}[Y_i(z_C, z_Y)]/dz_Y}{dP(z_C, z_Y)/dz_Y} - \frac{d\mathbf{E}[Y_i(z_C, z_Y)]/dz_C}{dP(z_C, z_Y)/dz_C}$$

[16] Additionally, behavioral agents may adopt treatment even when benefits are less than costs, or fail to adopt when benefits are greater than costs. Methods allowing for flexible violations of this form have been studied at length in the behavioral literature, and are discussed in Bernheim & Rangel (2009) and Mullainathan et al. (2012).

Note that in this case, the estimand $\tilde{\text{MSE}}$ is now a function of both instruments, instead of being a function of them through the index $P(z_C, z_Y)$. Moreover, define $V_i(z_C, z_Y) = -Y_{1i}(z_Y) + C_{1i}(z_C) + Y_{0i}$ to be agent i's index of surplus from adopting treatment, so the lowest $V_i(z_C, z_Y)$ agents have the highest potential surplus from adopting treatment.

$$\frac{d\mathbf{E}[\pi_i(z_C, z_Y)]/dz_Y}{dP(z_C, z_Y)/dz_Y} = \tilde{\text{MSE}}(z_C, z_Y) + \underbrace{(\text{MTE}_{z_C}(z_C, z_Y) - \text{MTE}_{z_Y}(z_C, z_Y))}_{\text{MTE bias}}$$

$$\frac{d\mathbf{E}[\pi_i(z_C, z_Y)]/dz_C}{dP(z_C, z_Y)/dz_C} = \underbrace{\left(\frac{\mathbf{E}\left[\frac{dC_{1i}(z_C)}{dz_C} \middle| D_i = 1\right] / \left[\frac{dC_{1i}(z_C)}{dz_C} \middle| V_i(z_C, z_Y) = 0\right]}{\mathbf{E}\left[\frac{dY_{1i}(z_Y)}{dz_Y} \middle| D_i = 1\right] / \left[\frac{dY_{1i}(z_Y)}{dz_Y} \middle| V_i(z_C, z_Y) = 0\right]} \right)}_{\text{complier/inframarginal bias}} \frac{d\mathbf{E}[\pi_i(z_C, z_Y)]/dz_Y}{dP(z_C, z_Y)/dz_Y}$$

There are two sources of bias. First, z_C and z_Y each induce a different set of compliers to adopt treatment. As a result, the subtracted off marginal treatment effect estimated using z_C may not be the same marginal treatment effect for z_Y compliers. Second, the share of agents adopting treatment is no longer a sufficient statistic for the impacts of shifts to the instruments on surplus. This "complier/inframarginal bias" occurs because it no longer the case that the relative impacts of z_C and z_Y on adoption by compliers can be used to infer the relative impacts of z_C and z_Y on surplus for inframarginal adopters. Under weak separability, each of these biases is 0, and it is unlikely that meaningful generalizations of weak separability are possible while eliminating either of these biases.

Next, consider a model in which two of the exclusion restrictions are violated: z_Y may enter C_{1i}, and z_C may enter Y_{1i}. However, we maintain the assumption that weak separability holds. In this case,

$$\begin{aligned}
Y_{1i}(z_C, z_Y) &= V_{\gamma i}\gamma_Y(z_C, z_Y) + V_{1i} \\
C_{1i}(z_C, z_Y) &= V_{\gamma i}\gamma_C(z_C, z_Y) + V_{Ci} \\
Y_{0i} &= V_{0i}
\end{aligned}$$

I continue to maintain the definitions of $\text{MSE}(u)$ and $\text{MTE}(u; z_C, z_Y)$ from Section 3.4.3, although note that the marginal treatment effect may now depend on z_C. Let

$B_Y \equiv \frac{d\gamma_C(z_C,z_Y)/dz_Y}{d(\gamma_Y(z_C,z_Y)-\gamma_C(z_C,z_Y))/dz_Y}$, and $B_C \equiv \frac{d\gamma_Y(z_C,z_Y)/dz_C}{d(\gamma_Y(z_C,z_Y)-\gamma_C(z_C,z_Y))/dz_C}$.

$$\begin{aligned}
\frac{d\mathbf{E}[Y_i(z_C,z_Y)]/dz_C}{dP(z_C,z_Y)/dz_C} &= \text{MTE}(P(z_C,z_Y);z_C,z_Y) + (1+B_Y)\text{MSE}(P(z_C,z_Y)) \\
\frac{d\mathbf{E}[Y_i(z_C,z_Y)]/dz_Y}{dP(z_C,z_Y)/dz_Y} &= \text{MTE}(P(z_C,z_Y);z_C,z_Y) + B_C\text{MSE}(P(z_C,z_Y)) \\
\frac{d\mathbf{E}[Y_i(z_C,z_Y)]/dz_Y}{dP(z_C,z_Y)/dz_Y} - \frac{d\mathbf{E}[Y_i(z_C,z_Y)]/dz_C}{dP(z_C,z_Y)/dz_C} &= (1+(B_Y-B_C))\,\text{MSE}(P(z_C,z_Y))
\end{aligned}$$

Each local instrumental variable estimator estimates the sum of a marginal treatment effect and a derivative term times the marginal surplus effect. When the exclusion restrictions are satisfied, $B_Y = B_C = 0$, and we get the results in Section 3.4 and 3.3. Each of these bias terms, B_Y and B_C, captures the violation: B_Y is the effect of z_Y on costs relative to the effect of z_Y on surplus, and B_C is the effect of z_C on potential outcome under treatment relative to the effect of z_C on surplus.

To understand when and why this bias might occur, following Jones (2015), it is worth considering a more restrictive model that yields such an exclusion restriction violation, when agents reoptimize in response to changes in each instrument. In Appendix Section B.4.1, consistent with my context, I present a brief model where households have Cobb-Douglas production functions over water, a variable composite, and a fixed input (land), and households have idiosyncratic endowments of land. Water does not enter the rainfed production function, but their irrigated production function requires water, plus a fixed cost that is proportional to the quantity of land irrigated. I assume z_Y shifts productivity under irrigated production, while z_C shifts the price of water and fixed costs by a constant proportion, consistent with fixed irrigation costs and variable pumping costs scaling linearly in depth to groundwater. With Cobb-Douglas, note that the increased productivity and the increased price of water shift revenue and costs in identical relative proportions; in other words, the only reason we can hope to separately identify MTE and MSE with z_C and z_Y is the presence of fixed costs affected by z_C (but not z_Y). Let α be the variable cost share for irrigated agriculture, let VC_W be variable expenditures on water, and let FC_W be fixed expenditures on water. In this case, the bias terms are

$$\begin{aligned}
B_Y &= \frac{\alpha}{1-\alpha} \\
B_C &= \frac{1}{1-\alpha}\frac{\text{VC}_W}{\text{VC}_W + \text{FC}_W}
\end{aligned}$$

Note that when $\mathrm{FC}_W = 0$, $B_Y - B_C = -1$, and it is impossible to identify the marginal surplus effect. However, when fixed costs are positive, estimates of α and $\frac{\mathrm{VC}_W}{\mathrm{VC}_W+\mathrm{FC}_W}$ make it possible to recover an unbiased estimate of MSE under stronger assumptions. Additionally, following Conley et al. (2012), priors over these terms make it possible to conduct inference robust to exclusion restriction violations.

4 Empirical strategy

4.1 Notation and context specific concerns

Following Section 3.4 and the end of Section 3.4.2, but adapting to my empirical context, I consider outcomes $(Y_i, D_i, Z_{Ci}, Z_{Yi}, (X_i, S_i))$ for each plot i. Y_i is plot i's realized gross revenue. D_i is an indicator for whether plot i is irrigated. Z_{Ci} is plot i's value of the cost instrument, its potential aquifer yield as discussed in Section 2.2. Z_{Yi} is plot i's value of the outcome instrument, its log relative potential irrigated crop yield, as discussed in Section 2.2. X_i is a vector of controls for plot i, which in my main specifications includes a constant and log potential rainfed crop yield, discussed in Section 2.2. S_i is a vector of state dummies.

The instruments, (Z_{Ci}, Z_{Yi}), and controls (X_i, S_i), are constant within district. I use n to index districts, and so I use (Z_{Cn}, Z_{Yn}) to denote the values of the instruments, and (X_n, S_n) to denote the values of the controls. I use $n(i)$ to denote the district of plot i, and 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_n for average gross revenue per hectare, and D_n for share of land irrigated at the district level. That Y_n and D_n might vary across districts with the same values of the instruments, even though we can treat Y_n and D_n 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 the Agricultural NSS, I observe plot level data.[17] Y_i is now gross revenue per hectare for plot i, and D_i is a dummy for irrigated. The sampling in the Agricultural NSS was stratified on village level irrigation status, an endogenous

[17]The data is 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.

outcome; 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 the Irrigation Census, 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 15 and 17. With a large number of clusters, one could estimate the conditional expectations of Z_{Cn} and Z_{Yn} nonparametrically. With the 222 districts I observe, I instead take a parametric approach and assume $\mathbf{E}[Z_{Cn}|Z_{Yn}, X_n, S_n]$ and $\mathbf{E}[Z_{Yn}|Z_{Cn}, X_n, S_n]$ are linear conditional on S_n. With this, I estimate by OLS

$$Y_i = \beta_C^{RF} Z_{Cn} + (Z_{Yn}, X_n)\gamma_{C,S_n}^{RF} + \epsilon_{i,C}^{RF} \tag{34}$$

$$D_i = \beta_C^{FS} Z_{Cn} + (Z_{Yn}, X_n)\gamma_{C,S_n}^{FS} + \epsilon_{i,C}^{FS} \tag{35}$$

$$Y_i = \beta_Y^{RF} Z_{Yn} + (Z_{Cn}, X_n)\gamma_{Y,S_n}^{RF} + \epsilon_{i,Y}^{RF} \tag{36}$$

$$D_i = \beta_Y^{FS} Z_{Yn} + (Z_{Cn}, X_n)\gamma_{Y,S_n}^{FS} + \epsilon_{i,Y}^{FS} \tag{37}$$

Note that coefficients on controls are allowed to vary by state S_n in all specifications. With these assumptions, $\beta_C^{IV} = \beta_C^{RF}/\beta_C^{FS}$, and $\beta_Y^{IV} = \beta_Y^{RF}/\beta_Y^{FS}$. I then use $\beta_Y^{IV} - \beta_C^{IV}$ as an estimate of a local average surplus effect, and $\frac{\beta_C^{IV}}{\beta_Y^{IV} - \beta_C^{IV}}$ as an estimate of a pseudo treatment effect elasticity of demand.

These estimators may be inconsistent if $\text{LATE}_Y \neq \text{LATE}_C$. I therefore also implement the weighted instrumental variable estimator constructed in 3.4.2; this estimator will be consistent for a local average welfare effect and a pseudo treatment effect elasticity of demand under the parametric assumption above, and if marginal treatment effects and P are both linear conditional on S_n.

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), there is a duality between costs and benefits in the generalized Roy model, the difference is only which is treated as observable. When using fixed costs as an outcome, I instead use potential aquifer yield as an outcome instrument (since it reduces fixed costs conditional on irrigating), and log relative potential irrigated crop yield as a cost instrument (since it shifts adoption of irrigation without affecting fixed costs). However, using fixed costs creates an exclusion restriction violation: potential aquifer yield also affects variable costs of irrigation, which are unobserved in my data. Additionally, fixed costs are a stock, instead of a flow. To interpret these results then, I assume that agents have a homogeneous discount factor, that fixed costs are a constant share of total relative costs of irrigation, and that the timing of construction is independent of any unobservables, all conditional on observables. Under these assumptions, we can estimate a pseudo treatment effect elasticity of demand with fixed costs as the outcome, which we can compare to estimates using agricultural revenue as an outcome; intuitively, this is because under these assumptions, costs of irrigation are just some multiple of fixed costs of irrigation, conditional on observables. However, the pseudo treatment effect elasticity of demand with fixed costs will be the negative of the pseudo treatment effect elasticity of demand with revenue; this is because while a 1% increase in the effect of irrigation on revenue will increase demand, a 1% increase in the effect of irrigation on costs will decrease demand.

4.3 Control function

To estimate the control function approach, I use the Agricultural NSS, 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 the Agricultural NSS data. I follow Section B.3 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_C and outcome instrument z_Y are never interacted with state fixed effects. Details of the approach are in Appendix B.3.

5 Results

5.1 Instrumental variables

Table 2 presents the instrumental variable regressions in the Agricultural Panel data. Columns (1) and (2) show a strong first stage with the cont instrument and the outcome instrument, with t-statistics of 5.0 and 4.2, respectively. Columns (3) and (4) present the reduced form for each instrument. Columns (5) and (6) present the instrumental variable regressions. The instrumental variable coefficient in Column (5), 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 coefficient in Column (6) is the sum of a local average treatment effect and a local average surplus effect. For now, note that this coefficient is larger than the coefficient as Column (5), as we would expect.

Table 3 presents results from the full set of instrumental variable specifications; for compactness, each cell corresponds to a single regression. Columns correspond to a single set of estimates, while rows correspond to estimators. Rows 1 through 6 of Column (1) present the same results as are in Table 2. Row 7 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 interpret this, one can take the ratio of the estimate of the local average treatment effect in Row 3 to the estimate of the local average surplus effect in Row 7: 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 the complier weights on different states for the cost instrument and the outcome instrument. To illustrate this impact, in Figure 3 I present densities of the weights placed on marginal treatment effects at different u (margin of adoption for a given share of agents adopting irrigation) and z_Y (value of the outcome instrument) by the cost instrument and outcome instrument local average treatment effects. Although these parameters were not targeted by the reweighting, under the assumptions for the weighted instrumental variable estimator to recover a local average surplus effect, these densities should be the same for the cost instrument and outcome instrument. Panels (a) and (b) of Figure 3 show that there is noticeable imbalance in the weights. The average $u\left(z_Y\right)$ for cost instrument compliers is 0.69 (0.61), but for outcome instrument compliers is 0.57 (0.71). Panels (c) and (d) show that reweighting corrects much of this imbalance. The densities appear more similar after reweighting, and the differences in average $u\left(z_Y\right)$ between the compliers decrease from 0.12 (0.10) to 0.02 (0.05). After reweighting, the estimated local average surplus effect increases, suggesting that the Column (1) estimate of local average surplus effect was biased downwards.

Column (3) presents the instrumental variable estimates from the Agricultural NSS; they are broadly similar to the results from Column (1), suggesting that comparing the control function results to the estimates based on the initial instrumental variable estimator is reasonable.

Column (4) presents the results with negative fixed costs as the outcome. Interestingly, the estimated local average treatment effect is twice as large as the OLS estimate, in contrast to IV with revenue per hectare as an outcome, where OLS and IV are indistinguishable. This provides suggestive evidence that much of the selection into irrigation is on costs, and not treatment effects, conditional on the controls. Consistent with this, in results available upon request, I find that marginal irrigation uses a larger share of deep tubewells (instead of shallow tubewells, a cheaper investment available in areas with low costs of irrigation). Additionally, the absolute value of the pseudo treatment effect elasticity of demand using fixed costs as an outcome, 0.68, is almost identical to the estimate using revenue as an outcome, 0.72, as we expected in Section 4.2. However, it is much more precisely estimated, and is my preferred estimate of a pseudo treatment effect elasticity of demand.

5.2 Control function

I present the estimated coefficients from the control function approach in Table 4. 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, σ_V, is large, consistent with the inelastic demand for irrigation implied by the estimated pseudo treatment effect elasticity of demand.

This estimate is also proportional to the control function estimate of the marginal surplus effect. To compare the control function and instrumental variable approaches, I estimate the informativeness of the instrumental variable estimator of the local average surplus effect for the control function estimate of σ_V is 0.120.[18] Third, the control function coefficients 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.

5.3 MSE

Estimated marginal surplus effects and local average surplus effects for the instrumental variable estimator (in the Agricultural Panel), the weighted instrumental variable estimator (in the Agricultural Panel), and the control function estimator (in the Agricultural NSS) are presented in Figure 4. The instrumental variable estimates of marginal surplus effects are constructed from the local average surplus effect estimates as described in Section 3.4.3. The control function estimate of the local average surplus effect is constructed from the marginal surplus effect estimate as described in Section 3.4.4. 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. Second, the control function estimate of the marginal surplus effect is larger than the IV estimate, but it is close to the weighted IV estimate over empirically relevant margins of adoption. As a result, for counterfactual exercises, I pick the "median" of the three estimates and use the weighted IV estimate of the marginal surplus effect. Third, 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

With an estimate of the marginal surplus effect, we can now use it to calculate the effects of declining water tables on surplus. To do so, it is now sufficient to have an es-

[18]As Andrews et al. (2018) note, this can be interpreted as the R^2 from the population regression of the control function estimate of σ_V on the instrumental variable estimate of the local average surplus effect in their joint asymptotic distribution.

timate of the impact of declining water tables on adoption of irrigation; combined with the marginal surplus effect, this provides us with an estimate of impact of a one meter decline in water tables on surplus. For this exercise, I calibrate $\frac{dP}{d\text{depth to water table}} = -.0024/\text{m}$ based on estimates from Fishman et al. (2017), which I assume to be constant.[19] This is convenient with a linear marginal surplus effect, as it implies

$$\frac{1}{P}\frac{d\mathbf{E}[\pi_i]}{d\text{depth to water table}} = \text{MSE}(1)\frac{dP}{d\text{depth to water table}}$$

For a linear marginal surplus effect, the effect of a one meter decline in the water table on surplus per irrigated hectare is just the slope of the marginal surplus effect times the effect of a one meter decline in the water table on adoption of irrigation. Intuitively, adoption linear in an instrument and a linear marginal surplus effect imply a constant effect on surplus per unit change in the instrument for the average inframarginal adopter.

I use this approach to calculate the impact of declining water tables on economic surplus, and report estimates in Table 6. Column 1 reports estimates of the impact of a 1m decline in water tables on economic surplus in Rs/ha. The Weighted IV 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 16m, implying a one standard deviation increase in depth to water table would cause a loss of surplus per irrigated hectare equal to 11.4% 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, which I estimate to be roughly 3 to 6.[20] The IV

[19]This, and all other calibrated parameters used in counterfactual exercises, are in Table 5.

[20]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 the share of non-fixed costs 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

and weighted IV estimates of the marginal surplus effect are 4.5 and 5.9 times larger than the increase in farmers' private electricity costs of pumping groundwater from a 1m decline in water tables, respectively, providing some validation of the method of estimating the marginal surplus effect and suggesting 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 weighted IV 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 464 Rs/ha, while back of the envelope calculations scaling increased electricity costs are 188 and 376 Rs/ha.

proportion to their aggregate shares. I calculate the share of fixed costs using the approach above, and I calculate electricity costs per irrigated hectare based on Fishman et al. (2016); this calculation yields an electricity cost share of 0.12. Fishman et al. (2016) estimate agricultural electricity consumption at 100,000 GWh in 2010; I divide this by 68 million irrigated hectares, and multiply by the 1 Rs/kWh implicit price of electricity paid by farmers; this estimates electricity costs per hectare of 1,470 Rs/ha, yielding the 0.12 share.

References

Adão, R. (2016). Worker heterogeneity, wage inequality, and international trade: Theory and evidence from brazil.

Allcott, H., Mullainathan, S., & Taubinsky, D. (2014). Energy policy with externalities and internalities. *Journal of Public Economics*, 112, 72–88.

Allen, T. & Atkin, D. (2015). Volatility, insurance and the gains from trade.

Andrews, I., Gentzkow, M., & Shapiro, J. M. (2018). On the informativeness of descriptive statistics for structural estimates.

Angrist, J. & Fernandez-Val, I. (2010). *Extrapolate-ing: External validity and overidentification in the late framework*. Technical report, National Bureau of Economic Research.

Angrist, J. D., Imbens, G. W., & Rubin, D. B. (1996). Identification of causal effects using instrumental variables. *Journal of the American statistical Association*, 91(434), 444–455.

Arnold, D., Dobbie, W., & Yang, C. S. (2018). Racial bias in bail decisions. *The Quarterly Journal of Economics*.

Badiani, R. & Jessoe, K. (2017). Electricity prices, groundwater and agriculture: the environmental and agricultural impacts of electricity subsidies in india.

Bernheim, B. D. & Rangel, A. (2009). Beyond revealed preference: choice-theoretic foundations for behavioral welfare economics. *The Quarterly Journal of Economics*, 124(1), 51–104.

Berry, J., Fischer, G., & Guiteras, R. (2018). Eliciting and utilizing willingness-to-pay: Evidence from field trials in northern ghana.

Bhattacharya, D. (2017). *Empirical welfare analysis for discrete choice: Some General Results*. Technical report, Cambridge University working paper.

Bhuller, M., Dahl, G. B., Løken, K. V., & Mogstad, M. (2016). Incarceration, recidivism and employment.

Bhuller, M., Dahl, G. B., Løken, K. V., & Mogstad, M. (2018). Incarceration, recidivism and employment.

Björklund, A. & Moffitt, R. (1987). The estimation of wage gains and welfare gains in self-selection models. *The Review of Economics and Statistics*, (pp. 42–49).

Brinch, C. N., Mogstad, M., & Wiswall, M. (2017). Beyond late with a discrete instrument. *Journal of Political Economy*, 125(4), 985–1039.

Brozović, N., Sunding, D. L., & Zilberman, D. (2010). On the spatial nature of the groundwater pumping externality. *Resource and Energy Economics*, 32(2), 154–164.

Bustos, P., Caprettini, B., & Ponticelli, J. (2016). Agricultural productivity and structural transformation: Evidence from brazil. *American Economic Review*, 106(6), 1320–65.

Carneiro, P., Heckman, J. J., & Vytlacil, E. J. (2011). Estimating marginal returns to education. *American Economic Review*, 101(6), 2754–81.

Chatterjee, S., Lamba, R., & Zaveri, E. (2017). The water gap: Environmental effects of agricultural subsidies in india.

Chernozhukov, V., Chetverikov, D., Demirer, M., Duflo, E., Hansen, C., Newey, W., & Robins, J. (2016). Double/debiased machine learning for treatment and causal parameters. *arXiv preprint arXiv:1608.00060*.

Chetty, R. (2009). Sufficient statistics for welfare analysis: A bridge between structural and reduced-form methods. *Annu. Rev. Econ.*, 1(1), 451–488.

Conley, T. G., Hansen, C. B., & Rossi, P. E. (2012). Plausibly exogenous. *Review of Economics and Statistics*, 94(1), 260–272.

Costinot, A., Donaldson, D., & Smith, C. (2016). Evolving comparative advantage and the impact of climate change in agricultural markets: Evidence from 1.7 million fields around the world. *Journal of Political Economy*, 124(1), 205–248.

D'Agostino, A. L. (2017). Technical change and gender wage inequality: Long-run effects of india's green revolution.

Das, M., Newey, W. K., & Vella, F. (2003). Nonparametric estimation of sample selection models. *The Review of Economic Studies*, 70(1), 33–58.

Dobbie, W., Goldin, J., & Yang, C. S. (2018). The effects of pretrial detention on conviction, future crime, and employment: Evidence from randomly assigned judges. *American Economic Review*, 108(2), 201–40.

Dubash, N. K. (2007). The electricity-groundwater conundrum: Case for a political solution to a political problem. *Economic and Political Weekly*, (pp. 45–55).

Duflo, E. & Pande, R. (2007). Dams. *The Quarterly Journal of Economics*, 122(2), 601–646.

Eisenhauer, P., Heckman, J. J., & Vytlacil, E. (2015). The generalized roy model and the cost-benefit analysis of social programs. *Journal of Political Economy*, 123(2), 413–443.

Evenson, R. E. & Gollin, D. (2003). Assessing the impact of the green revolution, 1960 to 2000. *science*, 300(5620), 758–762.

Fishman, R., Jain, M., & Kishore, A. (2017). When water runs out: Adaptation to gradual environmental change in indian agriculture.

Fishman, R., Lall, U., Modi, V., & Parekh, N. (2016). Can electricity pricing save india's groundwater? field evidence from a novel policy mechanism in gujarat. *Journal of the Association of Environmental and Resource Economists*, 3(4), 819–855.

Flores, C. A. & Flores-Lagunes, A. (2013). Partial identification of local average treatment effects with an invalid instrument. *Journal of Business & Economic Statistics*, 31(4), 534–545.

Foster, A. D. & Rosenzweig, M. R. (2010). Microeconomics of technology adoption. *Annu. Rev. Econ.*, 2(1), 395–424.

Gandhi, V. P. & Bhamoriya, V. (2011). Groundwater irrigation in india: Growth, challenges, and risks.

Gine, X. & Jacoby, H. G. (2016). *Markets, contracts, and uncertainty in a groundwater economy*. The World Bank.

Gisser, M. & Sanchez, D. A. (1980). Competition versus optimal control in groundwater pumping. *Water resources research*, 16(4), 638–642.

Government of India (2018). Economic survey of india (2017-18).

Hausman, J. A. (1978). Specification tests in econometrics. *Econometrica: Journal of the econometric society*, (pp. 1251–1271).

Heckman, J. J. & Vytlacil, E. (2005). Structural equations, treatment effects, and econometric policy evaluation. *Econometrica*, 73(3), 669–738.

Heckman, J. J. & Vytlacil, E. J. (1999). Local instrumental variables and latent variable models for identifying and bounding treatment effects. *Proceedings of the national Academy of Sciences*, 96(8), 4730–4734.

Heckman, J. J. & Vytlacil, E. J. (2007a). Econometric evaluation of social programs, part i: Causal models, structural models and econometric policy evaluation. *Handbook of econometrics*, 6, 4779–4874.

Heckman, J. J. & Vytlacil, E. J. (2007b). Econometric evaluation of social programs, part ii: Using the marginal treatment effect to organize alternative econometric estimators to evaluate social programs, and to forecast their effects in new environments. *Handbook of econometrics*, 6, 4875–5143.

Hendren, N. (2014). *Efficient Welfare Weights*. Technical report, National Bureau of Economic Research.

Hendren, N. (2016). The policy elasticity. *Tax Policy and the Economy*, 30(1), 51–89.

Hussam, R., Rigol, N., & Roth, B. (2017). Targeting high ability entrepreneurs using community information: Mechanism design in the field.

Imbens, G. W. & Angrist, J. D. (1994). Identification and estimation of local average treatment effects. *Econometrica (1986-1998)*, 62(2), 467.

Jacoby, H. G. (2017). "well-fare" economics of groundwater in south asia. *The World Bank Research Observer*, 32(1), 1–20.

Jones, D. (2015). *The economics of exclusion restrictions in iv models*. Technical report, National Bureau of Economic Research.

Karlan, D., Osei, R., Osei-Akoto, I., & Udry, C. (2014). Agricultural decisions after relaxing credit and risk constraints. *The Quarterly Journal of Economics*, 129(2), 597–652.

Kitagawa, T. (2015). A test for instrument validity. *Econometrica*, 83(5), 2043–2063.

Kline, P. & Walters, C. R. (2016). Evaluating public programs with close substitutes: The case of head start. *The Quarterly Journal of Economics*, 131(4), 1795–1848.

Kline, P. & Walters, C. R. (2017). Through the looking glass: Heckits, late, and numerical equivalence. *arXiv preprint arXiv:1706.05982*.

Koundouri, P. (2004). Potential for groundwater management: Gisser-sanchez effect reconsidered. *Water Resources Research*, 40(6).

Kowalski, A. E. (2016). Doing more when you're running late: Applying marginal treatment effect methods to examine treatment effect heterogeneity in experiments.

Matzkin, R. L. (2007). Nonparametric identification. *Handbook of Econometrics*, 6, 5307–5368.

Mogstad, M., Santos, A., & Torgovitsky, A. (2017). *Using instrumental variables for inference about policy relevant treatment effects*. Technical report, National Bureau of Economic Research.

Mountjoy, J. (2018). Community colleges and upward mobility.

Mullainathan, S., Schwartzstein, J., & Congdon, W. J. (2012). A reduced-form approach to behavioral public finance. *Annu. Rev. Econ.*, 4(1), 511–540.

Narain, P., Khan, M., & Singh, G. (2006). *Potental for Water Conservation and Havesting Against Drought in Rajasthan*, volume 104. IWMI.

Rodell, M., Velicogna, I., & Famiglietti, J. S. (2009). Satellite-based estimates of groundwater depletion in india. *Nature*, 460(7258), 999.

Roy, A. D. (1951). Some thoughts on the distribution of earnings. *Oxford economic papers*, 3(2), 135–146.

Schlenker, W., Hanemann, W. M., & Fisher, A. C. (2007). Water availability, degree days, and the potential impact of climate change on irrigated agriculture in california. *Climatic Change*, 81(1), 19–38.

Sekhri, S. (2013). Sustaining groundwater: Role of policy reforms in promoting conservation in india. *India Policy Forum 2012-13, Volume 9*.

Sekhri, S. (2014). Wells, water, and welfare: the impact of access to groundwater on rural poverty and conflict. *American Economic Journal: Applied Economics*, 6(3), 76–102.

Shah, T. (2009). Climate change and groundwater: India's opportunities for mitigation and adaptation. *Environmental Research Letters*, 4(3), 035005.

Small, K. A. & Rosen, H. S. (1981). Applied welfare economics with discrete choice models. *Econometrica: Journal of the Econometric Society*, (pp. 105–130).

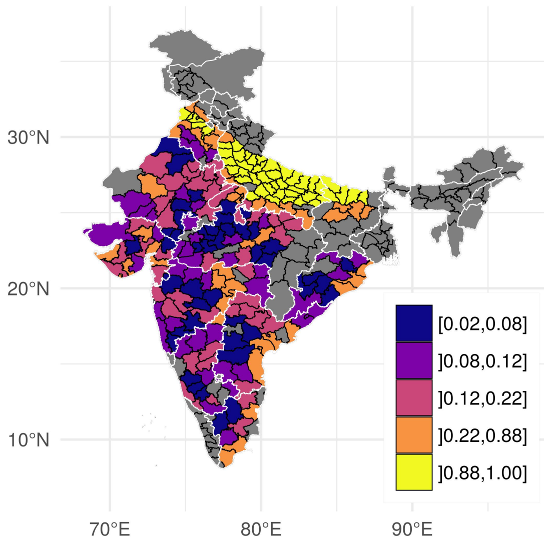
Suhag, R. (2016). Overview of ground water in india.

Suri, T. (2011). Selection and comparative advantage in technology adoption. *Econometrica*, 79(1), 159–209.

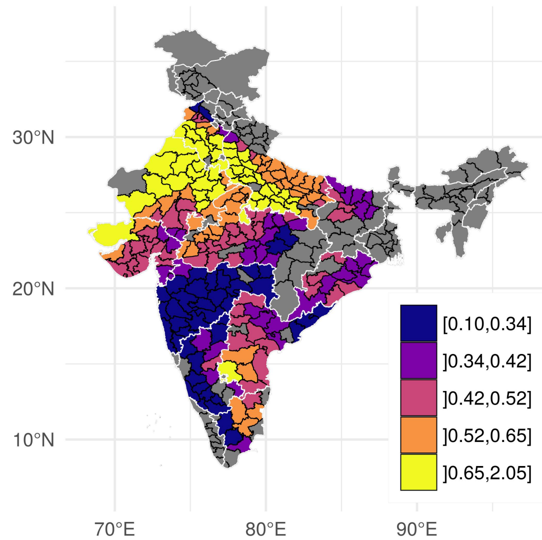
Willig, R. D. (1978). Incremental consumer's surplus and hedonic price adjustment. *Journal of Economic Theory*, 17(2), 227–253.

Willis, R. J. & Rosen, S. (1979). Education and self-selection. *Journal of political Economy*, 87(5, Part 2), S7–S36.

Figure 1: Cost and benefit shifters



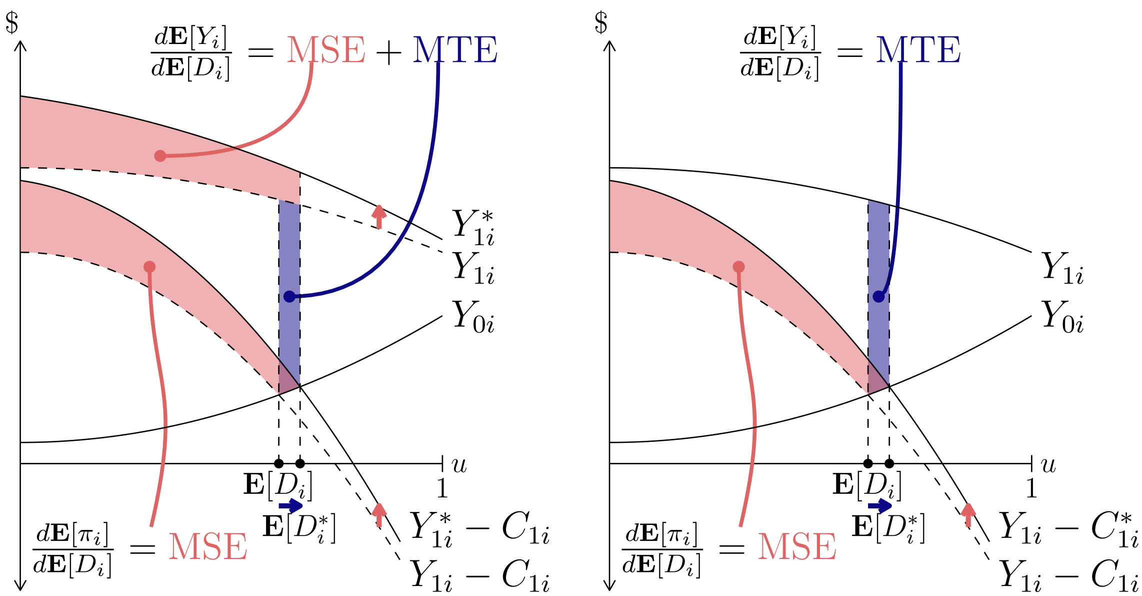
(a) Potential aquifer yield



(b) log relative potential irrigated crop yield

Notes: Variation in the cost instrument (potential aquifer yield, Panel (a)) and the outcome instrument (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.

Figure 2: Model comparative statics



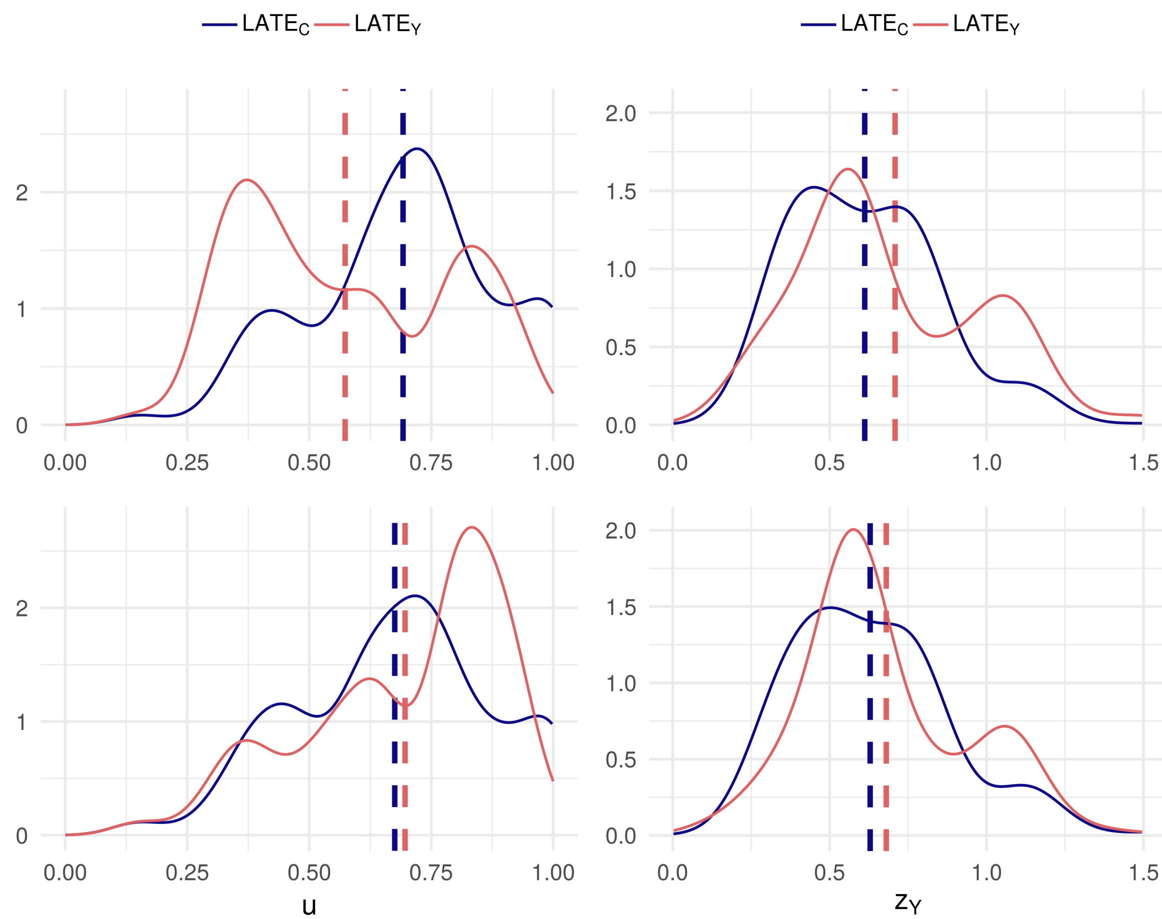
(a) Increased outcome under treatment

(b) Decreased costs of treatment

Notes: Panel (a) shows the effects of shifting z_Y, the instrument for potential outcome under treatment ("outcome instrument", which shifts potential outcome under treatment Y_{1i} to Y_{1i}^*), while Panel (b) shows the effects of shifting z_C, the instrument for costs of adopting treatment ("cost instrument", which shifts costs C_{1i} to C_{1i}^*). Changes in the share of agents adopting treatment, from P to P^*, 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 the cost instrument. 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 the cost instrument or the outcome instrument. The change in average surplus caused by both the cost instrument and the outcome instrument is proportional to the marginal surplus effect. However, the change in average outcomes caused by the cost instrument is proportional to the marginal treatment effect, while the change in average outcomes caused by the outcome instrument is proportional to the marginal surplus effect plus the marginal treatment effect.

Figure 3: Instrumental variables weights

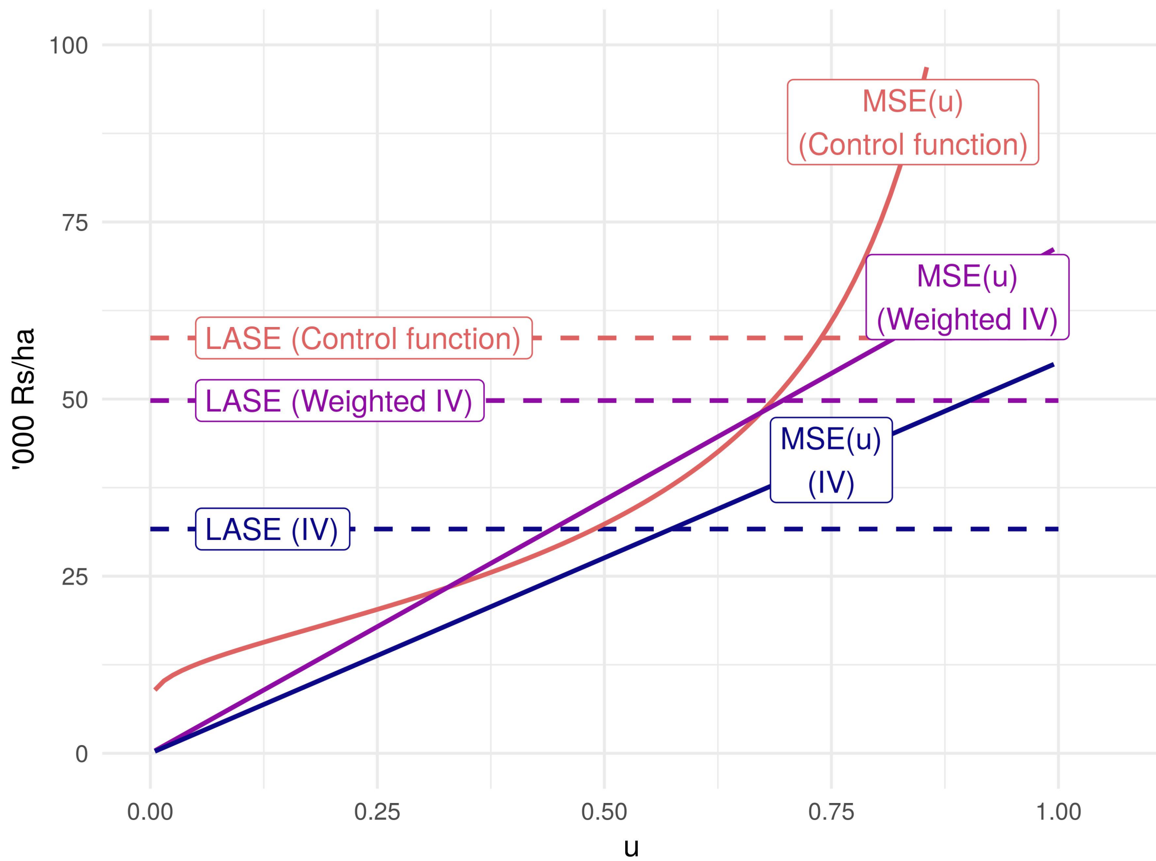
(a) IV, u (b) IV, z_Y



(c) Weighted IV, u (d) Weighted IV, z_Y

Notes: Each plot shows the densities of weights placed on the marginal treatment effect MTE($u; z_Y, x$) by u (share of land irrigated, Panel (a) and (c)) and z_Y (the outcome instrument, log relative potential irrigated crop yield, Panel (b) and (d)) by a different local average treatment effect. Weights from LATE$_C$ (the local average treatment effect from the cost instrument) and LATE$_Y$ (the local average treatment effect from the outcome instrument) for the IV estimators (Section 3.4.1, Panel (a) and (b)) and the weighted IV estimators (Section 3.4.1 and 3.4.2, Panel (c) and (d)); coefficients from these estimators are presented in Table 3. Vertical dotted lines are at the average values of u and z_Y weighted in LATE$_C$ and LATE$_Y$. Densities are calculated using a Gaussian kernel with bandwidth 0.05 for u and 0.1 for z_Y, using the procedure described in Appendix B.2.

Figure 4: 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 3.4.3. The control function estimate of the local average surplus effect is constructed using estimated weights the instrumental variable estimator places on the marginal surplus effect for different u (share of agricultural land irrigated).

Table 2: Instrumental variables estimates

	Share irrigated		Agricultural productivity ('000 Rs/ha)				
	First stage $\left(\beta_{(\cdot)}^{FS}\right)$		Reduced form $\left(\beta_{(\cdot)}^{RF}\right)$		OLS	IV $\left(\beta_{(\cdot)}^{IV} = \frac{\beta_{(\cdot)}^{RF}}{\beta_{(\cdot)}^{FS}}\right)$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Z_{Cn} (cost instrument)	0.278***		6.3				
	(0.056)		(4.1)				
Z_{Yn} (outcome instrument)		0.791***		42.9***			
		(0.188)		(10.2)			
Share irrigated					23.9***	22.6*	54.3***
					(2.8)	(13.1)	(14.5)
Instrument (IV only)	-	-	-	-	-	Z_{Cn}	Z_{Yn}
State FE	X	X	X	X	X	X	X
State FE × X_n	X	X	X	X	X	X	X
State FE × Z_{Cn}	-	X	-	X	-	-	X
State FE × Z_{Yn}	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 2007-2011 of the Agricultural Panel data set using potential aquifer flow as a cost instrument (Z_{Cn}) and log relative potential irrigated crop yield as an outcome instrument (Z_{Yn}). In each case, the effect of share irrigated on agricultural productivity per hectare is instrumented for. Controls in all specifications include state fixed effects ("State FE") and state fixed effects interacted with log potential rainfed crop yield ("State FE × X_n"). Columns 1 and 2 are first stage regressions, Columns 3 and 4 and reduced form regressions, Column 5 includes OLS of agricultural productivity per hectare on share irrigated for comparison, and Columns 6 and 7 are the instrumental variable regressions using Z_{Cn} and Z_{Yn} as instruments, respectively. 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 1: Comparison to existing approaches

	$\mathbf{E}[Y_{di}(w) \mid D_i(w,z) = d]$
This paper	$1\{d=1\}\eta(\mathbf{E}[D_i(w,z)])\gamma_Y(w) + \lambda_d(\mathbf{E}[D_i(w,z)])$
EHV '15	$\gamma_{Yd}(w) + \lambda_d(\mathbf{E}[D_i(w,z)])$
DNV '03	$\gamma_{Yd}(w) + \lambda_d(\mathbf{E}[D_i(w,z)])$
EHV '15 (η)	$1\{d=1\}\eta(\mathbf{E}[D_i(w,z)])\gamma_Y(w) + \lambda_d(\mathbf{E}[D_i(w,z)])$
DNV '03 (η)	$1\{d=1\}\eta(\mathbf{E}[D_i(w,z)])\gamma_Y(w) + \lambda_d(\mathbf{E}[D_i(w,z)])$

	$\mathrm{MSE}(w,z)$
This paper	$\frac{\partial \mathbf{E}[Y_i(w,z)]/\partial w}{\partial \mathbf{E}[D_i(w,z)]/\partial w} - \frac{\partial \mathbf{E}[Y_i(w,z)]/\partial z}{\partial \mathbf{E}[D_i(w,z)]/\partial z}$
EHV '15	$\frac{(\mathbf{E}[D_i(w,z)])\,(\partial^2 \mathbf{E}[D_i(w,z)]/\partial w \partial z)}{(\partial \mathbf{E}[D_i(w,z)]/\partial w)\,(\partial \mathbf{E}[D_i(w,z)]/\partial z)} \left(\frac{\partial^2 \mathbf{E}[Y_i(w,z)]/\partial w \partial z}{\partial^2 \mathbf{E}[D_i(w,z)]/\partial w \partial z} - \frac{\partial \mathbf{E}[Y_i(w,z)]/\partial z}{\partial \mathbf{E}[D_i(w,z)]/\partial z} \right)$
DNV '03	$\mathbf{E}[D_i(w,z)] \left[\left(\frac{\partial \mathbf{E}[Y_i(w,z) \mid D_i(w,z)=1]/\partial w}{\partial \mathbf{E}[D_i(w,z)]/\partial w} - \frac{\partial \mathbf{E}[Y_i(w,z) \mid D_i(w,z)=1]/\partial z}{\partial \mathbf{E}[D_i(w,z)]/\partial z} \right) - \left(\frac{\partial \mathbf{E}[Y_i(w,z) \mid D_i(w,z)=0]/\partial w}{\partial \mathbf{E}[D_i(w,z)]/\partial w} - \frac{\partial \mathbf{E}[Y_i(w,z) \mid D_i(w,z)=0]/\partial z}{\partial \mathbf{E}[D_i(w,z)]/\partial z} \right) \right]$
EHV '15 (η)	$\frac{\int_0^{\mathbf{E}[D_i(w,z)]} \frac{\partial^2 \mathbf{E}[D_i(w,z')]/\partial w \partial z}{\partial \mathbf{E}[D_i(w,z')]/\partial z} \left(\frac{\partial^2 \mathbf{E}[Y_i(w,z')]/\partial w \partial z}{\partial^2 \mathbf{E}[D_i(w,z')]/\partial w \partial z} - \frac{\partial \mathbf{E}[Y_i(w,z')]/\partial z}{\partial \mathbf{E}[D_i(w,z')]/\partial z} \right) \Big|_{\mathbf{E}[D_i(w,z')]=u} du}{\partial \mathbf{E}[D_i(w,z)]/\partial w}$
DNV '03 (η)	$\mathbf{E}[D_i(w,z)] \left[\left(\frac{\partial \mathbf{E}[Y_i(w,z) \mid D_i(w,z)=1]/\partial w}{\partial \mathbf{E}[D_i(w,z)]/\partial w} - \frac{\partial \mathbf{E}[Y_i(w,z) \mid D_i(w,z)=1]/\partial z}{\partial \mathbf{E}[D_i(w,z)]/\partial z} \right) - \underbrace{\left(\frac{\partial \mathbf{E}[Y_i(w,z) \mid D_i(w,z)=0]/\partial w}{\partial \mathbf{E}[D_i(w,z)]/\partial w} - \frac{\partial \mathbf{E}[Y_i(w,z) \mid D_i(w,z)=0]/\partial z}{\partial \mathbf{E}[D_i(w,z)]/\partial z} \right)}_{=0} \right]$

	Data requirements	Exclusion restrictions[a]	Support condition
This paper	$\mathbf{E}[Y_i \mid Z_i = z, W_i = w]$	$W_i \not\Rightarrow (C_{1i}, Y_{0i}),\ Z_i \not\Rightarrow (Y_{0i}, Y_{1i})$	Local
EHV '15	$\mathbf{E}[Y_i \mid Z_i = z, W_i = w]$	$W_i \not\Rightarrow C_{1i},\ Z_i \not\Rightarrow (Y_{0i}, Y_{1i})$	Local
DNV '03	$\mathbf{E}[Y_i \mid D_i(z,w) = d, Z_i = z, W_i = w]$	$W_i \not\Rightarrow C_{1i},\ Z_i \not\Rightarrow (Y_{0i}, Y_{1i})$	Local
EHV '15 (η)	$\mathbf{E}[Y_i \mid Z_i = z, W_i = w]$	$W_i \not\Rightarrow (C_{1i}, Y_{0i}),\ Z_i \not\Rightarrow (Y_{0i}, Y_{1i})$	Local, $\mathrm{Supp}(P(w',z) \mid w' = w) = [0, P(w,z)]$
DNV '03 (η)	$\mathbf{E}[Y_i \mid D_i(z,w) = d, Z_i = z, W_i = w]$	$W_i \not\Rightarrow (C_{1i}, Y_{0i}),\ Z_i \not\Rightarrow (Y_{0i}, Y_{1i})$	Local

Notes: This table presents a comparison of the approach developed in Section 3.3 to estimating the marginal surplus effect, as defined in Section 3.2, to approaches developed in Eisenhauer et al. (2015) (EHV '15) and Das et al. (2003) (DNV '03) which extend naturally to the estimation of the marginal surplus effect. The approaches in EHV '15 and DNV '03 are presented both under the additively separable model each paper considers and the weakly separable model this paper develops in Section 3.1. The modeling assumption is presented in the first subtable, the natural estimator of the marginal surplus effect using each approach is presented in the second subtable, and the data requirements, exclusion restrictions, and support conditions required for each approach are presented in the third subtable. The expressions for $\mathrm{MSE}(w,z)$ based on the EHV '15 estimator can be expressed more simply in terms of derivatives of the marginal treatment effect. Additionally, note that the local estimator in this paper and the local estimator from DNV '03 are equivalent when the exclusion restriction holds.

[a] The exclusion restriction that $W_i \not\Rightarrow Y_{0i}$ for EHV '15 (η) is not required, but without it the support condition is strengthened to $\mathrm{Supp}(P(w',z) \mid w' = w) = [0,1]$. The exclusion restriction that $W_i \not\Rightarrow Y_{0i}$ for DNV '03 (η) is not required.

Table 3: Local average surplus effect estimates

	Agricultural productivity			(−) Fixed costs
	Panel '07-'11		NSS '12	Irr '07
	IV	WIV	IV	IV
	(1)	(2)	(3)	(4)
Z_{Cn}				
β_C^{FS} (first stage)	0.278***	0.245***	0.289***	0.574***
	(0.056)	(0.073)	(0.073)	(0.217)
β_C^{RF} (reduced form)	6.3	8.0*	10.8**	-33.9***
	(4.1)	(4.5)	(4.5)	(13.1)
$\beta_C^{IV} = \frac{\beta_C^{RF}}{\beta_C^{FS}} = \text{LATE}_C$	22.6*	32.9**	37.5***	-59.1**
	(13.1)	(15.7)	(13.9)	(25.5)
Z_{Yn}				
β_Y^{FS} (first stage)	0.791***	0.654***	0.834***	0.275***
	(0.188)	(0.216)	(0.226)	(0.068)
β_Y^{RF} (reduced form)	42.9***	54.0***	56.6***	7.8*
	(10.2)	(15.1)	(18.0)	(4.1)
$\beta_Y^{IV} = \frac{\beta_Y^{RF}}{\beta_Y^{FS}} = \text{LASE}_Y + \text{LATE}_Y$	54.3***	82.7***	67.9***	28.3
	(14.5)	(28.5)	(23.9)	(18.2)
$\beta_Y^{IV} - \beta_C^{IV} \approx \text{LASE}_Y$	31.7*	49.8	30.4	87.4***
	(17.9)	(30.8)	(26.3)	(33.7)
$\frac{\beta_C^{IV}}{\beta_Y^{IV} - \beta_C^{IV}} \approx$ Treatment effect elasticity of demand	0.715	0.660	1.235	-0.676***
	(0.733)	(0.607)	(1.332)	(0.156)
# of observations	884	884	33,778	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, 2, and 3 are directly comparable, while the relative interpretation of estimates from Column 4 is discussed in Section 4.2 and 5.1. Rows 1 and 4 report first stage coefficients with share of agricultural land irrigated (for columns 1, 2, and 4) or a dummy for irrigation (for column 3) as the dependent variable (treatment D). Rows 2 and 5 report reduced form coefficients with gross revenue (for columns 1, 2, and 3) or negative fixed costs of irrigation infrastructure (for column 4) as the dependent variable (outcome Y, units of '000 Rs/ha). Rows 3 and 6 report instrumental variable estimates. Row 7 reports estimates of the local average surplus effect, and Row 8 reports estimates of a pseudo treatment effect elasticity of demand. Columns 1 and 4 use OLS for estimation. Column 2 uses weighted OLS, with construction of weights to balance LATE weights within state across estimators as detailed in Appendix B.2.2. Column 3 uses weighted OLS, with weights proportional to survey weights times area, normalized to sum to 1 for each district. Observations in Columns 1 and 2 are at the district-year level, observations in Column 3 are at the household-crop-irrigation status level, and observations in Column 4 are at the district level. Exact specifications, including controls, are detailed in Section 4.2. Z_{Cn}, the cost instrument on which coefficients are reported in Rows 1 and 2, is potential aquifer flow in Columns 1, 2, and 3, and log relative potential irrigated crop yield in Column 4. Z_{Yn}, the outcome instrument on which coefficients are reported in Rows 4 and 5, is log relative potential irrigated crop yield in Columns 1, 2, and 3, and potential aquifer flow in Column 4.

Table 4: 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 3.4.4 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.

Table 5: Calibrated parameters

Parameter	Value [Low, High]	Source
Groundwater use/irrigated ha	0.43 m ha/ha	Use from Shah (2009), area author's calculations
$\epsilon_{W,p}$	-0.18	Badiani & Jessoe (2017)
$\epsilon_{mW,p}$	-0.18	Approximation based on Badiani & Jessoe (2017)
p	1 Rs/kWh	Fishman et al. (2016), Badiani & Jessoe (2017)
c	3 Rs/kWh	Fishman et al. (2016), Badiani & Jessoe (2017)
$\frac{m}{\text{depth to water table}}$	6.8 Wh/m^3/m	Shah (2009)
$\frac{dP}{d\text{depth to water table}}$	-.0024/m	Fishman et al. (2017)
specific yield	[0.015, 0.068]	Narain et al. (2006)
depth to water table	[5m, 66m]	Indian Central Groundwater Board
aquifer share irrigated	[0.015, 0.492]	Author's calculations
MSE(u)	71,500u Rs/ha	Section 5.3

Notes: This table contains the calibrated parameters for the counterfactual exercises in Section 5.4 and Section **??**. Values are provided as points when a single estimate is used, and as a range when multiple values are tried for robustness (α and $\frac{\text{VC}_W}{\text{VC}_W+\text{FC}_W}$) or when the value used is allowed to vary across districts (specific yield, depth to water table, and aquifer share irrigated). Ranges for specific yield, depth to water table, and aquifer share irrigated are specific to Rajasthan. Aquifer share irrigated may be greater than one due to multiple cropping. Depth to water table is estimated as the median post monsoon Kharif reading from the network of monitoring dug wells, bottom winsorized at 5m.

Table 6: 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, PRSE	132	282 [0.90%]
Weighted IV		
LASE		394 [1.26%]
MSE, PRSE	172	365 [1.16%]
Control Function		
LASE		464 [1.48%]
Back of envelope		
3x Electricity costs	88	188 [0.60%]
6x Electricity costs	177	376 [1.20%]

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 5. 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 5. 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). Approaches using an estimated local average surplus effect or policy relevant surplus effect multiply it by the calibrated impact of a 3.3m decline in the water table on adoption of irrigation. The policy relevant surplus effect is calculated from the average marginal surplus effect evaluated at the share of land irrigated in Haryana, Punjab, and Rajasthan; this average marginal surplus effect just equals the marginal surplus effect evaluated at the average share, a consequence of the assumption of a linear marginal surplus effect with homogeneous slope.

A Data appendix

A.1 Construction of z_{Yn}

I construct two variables using potential crop yield: log relative potential irrigated crop yield, and log potential rainfed crop yield. Define A^I_{nc} and A^R_{nc} to be the FAO GAEZ potential crop yield in district n 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_{nct} be the land allocated to crop c in district n in year t, observed in the agricultural panel. Let $L_{sc} = \sum_{n\in s,t} L_{nct}$ be the total area, across all years in the agricultural panel, allocated to crop c in state s. I define

$$\begin{aligned} z_{Yn} &\equiv \log \frac{\sum_c L_{s(n)c} \min\{A^I_{nc}, 10A^R_{nc}\}}{\sum_c L_{s(n)c} A^R_{nc}} \\ \log \text{RF yield}_n &\equiv \log \frac{\sum_c L_{s(n)c} A^R_{nc}}{\sum_c Z_{s(n)c}} \end{aligned}$$

where z_{Yn} is the log relative potential irrigated crop yield, and RF yield$_n$ 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 z_{Yn} 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 $\min\{A^I_{nc}, 10A^R_{nc}\}$ is similar to winsorizing z_{Yn} at $\log 10$. 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 z_{Yn}, 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 z_{Yn}. Third, controlling for $\log$ RF yield$_n$ and a state fixed effect, the coefficient on z_{Yn} would be the same if instead $z_{Yn} = \log \frac{\sum_c L_{s(n)c} \min\{A^I_{nc}, 10A^R_{nc}\}}{\sum_c L_{s(n)c}}$, or log potential irrigated crop yield.

B Model appendix

B.1 Proof appendix

Proof of Equation 3 and 4. Calculating each derivative,

$$\begin{aligned}
\frac{d\mathbf{E}[Y_i(z_C, z_Y)]}{dz_C} &= f_V(F_V^{-1}(P(z_C, z_Y)))\gamma_C'(z_C)\mathbf{E}[Y_{1i}(z_Y) - Y_{0i}|U_i = P(z_C, z_Y)] \\
\frac{d\mathbf{E}[\pi_i(z_C, z_Y)]}{dz_C} &= -P(z_C, z_Y)\mathbf{E}[V_{\gamma i}|U_i < P(z_C, z_Y)]\gamma_C'(z_C) \\
\frac{d\mathbf{E}[\pi_i(z_C, z_Y)]}{dz_Y} &= -P(z_C, z_Y)\mathbf{E}[V_{\gamma i}|U_i < P(z_C, z_Y)]\gamma_Y'(z_Y) \\
\frac{dP(z_C, z_Y)}{dz_C} &= f_V(F_V^{-1}(P(z_C, z_Y)))\gamma_C'(z_C) \\
\frac{dP(z_C, z_Y)}{dz_Y} &= f_V(F_V^{-1}(P(z_C, z_Y)))\gamma_Y'(z_Y)
\end{aligned}$$

Some algebra then yields the desired result. □

Proof of Equation 9. Calculating the derivative of $\text{TOT}(u; z_Y)$ yields

$$\frac{d\text{TOT}(u; z_Y)}{dz_Y} = \mathbf{E}[V_{\gamma i}|U_i < u]\gamma_Y'(z_Y)$$

Some algebra, and results from the proof of Equation 3 and 4, yields the desired result. □

Proof of Equation 12. Calculating each derivative,

$$\begin{aligned}
\frac{d\mathbf{E}[Y_i(z_C, z_Y)]}{dz_Y} = \big(&f_V(F_V^{-1}(P(z_C, z_Y)))\mathbf{E}[Y_{1i}(z_Y) - Y_{0i}|U_i = P(z_C, z_Y)] + \\
&P(z_C, z_Y)\mathbf{E}[V_{\gamma i}|U_i < P(z_C, z_Y)]\big)\,\gamma_Y'(z_Y)
\end{aligned}$$

Some algebra, and results from the proof of Equation 3 and 4, yields the desired result. □

Proof of Equation 20. First note that $\int \omega_Y(u; z_Y, x)dz_Y = \omega_Y^*(u; x)$. Let $\overline{\text{MTE}}(u; x) = \int \text{MTE}(u; z_Y, x)\omega_Y(u; z_Y, x)dz_Y$. Then $\frac{\text{LATE}_Y}{\text{LASE}_Y} = \frac{\int \overline{\text{MTE}}(u;x)\omega_Y^*(u;x)dudx}{\int \text{MSE}(u;x)\omega_Y^*(u;x)dudx}$. Since (Z_{Ci}, Z_{Yi}, X_i) has a smooth density with convex support, $\omega_Y^*(u; x)$ is smooth and has convex support. $\text{MSE}(u; x)$ is always positive by definition. Therefore there exists (u', x') such that

$\frac{\text{LATE}_Y}{\text{LASE}_Y} = \frac{\overline{\text{MTE}}(u';x')}{\text{MSE}(u';x')}$. An application of the mean value theorem yields that there exists z'_Y such that $\frac{\text{LATE}_Y}{\text{LASE}_Y} = \frac{\text{MTE}(u';z'_Y,x')}{\text{MSE}(u';x')} = \epsilon(u';z'_Y,x')$. □

B.2 Weights

B.2.1 LATE and LASE weights

First, a helpful result is the standard one that OLS estimates a weighted average of derivatives of the conditional expectation function; this section closely follows the approach laid out in Heckman & Vytlacil (2005). Let W be an outcome, T be a continuous covariate of interest, and X be a vector of discrete covariate controls; similar results hold if X is continuous. OLS estimates[21]

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

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

The first expression shows that the coefficient on T, controlling for X, estimates a weighted average of derivatives of the conditional expectation function of W 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

[21] An intuitive proof is as follows; let $f_{T|X}(t;x)$ denote the conditional density of T evaluated at $T=t$ given $X=x$. Note that

$$\begin{aligned}
\text{Cov}(W, T-\mathbf{E}[T|X]|X=x) &= && \text{(LIE)}\\
\text{Cov}(\mathbf{E}[W|T,X], T-\mathbf{E}[T|X]|X=x) &= && \text{(Def'n of Cov)}\\
\int \mathbf{E}[W|T=t,X=x](t-\mathbf{E}[T|X=x])f_{T|X}(t;x)dt &= && \text{(Add constant)}\\
\int (\mathbf{E}[W|T=t,X=x]-\mathbf{E}[W|T=-\infty,X=x])(t-\mathbf{E}[T|X=x])f_{T|X}(t;x)dt &= && \text{(FTC)}\\
\int\int_{-\infty}^{t'} \frac{\partial \mathbf{E}[W|T=t',X=x]}{\partial t'} f_{T|X}(t';x)dt'(t-\mathbf{E}[T|X=x])f_{T|X}(t;x)dt &= && \text{(Fubini's Thm)}\\
\int \frac{\partial \mathbf{E}[W|T=t,X=x]}{\partial t}\Pr[T>t|X=x]\mathbf{E}[T-\mathbf{E}[T|X]|T>t,X=x]dt & &&
\end{aligned}$$

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 $X = x$.

We can now apply this to $\beta_C^{IV} = \frac{\text{Cov}(Y_i, Z_{Ci} - \mathbf{E}[Z_{Ci}|Z_{Yi}, X_i])}{\text{Cov}(D_i, Z_{Ci} - \mathbf{E}[Z_{Ci}|Z_{Yi}, X_i])} = \text{LATE}_C$. 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 $\frac{\partial \overline{Y}(z_C, z_Y; x)}{\partial z_C} = \frac{\partial P(z_C, z_Y; x)}{\partial z_C}\text{MTE}(P(z_C, z_Y; x); z_Y, x)$. Once again, I express weights as if control variables are discrete, but similar results apply when they are continuous. Applying these results yields

$$\begin{aligned}
\text{LATE}_C &= \int \text{MTE}(u; z_Y, x)\omega_C(u; z_Y, x)du dz_Y dx \\
\omega_C(u; z_Y, x) &= (\Pr[P(Z_{Ci}, Z_{Yi}; X_i) > u, Z_{Yi} = z_Y, X_i = x] \cdot \\
&\quad \mathbf{E}[Z_{Ci} - \mathbf{E}[Z_{Ci}|Z_{Yi}, X_i]|P(Z_{Ci}, Z_{Yi}; X_i) > u, Z_{Yi} = z_Y, X_i = x]) \,/ \\
&\quad \Bigg(\int\int\int \Pr[P(Z_{Ci}, Z_{Yi}; X_i) > u', Z_{Yi} = z_Y', X_i = x'] \cdot \\
&\quad \mathbf{E}[Z_{Ci} - \mathbf{E}[Z_{Ci}|Z_{Yi}, X_i]|P(Z_{Ci}, Z_{Yi}; X_i) > u', Z_{Yi} = z_Y', X_i = x'] du' dz_Y' dx'\Bigg)
\end{aligned}$$

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 $P(Z_{Ci}, Z_{Yi}; X_i)$. Again, for interpretation it is helpful to integrate over u to estimate the weight placed on observations with $(Z_{Yi}, X_i) = (z_Y, x)$. When P is linear in z_C conditional on $(Z_{Yi}, X_i) = (z_Y, x)$, so the propensity score is in effect correctly specified, we can derive

$$\int \omega_C(u; z_Y, x)du = \frac{\text{Var}(P(Z_{Ci}, Z_{Yi}; X_i)|Z_{Yi} = z_Y, X_i = x)\Pr[Z_{Yi} = z_Y, X_i = x]}{\int\int \text{Var}(P(Z_{Ci}, Z_{Yi}; X_i)|Z_{Yi} = z_Y', X_i = x')\Pr[Z_{Yi} = z_Y', X_i = x']dz_Y' dx'}$$

The most weight is placed on values of (Z_{Yi}, 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 Z_{Yi} as an instrument, $\beta_Y^{IV} = \frac{\text{Cov}(Y_i, Z_{Yi} - \mathbf{E}[Z_{Yi}|Z_{Ci}, X_i])}{\text{Cov}(D_i, Z_{Yi} - \mathbf{E}[Z_{Yi}|Z_{Ci}, X_i])} = \text{LASE}_Y + \text{LATE}_Y$. 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 $\frac{\partial \mathbf{E}[Y_i(z_C,z_Y;x)]}{\partial z_Y} = \frac{\partial P(z_C,z_Y;x)}{\partial z_Y}(\text{MSE}(P(z_C,z_Y;x);x) + \text{MTE}(P(z_C,z_Y;x);z_Y,x))$. It will also be necessary to define implicitly $\check{Z}_C(u;z_Y,x)$ by $u = P(\check{Z}_C(u;z_Y,x),z_Y;x)$; $\check{Z}_C$ inverts the propensity score to recover the value of z_C that will set the propensity score equal to u given $(Z_{Yi},X_i) = (z_Y,x)$. Then,

$$
\begin{aligned}
\text{LATE}_Y &= \int \text{MTE}_Y(u;z_Y,x)\omega_Y(u;z_Y,x)du dz_Y dx \\
\omega_Y(u;z_Y,x) &= \Bigg(\frac{\partial P(\check{Z}_C(u;z_Y,x),z_Y;x)/\partial z_Y}{\partial P(\check{Z}_C(u;z_Y,x),z_Y;x)/\partial z_C}\cdot \\
&\quad \Pr[Z_{Yi} > z_Y, P(Z_{Ci},Z_{Yi};X_i) = u, X_i = x]\cdot \\
&\quad \mathbf{E}[Z_{Yi} - \mathbf{E}[Z_{Yi}|Z_{Ci},X_i]|Z_{Yi} > z_Y, P(Z_{Ci},Z_{Yi};X_i) = u, X_i = x]\Bigg) / \\
&\quad \Bigg(\int\int\int \frac{\partial P(\check{Z}_C(u';z'_Y,x'),z'_Y;x')/\partial z_Y}{\partial P(\check{Z}_C(u';z'_Y,x'),z'_Y;x')/\partial z_C}\cdot \\
&\quad \Pr[Z_{Yi} > z'_Y, P(Z_{Ci},Z_{Yi};X_i) = u', X_i = x']\cdot \\
&\quad \mathbf{E}[Z_{Yi} - \mathbf{E}[Z_{Yi}|Z_{Ci},X_i]|Z_{Yi} > z'_Y, P(Z_{Ci},Z_{Yi};X_i) = u', X_i = x']du' dz'_Y dx'\Bigg) \\
\text{LASE}_Y &= \int \text{MSE}(u;x)\omega^*_Y(u;x)du dx \\
\omega^*_Y(u;x) &= (\Pr[P(Z_{ci},Z_{Yi};X_i) \geq u, X_i = x]\cdot \\
&\quad \mathbf{E}[Z_{Yi} - \mathbf{E}[Z_{Yi}|Z_{Ci},X_i]|P(Z_{ci},Z_{Yi};X_i) \geq u, X_i = x]) / \\
&\quad \Bigg(\int\int \Pr[P(Z_{ci},Z_{Yi};X_i) \geq u, X_i = x]\cdot \\
&\quad \mathbf{E}[Z_{Yi} - \mathbf{E}[Z_{Yi}|Z_{Ci},X_i]|P(Z_{ci},Z_{Yi};X_i) \geq u', X_i = x']du' dx'\Bigg)
\end{aligned}
$$

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

Finally, these expressions are all functions of $P(z_C,z_Y;x)$ and the joint distribution of (Z_{Ci},Z_{Yi},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 $P(Z_{Ci},Z_{Yi};X_i)$.

B.2.2 Efficient reweighting

Let $\omega_{Y,s} = \int \omega_Y(u; z_Y, (x,s))du dz_Y dx$ and $\omega_{C,s} = \int \omega_C(u; z_Y, (x,s))du dz_Y dx$. Given this, for $\beta_C^{WIV}(w_C)$ and $\beta_Y^{WIV}(w_Y)$ to place the same weight on observations with $S_i = s$, it must be the case that

$$w_C(s)\omega_{C,s} = w_Y(s)\omega_{Y,s}$$

Under the simplifying assumptions, the weights simplify to

$$\omega_{Y,s} = \frac{\text{Var}(Z_{Yi} - \mathbf{E}[Z_{Yi}|Z_{Ci},(X_i,S_i)]|S_i = s)\Pr[S_i = s]}{\text{Var}(Z_{Yi} - \mathbf{E}[Z_{Yi}|Z_{Ci},(X_i,S_i)])}$$
$$\omega_{C,s} = \frac{\text{Var}(Z_{Ci} - \mathbf{E}[Z_{Ci}|Z_{Yi},(X_i,S_i)]|S_i = s)\Pr[S_i = s]}{\text{Var}(Z_{Ci} - \mathbf{E}[Z_{Ci}|Z_{Yi},(X_i,S_i)])}$$

I now solve

$$w = \arg\min_m \text{Var}\left[\hat{\beta}_Y^{WIV}(w_Y) - \hat{\beta}_C^{WIV}(w_C)\right]$$
$$\text{s.t. } w_C(s)\omega_{C,s} = w_Y(s)\omega_{Y,s}$$

Define $g_C \equiv \frac{\text{Cov}(D_i, Z_{Ci} - \mathbf{E}[Z_{Ci}|Z_{Yi},X_i])}{\text{Var}(Z_{Ci} - \mathbf{E}[Z_{Ci}|Z_{Yi},X_i])}$ and $g_Y \equiv \frac{\text{Cov}(D_i, Z_{Yi} - \mathbf{E}[Z_{Yi}|Z_{Ci},X_i])}{\text{Var}(Z_{Yi} - \mathbf{E}[Z_{Yi}|Z_{Ci},X_i])}$; that g_C and g_Y are constants follows from the assumption that $P(z_C, z_Y; (x,s))$ is linear in (z_C, z_Y). The optimal weights satisfy

$$w_C(s) = \frac{g_Y^2\text{Var}(Z_{Yi} - \mathbf{E}[Z_{Yi}|Z_{Ci},(X_i,S_i)])\omega_{Y,s}}{g_C^2\text{Var}(Z_{Ci} - \mathbf{E}[Z_{Ci}|Z_{Yi},(X_i,S_i)])\omega_{C,s} + g_Y^2\text{Var}(Z_{Yi} - \mathbf{E}[Z_{Yi}|Z_{Ci},(X_i,S_i)])\omega_{Y,s}}$$
$$w_Y(s) = \frac{g_C^2\text{Var}(Z_{Ci} - \mathbf{E}[Z_{Ci}|Z_{Yi},(X_i,S_i)])\omega_{C,s}}{g_C^2\text{Var}(Z_{Ci} - \mathbf{E}[Z_{Ci}|Z_{Yi},(X_i,S_i)])\omega_{C,s} + g_Y^2\text{Var}(Z_{Yi} - \mathbf{E}[Z_{Yi}|Z_{Ci},(X_i,S_i)])\omega_{Y,s}}$$

To interpret this expression, note that the realized equivalent of $\frac{g_C^2\text{Var}(Z_{Ci}|Z_{Yi},(X_i,S_i))}{g_Y^2\text{Var}(Z_{Yi}|Z_{Ci},(X_i,S_i))}$ 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.2.3 Estimating weights

To estimate weights, I first use the analogy principle to construct an estimator of each weight. Note that the numerator of $\omega_Y^*(u;x)$ can be rewritten as

$$\Pr[P(Z_{Ci}, Z_{Yi}; X_i) \geq u, X_i = x]\mathbf{E}[Z_{Yi} - \mathbf{E}[Z_{Yi}|Z_{Ci}, X_i]|P(Z_{Ci}, Z_{Yi}; X_i) \geq u, X_i = x] = \int \mathbf{1}\{P(Z_{Ci}, Z_{Yi}; X_i) \geq u, X_i = x\}(Z_{Yi} - \mathbf{E}[Z_{Yi}|Z_{Ci}, X_i])di$$

This suggests an estimator of $\omega_Y^*(u;x)$ by the analogy principle. I estimate this numerator using (summed over districts n)

$$\sum_n \mathbf{1}\{P(Z_{Cn}, Z_{Yn}; X_n) \geq u, X_n = x\}(Z_{Yn} - \mathbf{E}[Z_{Yn}|Z_{Cn}, X_n])$$

Next, I specify the following linear models. Partitioning the controls into (X_n, S_n),

$$\mathbf{E}[Z_{Yn}|Z_{Cn}, (X_n, S_n)] = (Z_{Cn} \;\; X_n)\, \delta_{S_n}$$
$$P(Z_{Cn}, Z_{Yn}; (X_n, S_n)) = g_C Z_{Cn} + g_Y Z_{Yn} + X_n \gamma_{S_n}$$

I estimate each of these by OLS. Let $P_n = P(Z_{Cn}, Z_{Yn}; (X_n, S_n))$. Note that $\mathbf{E}[P_n|Z_{Cn}, (X_n, S_n)] = P(Z_{Cn}, \mathbf{E}[Z_{Yn}|Z_{Cn}, (X_n, S_n)]; (X_n, S_n))$ and $P_n - \mathbf{E}[P_n|Z_{Cn}, (X_n, S_n)] = g_Y(Z_{Yn} - \mathbf{E}[Z_{Yn}|Z_{Cn}, (X_n, S_n)])$. With these results, we can simplify the sum above to

$$\frac{1}{g_Y} \sum_n \mathbf{1}\{P_n \geq u, X_n = x, S_n = s\}(P_n - \mathbf{E}[P_n|Z_{Cn}, (X_n, S_n)])$$

Finally, summing over $X_n = x$ and $S_n = s$ and normalizing yields the following estimator of the weights on $P(Z_{Cn}, Z_{Yn}; (X_n, S_n)) = u$

$$\hat{\omega}_Y^*(u) = \frac{\sum_n \mathbf{1}\{P_n \geq u\}(P_n - \mathbf{E}[P_n|Z_{Cn}, (X_n, S_n)])}{\int \sum_n \mathbf{1}\{P_n \geq u'\}(P_n - \mathbf{E}[P_n|Z_{Cn}, (X_n, S_n)])du'}$$

which I approximate by calculating for u at intervals of .001.

B.3 Control function

The control function approach is predicated on the normality assumption

$$\begin{pmatrix} Y_{1i} \\ C_{1i} \\ Y_{0i} \end{pmatrix} \sim N\left(\begin{pmatrix} g_Y Z_{Yi} + X_i'\mu_1 \\ g_C Z_{Ci} + X_i'\mu_C \\ c_0 Z_{Yi} + X_i'\mu_0 \end{pmatrix}, \begin{pmatrix} \Sigma_{11} & \Sigma_{1c} & \Sigma_{10} \\ \Sigma_{1c} & \Sigma_{cc} & \Sigma_{c0} \\ \Sigma_{10} & \Sigma_{c0} & \Sigma_{cc} \end{pmatrix}\right)$$

Under this model,

$$P(z_C, z_Y; x) = \Phi\left(\frac{-x'\mu_V + g_Y z_Y - g_C z_C}{\sigma_V}\right)$$

where Φ is the normal CDF, $\mu_V = -\mu_1 + \mu_C + \mu_0$,[22] 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 z_Y on treatment effects. I do this in the second step, using the identity

$$\mathbf{E}\left[Y_{di}|D_i = d, Z_{Ci} = z_C, Z_{Yi} = z_Y, X_i = x\right] = X_i'\mu_d + c_d z_Y + b_d \lambda_d(P(z_C, z_Y; x))$$

where $c_0 = 0$, $c_1 - c_0 = g_Y$, $b_0 = \frac{\mathrm{Cov}(V_{0i}, V_i|X_i)}{\sigma_V}$, $b_1 = -\frac{\mathrm{Cov}(V_{1i}, V_i|X_i)}{\sigma_V}$, $\lambda_0(u) = \frac{\phi(\Phi^{-1}(u))}{1-u}$, and $\lambda_1(u) = \frac{\phi(\Phi^{-1}(u))}{u}$. I estimate this conditional expectation function by OLS. Note the exclusion restriction that Z_{Ci} 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. Further note the overidentification test from $c_0 = 0$. As in Björklund & Moffitt (1987), the model is also underidentified; I follow them and normalize $\Sigma_{1c} - \Sigma_{0c} = 0$. This normalization does not affect estimates of any reported parameters, including MTE and MSE.

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

B.4 Robustness

B.4.1 A model with exclusion restriction violations

Suppose

$$\begin{aligned} Y_{1i} &= (z_Y L_i)^{1-\alpha} W_i^{\alpha_W} M_i^{\alpha-\alpha_W} + V_{1i} \\ C_{1i} &= z_C p W_i + q M_i + z_C F L_i + V_{Ci} \\ Y_{0i} &= V_{0i} \end{aligned}$$

where z_Y is a productivity shifter, L_i is farmer i's landholdings, W_i is farmer i's water use (chosen to maximize profits conditional on irrigating), M_i is farmer i's other variable input use (chosen to maximize profits conditional on irrigating), z_C is a cost shifter (such as depth to water table), p is the price of water W_i, q is the price of other variable inputs M_i, and F is a fixed cost shifter. Suppose Y_{0i} is already the solution to a profit maximization problem. Profit maximization yields

$$\begin{aligned} Y_{1i} &= \underbrace{\left[(\alpha-\alpha_W)^{\frac{\alpha-\alpha_W}{1-\alpha}} (\alpha_W)^{\frac{\alpha_W}{1-\alpha}} q^{\alpha-\alpha_W} p^{\alpha_W} z_C^{\alpha_W} z_Y L_i\right]}_{\text{profit maximizing revenue}} + V_{1i} \\ C_{1i} &= \underbrace{\alpha\left[(\alpha-\alpha_W)^{\frac{\alpha-\alpha_W}{1-\alpha}} (\alpha_W)^{\frac{\alpha_W}{1-\alpha}} q^{\alpha-\alpha_W} p^{\alpha_W} z_C^{\alpha_W} z_Y L_i\right]}_{\text{profit maximizing costs}=\alpha(\text{profit maximizing revenue})} + z_C F L_i + V_{Ci} \\ Y_{0i} &= V_{0i} \end{aligned}$$

Next, define $V_{\gamma i} = L_i$, $\gamma_Y(z_C, z_Y) = (\alpha-\alpha_W)^{\frac{\alpha-\alpha_W}{1-\alpha}} (\alpha_W)^{\frac{\alpha_W}{1-\alpha}} q^{\alpha-\alpha_W} p^{\alpha_W} z_C^{\alpha_W} z_Y$, and $\gamma_C(z_C, z_Y) = \alpha\gamma_Y(z_C, z_Y) + F z_C$. We can then write this model as

$$\begin{aligned} Y_{1i} &= V_{\gamma i}\gamma_Y(z_C, z_Y) + V_{1i} \\ C_{1i} &= V_{\gamma i}\gamma_C(z_C, z_Y) + V_{Ci} \\ Y_{0i} &= V_{0i} \end{aligned}$$

We can now apply the bias formula for exclusion restriction violations from Section 3.5 to calculate the bias terms. Let $\mathrm{VC}_W \equiv z_C p W_i = \alpha_W(\alpha-\alpha_W)^{\frac{\alpha-\alpha_W}{1-\alpha}} (\alpha_W)^{\frac{\alpha_W}{1-\alpha}} q^{\alpha-\alpha_W} p^{\alpha_W} z_C^{\alpha_W} z_Y$

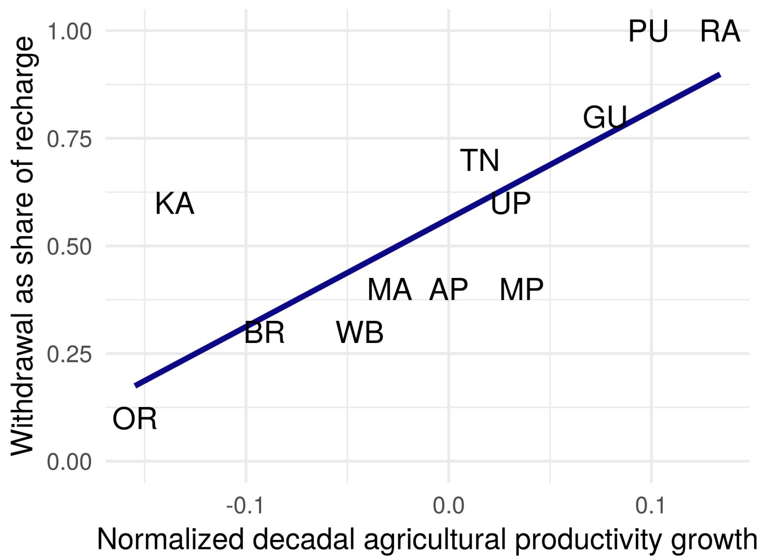
and $\mathrm{FC}_W = F z_C$. Some algebra yields

$$\frac{d\gamma_C(z_C, z_Y)/dz_Y}{d(\gamma_Y(z_C, z_Y) - \gamma_C(z_C, z_Y))/dz_Y} = \frac{\alpha}{1-\alpha}$$
$$\frac{d\gamma_Y(z_C, z_Y)/dz_C}{d(\gamma_Y(z_C, z_Y) - \gamma_C(z_C, z_Y))/dz_C} = \frac{1}{1-\alpha}\frac{\mathrm{VC}_W}{\mathrm{VC}_W - \mathrm{FC}_W}$$

which is the desired result.

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 $R^2 = 0.63$.