Left in the Dust? Pecuniary and Environmental Externalities in Water Markets

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Abstract

The use of markets to reallocate water in arid regions has elicited political criticism for reducing agricultural output and causing negative environmental effects. We develop a general equilibrium model to demonstrate how liberalizing water trade creates pecuniary and environmental externalities and then test the model's predictions using synthetic control and difference-in-differences analysis of the largest ever water transfer in United States. Our results show declines in agricultural employment and increased dust pollution in the water-exporting region. Back-of-the-envelope calculations suggest health costs due to increased PM 10 and PM 2.5 are high, but do not exceed transfer revenues.

Keywords: Trade and Environment; Water; Synthetic Control; Ecosystem Services; Policy Evaluation.
JEL Codes: Q25, Q24, Q15.

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1 Introduction

In the world's arid and semi-arid regions, as much as 80% or more of freshwater consumption occurs in agriculture. Growing urban populations and shifting precipitation patterns under a changing climate provide market incentives to transfer some agricultural water to urban use (Grafton et al., 2012; Hagerty, 2019). Economic analysis consistently suggests that doing so creates large gains from trade (Ayres et al., 2021; Rafey, 2023).

Often overlooked, however, is the local impact of water tranfers to the water exporting region. Historically, opposition to the liberalization of water markets has been strong, focusing on the potential loss of jobs in the originating region (Mann and Wüstemann, 2008; Holcombe and Sobel, 2001). Permanent transfers of water limit future economic development in the area of origin and lead to out-migration, although negative outcomes in exporting regions are more limited when sellers receive substantial benefits and do not sell a large portion of their water (Rosegrant, 1997; Rosegrant and Ringler, 2000). These pecuniary effects, although not typically viewed as relevant to efficient resource allocation, may nonetheless trigger political opposition (Weingast et al., 1981).

Politics matter to the efficiency of economic outcomes when they alter the choices governments make about trade policy (Baldwin, 1989). For instance, the loss of domestic jobs in certain industries creates a constituency for imposing tariffs and reducing the inflow of goods (Rodrik, 1995). While work on these topics traditionally examines trade between countries, similar policies can exist sub-nationally when local jurisdictions regulate trade. In the United States, counties and public water management organizations enact policies to restrict the trade of water to preserve the use of the resource in local agricultural economies (Hanak and Dyckman, 2003; Edwards and Libecap, 2015).

Negative environmental outcomes have also emerged as a key issue in the trade in natural resources (Chichilnisky, 1994; Brander and Taylor, 1998; Copeland and Taylor, 2009). Key case studies in bison and fisheries have pointed to a direct, deleterious effect on renewable resource stocks due to export when foreign markets are opened (Taylor, 2011; Eisenbarth, 2022), although this literature is relatively small (Copeland et al., 2022). For market transfers of water, especially those that move water from one basin to another, negative externalities arise due to reductions in water quality, water availability, and in-stream flows (Howe et al., 1990).

In this study, we examine the pecuniary and environmental externalities of the largest ever agriculture-to-urban water sale in the United States, the transfer of agricultural irrigation water from Imperial County to urban use in San Diego County, California. Our interest in pecuniary effects and complex environmental-economic interactions inform our choice to develop a general equilibrium water trade model to formalize how ecosystem services and labor markets respond to transfers. The model is used to generate testable predictions on agricultural employment, skilled-unskilled wage gap, and ecosystem service outcomes.

We test the model's predictions using reduced form econometric approaches. Synthetic control and difference-in-differences analysis show that the water transfer reduced environmental quality and agricultural jobs, and increased the skilled-unskilled wage gap. Key environmental health externalities occured due to increased particulate concentrations (PM 10 and PM 2.5) linked to dust from the desiccation of the region's large saline lake, the Salton Sea (Heft-Neal et al., 2020; Jones, 2020; Adhvaryu et al., 2019; Griffin and Kellogg, 2004). Similar dust pollution has been caused by drying lakes throughout the world, such as the Aral Sea (Glantz, 1999; O'Hara et al., 2000; Whish-Wilson, 2002), and previously dried lakes, such as those in the Bodélé Depression in Chad (Wurtsbaugh et al., 2017; Heft-Neal et al., 2020). We perform a benefits transfer exercise that estimates these costs; for our preferred method using PM 2.5 estimates, they exceed \$20 million in several years. These costs are smaller than transfer revenues, which exceed \$100 million in later years of the agreement, but the majority of the health costs are borne by groups who do not receive any benefits from the transfer.

In addition to contributing to the literature on water markets and water trade policy, the paper provides key insight into broader issues related to the market induced distribution of environmental quality across populations (see, for instance, Banzhaf et al. (2019); Hernandez-Cortes and Meng (2023)). Climate change will require the reallocation of scarce natural resources like water and smoothly operating markets offer significant efficiency advantages over other means of allocation (Libecap, 2011; Anderson et al., 2019). Our results suggest that the benefits and costs of water transfers are not uniformly spread across the population. Groups with political power can engage in the political process to prevent paying these costs. In contrast, groups without access to the institutional decision making process may bear externality costs that are ignored in market design. Understanding environmental and pecuniary externalities when designing environmental markets is critical. As we will discuss, the Imperial to San Diego transfer demonstrates how water markets can be designed to maintain ecosystem services while allowing trade, but that this is a policy choice that faces opposition when it imposes costs on key constituency groups.

2 Empirical Setting

2.1 The Transfer Agreement

The Colorado River is the largest water source in the southwestern United States. Its waters are divided between seven states, two countries, and tribal nations (Pulwarty et al., 2005). California's allocation of Colorado River water of 4.4 million acre-feet (MAF) was the result of a 1922 agreement that divided 15 MAF of Colorado River water.[1] In the early 2000s, California's ongoing use was in excess of its allocation, around 5.2 MAF, of which 3.1 MAF was for the Imperial Irrigation District (IID).

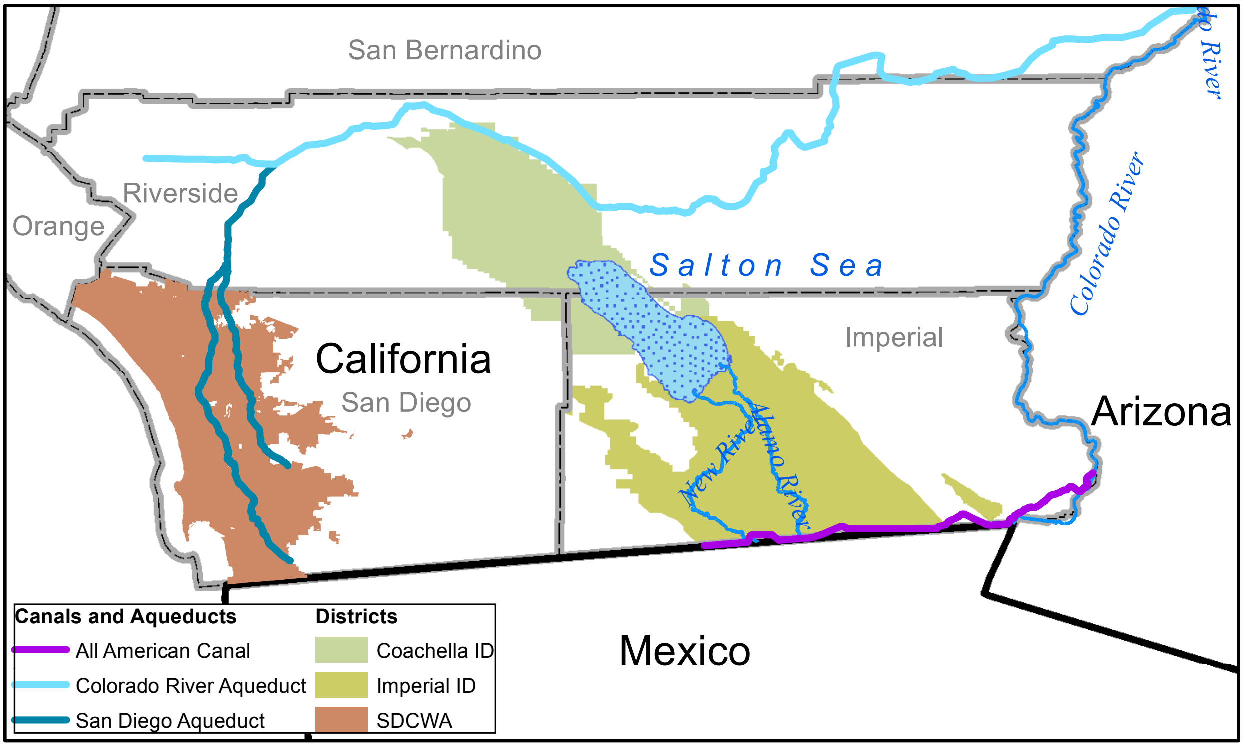
The long-term average annual flow of the Colorado has proven to be less than the 1922 allocation, around 12.4 MAF, meaning IID holds rights to a quarter of the annual flow in an average year. IID is the largest irrigation district in the country and encompasses a bulk of the land area in Imperial County, diverting Colorado River water through the All-American Canal just north of the border with Mexico. The geographic region of study is shown in figure 1. Imperial County is one of the top agricultural producing counties in the United States, with agricultural production and processing estimated to contribute $4.5 billion and 24,429 jobs to the local economy (Ortiz and Dessert, 2017).

In the 1980s and 1990s, California faced pressure to reduce its excess diversions.[2] California and the US federal government pressured IID to transfer water to the San Diego County Water Authority (SDCWA), allowing overall reductions in Colorado River diversions while maintaining water supply to what had become the country's eighth largest city. While initially opposed to transferring water out of the local agricultural economy, IID reached an agreement in 2003, the Quantification Settlement Agreement (QSA), transferring up to 200,000 AF per year of water from

[1] An acre-foot is 326,000 gallons and is enough to supply 1-2 California households with water each year, meaning 4.4 MAF could supply water for up to 22 million people.

[2] This was primarily due to Arizona's new development and use of Colorado River water via the Central Arizona Project.

Figure 1: Map of Study Region.

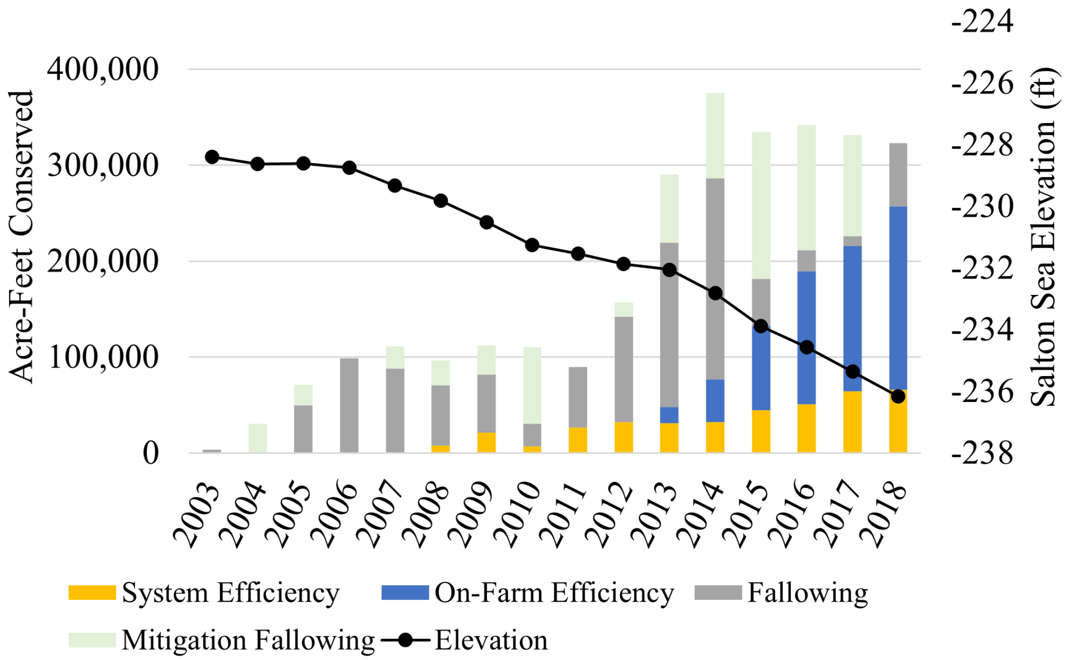


Source: Author created map made using data from the State of California and the US Census Bureau.

Imperial County to San Diego County for 35-70 years; in 2020, the agreement transferred 190,000 AF of water with payments totaling $129 million. The agreement is commonly described as the largest agriculture-to-urban water transfer in the history of the United States (Perry, 2013).

To provide water as stipulated in the QSA, IID began various programs to pay farmers to conserve water. The amount of water generated under these programs is shown in figure 2. While this figure represents our best estimates of actual program implementation, these are accounting estimates, not confirmed water savings (see Wright et al. (2023) for a discussion of how water accounting estimates differ from on-the-ground reductions in water use). The figure shows that from 2004 to 2011 the programs conserved around 100,000 AF of water annually, primarily via fallowing (temporarily removing fields from irrigated production), and then increased the amount of conservation to over 300,000 AF for the period 2014-2018. The mix of programs used to generate water for transfer also shifted between 2012 and 2014 to system efficiency measures (e.g., canal lining projects and canal seepage recovery) and on-farm efficiency measures (e.g., precision irrigation and tailwater reuse). A key policy related to the fallowing program was mitigation fal-

Figure 2: Imperial Irrigation District Water Conservation.



Sources: Imperial Irrigation District (IID) (2018, p.69) and USGS Station 10254005: Salton Sea NR Westmorland CA.

lowing, which sent a portion of conserved water directly to the Salton Sea in an attempt to offset some negative impacts of the fallowing program (described below). Mitigation fallowing water is thus conserved and remains in the local hydrologic system to provide ecosystem services. There was no mitigation program for system or on-farm efficiency programs.

IID has continually opposed fallowing programs because they remove agricultural land from production. Opposition to fallowing programs was strong in IID prior to the agreement and for this reason the 2003 QSA phased out fallowing over time (Perry, 2002). The inclusion of fallowing in the initial stage, from IID's perspective, was to temporarily create water for transfer as other conservation programs were developed. Fallowing can occur the next irrigation season, but programs to install new sprinklers or large canal lining projects can take years to implement.[3]

[3]Whether the fallowed fields themselves change dust pollution levels depends on time of year and the type of crop being replaced. While idled land receives no irrigation water and so may be drier, it also receives less disturbance activity, e.g., tractors (Ayres et al., 2022).

2.2 Ecosystem Services

Soon after its ratification in October 2003, IID began the fallowing program, reducing agricultural production and making water available for transfer. Concerns were raised at the time about the health of the Salton Sea, a large terminal saline lake directly north of the district. The Salton Sea was created by an accidental diversion of a flood on the Colorado River in 1905. Because the lake has extremely limited natural inflow, its continued existence is the result of "return flows" from irrigated agriculture, both surface (tailwater) and underground (drainage water). Around 85% of the inflow to the Salton Sea is estimated to come from IID return flows, with around one-third (0.963 MAF) of IID's total diversions eventually ending up in the lake (Jones et al., 2022).

Under the initial fallowing program, for every three units of land fallowed, water from two units went to San Diego and one went directly to the Salton Sea (Cohen, 2014). The goal of this program was for all reductions in water use to come from the agricultural sector, reducing crop acreage, but not Salton Sea inflows. In contrast to fallowing, conservation via system efficiency and on-farm efficiency included no controls to retain some portion of transferred water for the Salton Sea.[4] Consensus has emerged that the result of the transfers was a decline in inflows to the Salton Sea:

> *"The Salton Sea is shrinking primarily because regional water policy—indirectly—is providing it a significantly smaller share of water from the Colorado River [...] To generate the water for transfer and sale, Imperial Irrigation District engaged in several activities to reduce the amount of water used for irrigation, including the fallowing of agricultural lands in the Imperial Valley early in the program, to be followed up later by improved irrigation efficiency. Both water-saving approaches conveyed the known side effect of drastically reducing inflows to the Salton Sea."* (Fogel et al., 2021, p.22)

Preserving the Salton Sea provides important ecosystems services, especially the prevention of dust pollution. As flows into the lake decreased, additional dry lakebed (playa) was exposed, providing a new potential source of local dust pollution. In Imperial County, airborne dust has been linked via chemical markers to Salton Sea playa (Frie et al., 2017, 2019). Like the Salton Sea,

[4] Hydro-economic modeling has shown fallowing programs generally result in more inflow to the Salton Sea than direct lease programs that generate conservation (Levers et al., 2019).

other terminal lakes have seen changes in agricultural diversions reduce water inflows, leading to dust pollution, including the Aral Sea, Lake Urmia, Owens Lake, and the Great Salt Lake (Wurtsbaugh et al., 2017). Prior to an investment in dust mitigation of over $2 billion dollars by the City of Los Angeles, Owens Lake — dried due to the full diversion of Owens River — was the largest source PM 10 in the United States (Kittle, 2000).

Dust pollution affects human health through the increase in airborne particulate concentrations (Griffin and Kellogg, 2004). For instance, atmospheric PM 2.5 due to dust storms has been shown to decrease birth weight and increase infant mortality (Jones, 2020; Heft-Neal et al., 2020). In the Salton Sea, decreases in lake elevation induced changes in PM 2.5 during the period 1998-2014, which led to serious health issues in the region (Fogel et al., 2021), including increases in respiratory mortality (Jones and Fleck, 2020). The future impact of this dust is also expected to impose significant health costs (Ayres et al., 2022; Jones et al., 2022). No previous study has causally linked dust pollution to the IID-San Diego water transfer or estimated the magnitude of the effect.

3 Economic Framework

In this section, we formalize our intuition about the behavior of the economy of Imperial County and its relationship to water using a general equilibrium model. While externality problems are often modeled in a partial equilibrium framework, our modelling approach allows us to address questions about the pecuniary externalities associated with water transfers. We derive predictions about ecosystem service production, labor outcomes, and the skilled-unskilled wage gap. After developing a general model, we adapt our approach to institutional specifics, in particular two policy scenarios implemented in Imperial County: a *fallow-transfer* program that was in place from 2003 to 2014 and an *unrestricted-transfer* program that started around 2012 and continues today.

We define the regional economy as three sectors: agriculture (A), manufacturing (M), and ecosystem services (E). We assume water availability, W, follows the equation of motion:

$$\frac{dW}{dt} \equiv \dot{W} = \bar{\sigma} - \zeta W - W_A - W_M - W_T \tag{1}$$

where $\bar{\sigma}$ is water inflow; ζW is water outflow (assumed a constant function of the amount of water); W_A and W_M are the amount of water used in the agricultural and manufacturing sectors, respectively; and W_T is the amount of water transferred.

The agricultural sector produces output using land, skilled labor, unskilled labor, and water, while the manufacturing sector uses skilled labor and water. The ecosystem service sector only uses unskilled labor and water that remains in the system.[5] Production technologies are represented by the following production functions:

$$Q_A = Q_A(L_A, S_A, U_A, W_A) \tag{2}$$

$$Q_M = Q_M(S_M, W_M) \tag{3}$$

$$Q_E = U_E W \tag{4}$$

where Q_j, S_j, U_j, and W_j are production quantity, skilled labor employed, unskilled labor employed, and water usage, respectively, in sector $j = A, E, M$, and L_A is land usage by agriculture. All the usual neoclassical assumptions are maintained for production functions in (2) and (3).[6] We assume the exporting region is small relative to the world economy and faces competitive markets. The full model and results are provided in appendix A; here we provide our results and general intuition. We first derive results for the exporting region relating water stock (W) to factor prices and levels of production.

Proposition 1. *Water price (skilled labor wage) is decreasing (increasing) in the steady-state level of water in the system if agriculture is more water intensive than manufacturing. Land price and the unskilled labor wage are increasing in the steady-state water level regardless of water intensity rankings.*

Land, unskilled labor wages, and skilled labor wages (provided agriculture is more water intensive than manufacturing) are increasing in W. This proposition, while somewhat intuitive, immediately demonstrates the pecuniary effect that occurs with a water transfer. While labor is a substitute for water in production due to our neoclassical assumptions, there are many moving pieces and the overall reduction in water still reduces labor demand.

[5] This model can be modified to include capital as another specific factor. However, our objective is to focus on water, land, and labor markets. This aside, such a modification has no bearing on our analysis and does not add much to the theoretical foundation that this section provides.

[6] The specific production function for ecosystem service sector is commonly used for resource sectors (see Schaefer, 1957; Brander and Taylor, 1998).

By comparing the wages of skilled and unskilled labor under a transfer we arrive at our second proposition which highlights the impact of water stock on inequality. Such an impact crucially depends on water elasticity of the skilled wage, denoted by ξ_S.

Proposition 2. *Assuming that agriculture is water intensive, the skilled-unskilled wage gap is decreasing in the steady state level of water if the skilled wage is water inelastic (i.e., $\xi_S < 1$).*

Proportional changes in skilled wages as a result of an increase in the steady state level of water will fall short of those of unskilled wages when $\xi_S < 1$. It can be shown that $\xi_S < 1$ if the distributive share of skilled labor in agriculture is sufficiently high. This condition is likely to be met in our empirical setting. To see why this may to be true, note that skilled laborers in agriculture must include agricultural engineers, farm managers, and farm owners whose share of income is likely to be high enough to meet this condition.

Next, we derive a proposition showing the relationship between water in the system and production:

Proposition 3. *Both agricultural and ecosystem production levels are increasing in the steady state level of water in the system. While the impact on manufacturing output is generally ambiguous, it is increasing in steady state level of water if the share of skilled labor employment in agriculture is sufficiently small.*

Finally, we can use these earlier propositions to demonstrate that total water use in the local economy declines after transfer (this is somewhat convoluted to prove mathematically, see appendix A).

Proposition 4. *A reduction in the steady state level of water in the system reduces the consumptive level of water.*

The remainder of the paper is focused on empirically testing these propositions, which requires more discussion of the relationship between key institutional details of transfer policy and the modeling framework. Under the fallow-transfer policy, land is fallowed and conserved water is exported, less some amount to leave the overall system water unchanged. Under the unrestricted-transfer policy, the transfer is allowed to decrease the amount of system water. We discuss how each program works and its testable implications in turn.

Fallow-Transfer. By design, this program sets the change in water in the system to zero. It follows from the preceding results that factor prices do not change. Because employment of skilled and unskilled labor in agriculture falls, and wages do not adjust, unskilled workers who lose their jobs in agriculture must join the pool of unemployed, while skilled workers move to manufacturing.[7] All in all, the consequences in factor markets would lead to a decrease in agricultural output and an increase in manufacturing output. Unemployment in this rural economy also rises. Since the steady state levels of water and employment in the ecosystem service sector remain unchanged, the sector output also remains unchanged. Hence, an increase in the water trade under the fallow-transfer policy will cause:

- a decrease in agricultural output;
- a decrease in the employment of skilled and unskilled workers;
- a decrease in aggregate income.[8]

Unrestricted-Transfer. Now suppose the water transfer takes place without being tied to the water consumption level in the regional economy. Because the steady-state level of water declines, it follows that factor prices for land, and skilled and unskilled labor fall while the factor price of water increases.[9] From these results, we make the following predictions for an unrestricted transfer:

- an increase in water value;
- a decrease in employment of skilled and unskilled workers;
- an increase in wage inequality;
- a decrease in agricultural and ecosystem service output.

As is typically the case, our empirical setting is not a perfect match for our stylized theoretical predictions. Generally, the first 10 years of the transfer program were designed similarly to the fallow-transfer regime, while the period thereafter was unrestricted. There are, however,

[7]We do not differentiate between unemployment or out-migration, which is not explicitly modelled but would serve a similar purpose mathematically in the model.

[8]Note that this decrease in income does not include income from the water transfer itself which could offset income losses.

[9]This result follows from propositions A1-A3 in appendix A.

institutional and practical exceptions.[10] In what follows, we utilize reduced form econometric approaches to test if the realized effects of the transfers are consistent with our economic intuition. We look at two broad categories of effects. First, in regards to pecuniary exernalities, we examine skilled and unskilled agricultural labor, wage inequality, and agricultural production. While both policies will lead to reductions in agricultural production and employment, the unrestricted policy allows factor prices to change, so may be less distortionary. Second, in regards to environmental externalities, we look for increases in dust pollution. Because the unrestricted transfer does not provide any protections for the steady-state water level, it is expected later years of the program will see larger declines in W and greater increases in dust pollution.

4 Empirical Framework

In this section, we describe our empirical strategy to quantify the impact of the QSA on economic and ecological outcomes of Imperial County—the treatment unit. The plausible identification of a treatment effect requires the specification of suitable control units that represent a counterfactual scenario. In our case, all the remaining counties in California—that are not affected by the QSA and that have not experienced water transfers of similar magnitude due to any other policy or agreement—serve as potential controls.

4.1 A Synthetic Control

Standard comparative case study methods, such as difference-in-differences, assume that all available control units are similar to the treatment unit (in terms of observable and unobservable characteristics) in the pre-intervention period, and thus assign an equal weight to all control units in the analysis. In practice, however, it is unlikely that any given control unit can fully match the treatment unit in all or most of its attributes in the pre-intervention period.

The synthetic control method adopted in this study avoids the above limitations by relying upon a data-driven procedure to obtain a suitable counterfactual unit (Abadie and Gardeazabal, 2003; Abadie et al., 2010; Abadie, 2021). A synthetically composed control unit (i.e., synthetic con-

[10] For example, the mitigation fallowing program was not necessarily concurrent with the transfer fallowing program. This meant that there were some decreases in steady state water level in the system even during the fallow-transfer program.

trol) is a weighted average of available control units (i.e., donor units), with weights determined based on how closely the attributes of each control unit approximate those of the treatment unit in the pre-intervention period. After the optimal sets of weights are estimated, a synthetic control unit is constructed using the weighted average of outcomes of control units. The counterfactual outcomes are then recovered by taking the weighted average of outcomes of control units for the post-intervention period, with the treatment effect measured by taking the difference between the predicted (counterfactual) outcome for the synthetic control and the actual outcome.

Similar to Abadie et al. (2010), let Y_{it} be the outcome of interest for county i, for $i = 1, ..., N+1$, in period t, for $t = 1, ..., T_0+1, ..., T$. Suppose the treatment county corresponds to $i = 1$, while the remaining N counties constitute the donor pool. Also, assume that the policy/intervention takes place in period $T_0 + 1$, so that the pre-treatment period covers $1, ..., T_0$ and the post-treatment period encompasses $T_0 + 1, ..., T$. Let Y_{it}^{noQSA} be the outcome of interest for county i at time t if county i is not exposed to the treatment (i.e., QSA) and let Y_{it}^{QSA} be the outcome for county i at time t if county i is exposed to the treatment.

The main requirement placed on a synthetic control unit is that it closely approximates all relevant attributes of the treatment unit in the *pre-treatment period*. Consider an $N \times 1$ vector of weights $\mathbf{W} = (w_2, ..., w_{N+1})'$, with $w_i \geq 0$ and $w_2 + ... + w_{N+1} = 1$. The optimal weights $\mathbf{W}^* = (w_2^*, ..., w_{N+1}^*)'$ are determined by minimizing the overall discrepancy in the attributes of the treatment and a synthetically composed unit (Abadie et al., 2010), given by:

$$||\mathbf{X}_1 - \mathbf{X}_0\mathbf{W}|| = \sqrt{(\mathbf{X}_1 - \mathbf{X}_0\mathbf{W})'\mathbf{V}(\mathbf{X}_1 - \mathbf{X}_0\mathbf{W})} \tag{5}$$

where $\mathbf{X}_1 = (\mathbf{Z}_1', \tilde{Y}_i^{\mathbf{K}_1}, ..., \tilde{Y}_i^{\mathbf{K}_M})'$ is a $(r + M) \times 1$ vector of pre-treatment period attributes of the treatment unit; $\mathbf{X}_0$ is a $(r + M) \times N$ matrix, with the jth column of $(\mathbf{Z}_j', \tilde{Y}_j^{\mathbf{K}_1}, ..., \tilde{Y}_j^{\mathbf{K}_M})'$, of pre-treatment period attributes of the control units; $\mathbf{Z}_i$ is an $r \times 1$ vector of observed explanatory variables of the outcome variable of interest;[11] $\tilde{Y}_i^{\mathbf{K}} = \sum_{t=1}^{T_0} k_t Y_{it}$ is a linear combination of pre-treatment outcomes of which there are M corresponding to M sets of $\mathbf{K}$-type weights, i.e., $\mathbf{K}_1, ..., \mathbf{K}_M$;[12] and $\mathbf{V}$ is a $(r + M) \times (r + M)$ symmetric and positive semidefinite matrix that

[11]See appendix C for the list of covariates considered for each outcome variable.

[12]The M linear combinations of the outcome variable allow for controlling for unobservable common confounders that vary over time (Abadie et al., 2010), which improves upon standard difference-in-differences method that can

weighs the variables in $\mathbf{X}_1$ and $\mathbf{X}_0$ based on their predictive power on the outcome.

The synthetic control unit is constructed using the optimal weights $\mathbf{W}^* = (w_2^*, ..., w_{N+1}^*)'$. The post-intervention values of the synthetically composed outcome can then replace the (unobservable) counterfactual outcome Y_{1t}^{noQSA}, producing the estimator for the treatment effect:

$$\delta_{1t} = Y_{1t}^{QSA} - \sum_{i=2}^{N+1} w_i^* Y_{it} \quad \text{for} \quad t > T_0 \tag{6}$$

To draw inferences on statistical significance of the measured treatment effect, a series of falsification tests need to be conducted (Abadie, 2021). Specifically, the treatment status is systematically assigned to each control unit in the donor pool, which is equivalent to treating control units with a placebo. The test carries out synthetic control analysis to measure the "treatment" (placebo) effect.[13] The estimated treatment effect for the exposed county (δ_{1t}, for $t > T_0$) is considered statistically significant if it is unusually large in magnitude relative to the "treatment" effects estimated for the unexposed counties in the post-treatment period. In contrast, if several unexposed counties can reproduce the effect that is comparable to that of the exposed unit, the treatment effect for the exposed unit is then deemed to be not statistically significant.[14]

To visualize this, we prefer the use of gap plots, which show the pre- and post-divergence of a synthetic control relative to the observed values of the treatment unit. The measured treatment effect is considered statistically significant if the gap plot for the treatment county lies below the gap plots for the placebo units (for a negative treatment effect) *or* above the gap plots for the placebo units (for the positive treatment effect) for *at least* one post-intervention year.[15] We place lower importance on RMSPE tests for reasons discussed in appendix E, but include RMSPE tests in the appendix (see table E2).

control for unobservable confounders that are time-invariant.

[13]In order to ensure that the synthetic control method produces a plausible synthetic control for each control unit in the donor pool, we consider control units for which the method produces, at least, as good a fit as that for a treatment unit in the pre-treatment period. Specifically, in our inferences from falsification tests, we consider control counties with pre-intervention root mean square prediction errors (RMSPEs) that are less than or equal to twice that of a treatment unit (Abadie et al., 2010). This helps us refine our inferences as placebo units with poor pre-intervention fit could increase inference uncertainty in the post-intervention period.

[14]Nonzero values of the placebo effects can be attributed to broader factors (e.g., economic, regional, environmental, etc.) that affect both the treatment and control units. Therefore, the falsification test allows one to distinguish the true treatment effect from other, more common factors.

[15]That is, the measured treatment effect (gap) for the treatment unit does not need to lie above/below the gap plots for the placebo units in the entire post-intervention period for statistical significance.

4.2 Difference-in-Differences

For comparison purposes, we also conduct an event study analysis using a difference-in-differences (DID) framework. We first estimate a standard panel DID specification given by:

$$Y_{it} = \alpha \left(\mathbf{1}[Imperial]_i \times \mathbf{1}[Post\text{-}Intervention]_t \right) + \mathbf{Z}_{it}\boldsymbol{\beta} + \mu_i + \lambda_t + \varepsilon_{it} \tag{7}$$

where Y_{it} is the outcome variable of interest for county i at time t; $\mathbf{1}[Imperial]_i$ is an indicator that equals 1 if county i represents Imperial County and zero otherwise; $\mathbf{1}[Post\text{-}Intervention]_t$ is an indicator variable that equals 1 if year t is in the post-intervention period (i.e., 2004-2018) and zero otherwise; $\mathbf{Z}_{it}$ is a vector of explanatory variables, which is similar to that under synthetic control; μ_i and λ_t are fixed county and year effects, respectively; and ε_{it} is the idiosyncratic error term. The average treatment effect (ATE) is captured by the parameter α. In cases where an outcome variable of interest is continuous in nature (e.g., harvested acres, labor employment, etc.), equation (7) is estimated using a standard panel linear model with two-way fixed effects. While, in cases where an outcome variable is count (e.g., PM 10 days, PM 2.5 days, etc.), we estimate the above equation using a fixed-effects (FE) Poisson regression under the panel generalized linear model framework.[16]

The DID estimation framework relies on several identifying assumptions. First, conditional on observable factors, the trends of an outcome variable in Imperial County and the control counties would be similar in the absence of the QSA (treatment). This is broadly known as the parallel (common) trends assumption. We test the validity of this assumption rigorously by performing event study analysis (Bartik et al., 2019), as discussed in the following section. We complement this analysis by also performing DID estimation using solely control counties that receive a nonzero weight in the synthetic control analysis.[17] The main advantage of a *synthetic-control-informed* DID is the selection of more suitable control counties (i.e., control counties that closely mimic the treatment county in the pre-treatment period) for the DID analysis. Its disadvantage, however, is a

[16]For robustness, we have also estimated count outcome variable models using (i) a standard panel linear model with two-way fixed effects and (ii) a FE negative binomial regression under the panel generalized linear model framework. The results, which are available upon request, were largely unaltered.

[17]The list of control counties that receive a nonzero weight from the synthetic control analysis for each outcome variable is provided in appendix table E1.

(substantial) reduction in the degrees of freedom, which thus entails exercising caution in interpreting the results from this approach.

Second, the water transfer from Imperial County to SDCWA should not affect agricultural and environmental outcomes in other Californian counties. If, for instance, the QSA depressed agricultural employment in Imperial County and, simultaneously, boosted agricultural employment (due to, for instance, migration flows) in control counties, then the measured employment effect could, at best, serve as the upper bound of the true effect. If such agricultural and/or environmental "leakage" effects do exist, they are likely to be most significant in neighboring counties, particularly Riverside and San Diego (see figure 1). As discussed in section 5, we exclude Riverside County from our analysis due to a water transfer and San Diego County does not receive a nonzero weight in any synthetic control analysis (see appendix table E1).

Finally, Bertrand et al. (2004) raise concerns about serial correlation, specifically how failure to account for it can lead to spurious inferences in the DID context, and suggest computing standard errors that are robust to serial correlation. Serial correlation becomes potentially an important issue with long time series. Accordingly, we report standard errors clustered at the county level that are robust to both heteroskedasticity and serial correlation. For FE Poisson regressions, we report cluster-robust standard errors as recommended by Cameron and Trivedi (2009) to control for potential overdispersion.

4.3 Event Study

Implementation of an event study analysis provides an internal validity check on the parallel trends assumption of DID estimation. If the trends of an outcome variable of interest are parallel between Imperial County and the control counties in the pre-intervention period, then such parallel trends were likely to have continued in the post-intervention period, had the policy not been implemented. Event study analysis also allows for the study of the evolution of the treatment effect over time.

The event study is constructed by replacing $\mathbf{1}[Imperial]_i \times \mathbf{1}[Post\text{-}Intervention]_t$ in (7) with a full set of $\mathbf{1}[Imperial]_i \times \mathbf{1}[Year]_t$ interaction terms, for $t = 1, ..., T_0 + 1, ..., T$, as in:

$$Y_{it} = \sum_t \alpha_t \left(\mathbf{1}[Imperial]_i \times \mathbf{1}[Year]_t \right) + \mathbf{Z}_{it}\boldsymbol{\beta} + \mu_i + \lambda_t + \varepsilon_{it} \tag{8}$$

where $\mathbf{1}[Year_t]$ is an indicator that equals 1 in year t and zero otherwise. The parameters of interest are α_t, for $t = 1, ..., T_0 + 1, ..., T$, which quantify the difference in an outcome variable of interest between Imperial County and control counties in year t, relative to the reference year (i.e., 2003). Depending on the nature of an outcome variable, equation (8) is estimated using either a standard panel linear model with two-way fixed effects or a FE Poisson regression under the panel generalized linear model framework. The 95% confidence bounds for the estimates of α_t are obtained using standard errors discussed in section 4.2. Statistical significance is determined if the confidence interval for any year lies entirely above or below zero.

For each outcome variable, we produce two different event studies. In the first event study, we include all the available control counties in the estimation. As noted earlier, this assumes that all control units are similar to the treatment unit in the pre-intervention period, which may not be necessarily true. In the second event study, we limit the control counties to only those that receive nonzero weight in the synthetic control analysis. Although this allows for the selection of more suitable control counties for the analysis, it comes at a cost of reduced sample size.[18]

5 Data

We build a yearly county-level panel on crop production, labor, and ambient air quality. The study variables are described in detail in appendix B. Crop production statistics come from the annual report of USDA's National Agricultural Statistics Service's California Field Office and are available for 1980-2018. From these reports we collect total harvested acreage and alfalfa and hay acreage, as well as several agriculture-related sales variables: cattle value, alfalfa and hay value, lettuce value, melon value, and other vegetable values.[19]

[18] In the interest of space, we present in the main article event studies using only control counties selected by the synthetic control analysis, while the event studies using all available control counties in appendix D. The results are qualitatively similar.

[19] Lettuce and melons are included because these categories are the most valuable specialty crops in Imperial County.

Labor employment and earnings variables are available for 1992-2018 from the Quarterly Workforce Indicators (QWI) of the United States Census Bureau's Longitudinal Employer-Household Dynamics (LEHD) survey. This dataset provides quarterly employment statistics data at the county-NAICS (2- and 3-digit) code level (Abowd and Vilhuber, 2011).[20] We create measures of average employment and earnings for skilled (above high-school education) and unskilled (high school education and below) employees. For agricultural labor data, we focus on the NAICS subsector 111 (*Crop Production*).[21]

Per capita income is obtained from Bureau of Economic Analysis (BEA), as are additional predictors to control for local economic development including farm proprietor's income and employment, wages and salaries, and proprietor's income and employment. Agricultural labor ratios—the ratio of male-to-female labor in the agricultural sector, the ratio of white-to-Hispanic labor in the agricultural sector, and the ratio of low-to-high skill workers in the agricultural sector—are obtained from the LEHD.

Measures of air quality come from the United States Environmental Protection Agency's Air Quality System (AQS). We collect data on air quality index "days" over short-term regulatory criteria for key pollutants: PM 10, PM 2.5, Ozone and NO_2. These represent the number of days the air quality exceeded the current short-term National Ambient Air Quality Standard. In addition to days exceeding the national standards, we collect annual mean PM 2.5 and PM 10 AQS data and supplement it with satellite PM 2.5 data from van Donkelaar et al. (2021). The data period for each pollutant reflects the data availability.

Our donor (control unit) pool is composed of the remaining counties in California. To avoid potential confounding effects, we exclude from our donor pool four California counties: Yuba, Stanislaus, San Joaquin, and Riverside. These counties engaged in sizable water transfers over the course of the study period.[22,23] Depending on the specification as well as outcome variable

[20]This is the best estimate of employment available at this spatial and industry scale, but the extent to which it is able to fully capture the important role of undocumented workers in California's economy, especially for agricultural labor, is not clear (see, for instance, Borjas, 2017).

[21]In appendix D (figures D13 and D14 and table D8), we also provide analysis for NAICS sector 11 (*Agriculture, Forestry, Fishing and Hunting*). The main results remain unaffected, though the magnitude of the treatment effects are somewhat elevated.

[22]For a comprehensive review of water transfers in California, see Hanak and Stryjewski (2012), particularly the study's technical appendix.

[23]While San Diego County, the buyer of Imperial County water, is included in the potential donor pool, it never receives positive weight. See appendix table E1.

examined, there is also a loss of a few control counties due to missing observations, as detailed under table and figure notes. Unlike the difference-in-differences method, the synthetic control approach requires data to be balanced for the construction of a counterfactual outcome. For summary statistics of each outcome variable, as well as the list of controls, see appendix C.

6 Results

6.1 Direct Effects

We begin by examining the effect of the water transfer on harvested acres (logged). Figure 3 shows the gap plot from the synthetic control analysis (left) and the event study (right). Event study diagrams are normalized to be relative to the level in 2003, the first year pre-treatment, with 95% confidence intervals. Harvested acres decline in both figures and for the synthetic control these declines are larger than those of placebo counties in almost all years post-treatment. The pattern in the change in harvested acres roughly corresponds to the timing of water conserved by fallowing shown in figure 2.

Although the event study is only statistically different from zero in one post-treatment year,[24] we rely on a DID approach for the average post-treatment effect. In table 1, we provide results for each outcome variable using (1) the full set of counties and (2) only those counties receiving a nonzero weight in the synthetic control. The results for harvested acres suggest relatively large, but noisy, point estimates. Specification (1) has a point estimate of -0.14. This corresponds to a 13% decrease in acreage (with a 95% CI of -2% to -23%).[25] At the average pre-treatment acreage cropped in Imperial County of around 560,000 acres, the 95% confidence interval for the crop acreage decline is between 11,200 and 129,000 acres. Actual acres fallowed under the various programs ranged from 6,000 to 53,000 between 2004-2018. The crop reductions come primarily from reductions in hay/alfalfa acreage post-2004 (see appendix figure D5), which we would expect as these are lower in value than other crops grown in the region.[26]

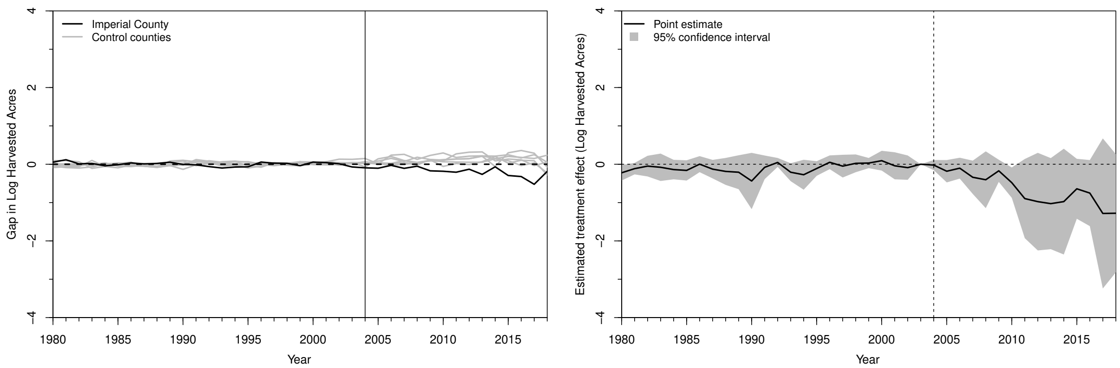
[24]The event study analysis using all available control counties produces multiple post-treatment years with nonzero effects (see figure D2).

[25]We also perform this analysis on harvested acre levels as shown in figures D3 and D4 and table C2.

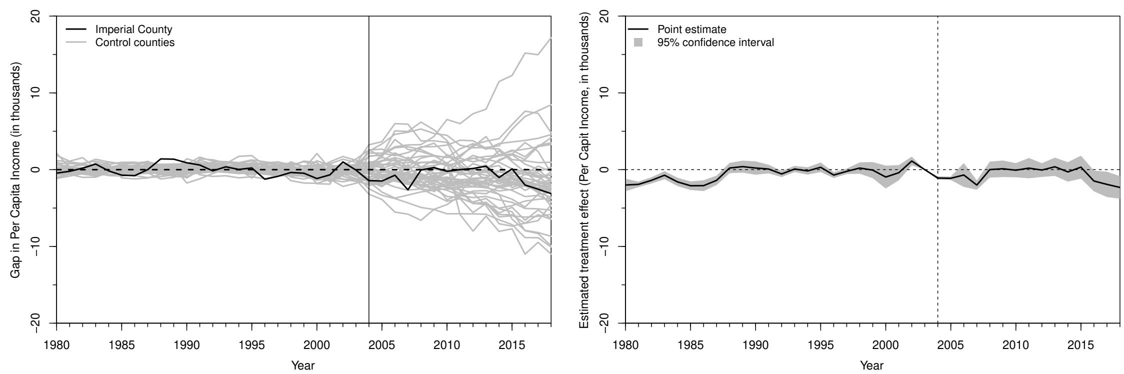
[26]The DID analysis on hay/alfalfa acreage uncovers a statistically significant negative effect of the transfer (see appendix table D4).

Figure 3: Direct Effects.

Panel A: Harvested Acres



Panel B: Per Capita Income



Notes: Panel A shows the graphical summary of synthetic control output (left) and the event study plot using counties that receive nonzero weights in the synthetic control (right) for harvested acres. Full results are shown in appendix figures D1 and D2 and table D2; summary statistics of the variables included in the analysis are in appendix table C1. Panel B shows the graphical summary of synthetic control output (left) and the event study plot using counties that receive nonzero weights in the synthetic control (right) for per capita income. Full results are shown in appendix figures D6 and D7 and table D5; summary statistics of the variables included in the analysis are in appendix table C4. All weights for synthetic controls are shown in appendix table E1 and RMSPE tests are shown in appendix table E2. In the falsification diagram we consider only control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit.

To explore the aggregate income effects of the transfer, we look at the change in per capita income. The synthetic control and event study plots are shown in panel B of figure 3. Changes in per capita income are limited, with small decreases at the beginning and end of the transfer period. The DID estimate in table 1 specification (1) suggests a loss in per capita income, but given the significant pre-trend inherent in including all counties in this regression, we find the null result in (2) more credible (see appendix figure D7).

There are three types of activities generating water for sale in Imperial County: fallowing, system efficiency, and on-farm efficiency. The majority of water sale revenue is spent paying

Table 1: Difference-in-Differences Estimates for Direct Effects.

	Harvested Acres (log)		Per Capita Income	
	(1)	(2)	(1)	(2)
Treatment Effect	-0.1403**	-0.1840	-5.9623***	0.0483
	(0.0621)	(0.1311)	(0.8793)	(0.3862)
Observations	1,555	195	2,106	195
R^2	0.0713	0.2168	0.3728	0.897
F Statistic	11.1777***	3.9308***	170.4042**	180.4013***

Notes: Difference-in-differences results for harvested acres and per capita income using (1) all available control counties and (2) counties that receive nonzero weights in the synthetic control. Appendix tables D2 and D5 provide complete estimation results, including the list of control variables included in the analysis of each outcome variable. Summary statistics of the variables included in the analysis are in appendix tables C1 and C4, respectively. All models control for county and year fixed effects. Harvested acres are measured in thousands of acres; per capita income is measured in thousands of dollars. Robust standard errors in parenthesis: *p<0.1; **p<0.05; ***p<0.01.

farmers to implement these programs. In addition, two other payment streams help offset other costs: environmental mitigation and local entity payments.[27] This result suggests that although agricultural production declines, the payments for the water are returning to Imperial County, limiting the impacts of these transfers on the local economy. In contrast, prior work in other settings has suggested that absentee owners receive a substantial fraction of rents from the change in property rights (Whited, 2010; Sutherland and Edwards, 2022).

6.2 Indirect Effects

6.2.1 Pecuniary Externalities

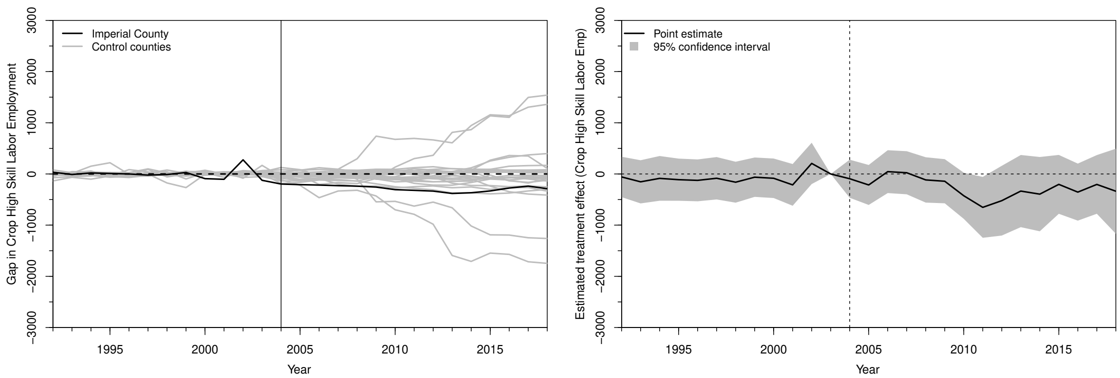
In the remainder of this section, we expore the indirect costs of the transfer. Our predictions suggest losses in crop-sector employment after treatment and an increase in the skilled-unskilled wage gap. These pecuniary externalities occur when wages decline as the agricultural sector becomes less productive as a result of reduced water inputs.

Figure 4 provides synthetic control and event study plots for these wage and employment measures. Employment reductions in both high- and especially low-skill categories are apparent in the synthetic control plots, but less clearly statistically different from zero in the event study

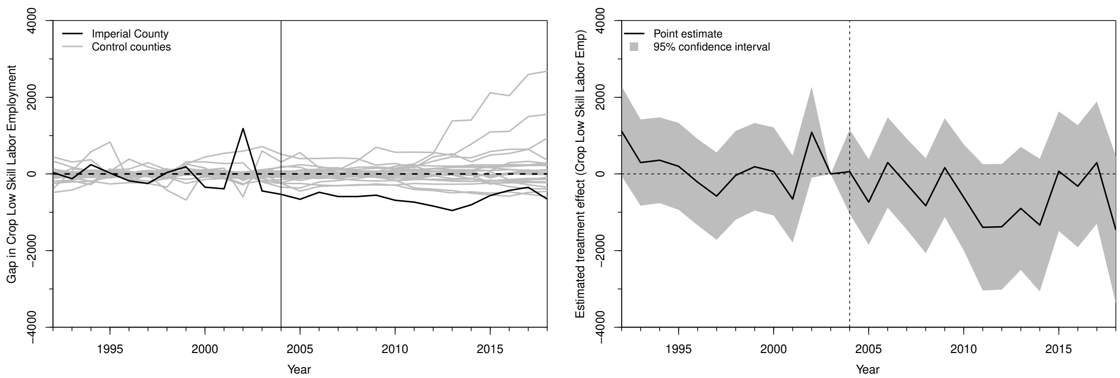
[27]Figure D8 shows the total revenue flowing to IID from SDCWA by category of payment. Environmental mitigation payments go directly to programs to reduce the environmental impacts of the water transfers. Local entity payments are mitigation funding "to farm service providers whose businesses were affected by fields contracted for fallowing by IID in support of the water transfer and mitigation programs" (Imperial Irrigation District Summary of Local Entity: www.iid.com/water/water-conservation/local-entity).

Figure 4: Imperial County Agricultural Labor.

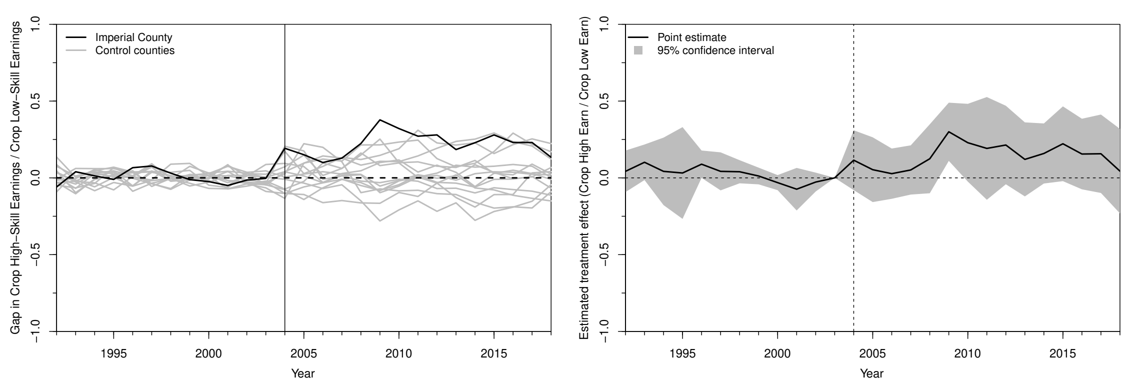
Panel A: High-Skill Labor Employment



Panel B: Low-Skill Labor Employment



Panel C: Wage Inequality



Notes: Panel A shows the graphical summary of synthetic control output (left) and the event study plot using counties that receive nonzero weights in the synthetic control (right) for high-skill labor employment. Full results are shown in appendix figures D9 and D10 and table D6; summary statistics of the variables included in the analysis are in appendix table C5. Panel B shows the graphical summary of synthetic control output (left) and the event study plot using counties that receive nonzero weights in the synthetic control (right) for low-skill labor employment. Full results are shown in appendix figures D11 and D12 and table D7; summary statistics of the variables included in the analysis are in appendix table C6. Panel C shows the graphical summary of synthetic control output (left) and the event study plot using counties that receive nonzero weights in the synthetic control (right) for the skilled-unskilled wage gap. Full results are shown in appendix figures D17 and D18 and table D10 summary statistics of the variables included in the analysis are in appendix table C9. Employment measures are for the crop sector (NAICS=111). All weights for synthetic controls are shown in appendix table E1 and RMSPE tests are shown in appendix table E2. In the falsification diagram we consider only control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit.

Table 2: Difference-in-Differences Estimates for Agricultural Labor.

	High-Skill Labor Employment		Low-Skill Labor Employment		Wage Inequality	
	(1)	(2)	(1)	(2)	(1)	(2)
Treatment Effect	-320.0928***	-67.9849	-438.2687***	-283.5757	0.0468*	0.1057
	(119.5283)	(56.4572)	(139.5125)	(284.9373)	(0.0240)	(0.0829)
Observations	1,008	135	1,029	135	1,350	135
R^2	0.4357	0.9344	0.4268	0.7533	0.0205	0.2514
F Statistic	50.7392***	91.5996***	49.9867***	19.6349***	3.7791***	4.6539***

Notes: Difference-in-differences results for high-skill labor employment, low-skill labor employment, and skilled-unskilled wage gap using (1) all available control counties and (2) counties that receive nonzero weights in the synthetic control. Appendix tables D6, D7, and D10 provide complete estimation results, including the list of control variables included in the analysis of each outcome variable. Summary statistics of the variables included in the analysis are in appendix tables C5, C6, and C9, respectively. All models control for county and year fixed effects. Employment measures are for the crop sector (NAICS=111). Robust standard errors in parenthesis: *p<0.1; **p<0.05; ***p<0.01.

plots, which is attributable to the small sample size when using solely relevant control counties.[28] In panels A and B, apparent increases in employment after 2014 relative to initial declines may indicate that the shift into on-farm and system efficiency reduced the labor impacts that occurred initially under the fallowing program.

The skilled-uskilled wage gap is commonly used as a measure of inequality in trade and development literature (e.g., Oladi and Beladi, 2008). Panel C shows an increase in the skilled-unskilled wage gap, especially the synthetic control plot, which is consistent with water transfers increasing wage inequality. Consistent with our model, water transfers reduce agricultural sector employment, especially for low-skill workers, and depress low-skill wages. Both impacts, although typically excluded from welfare calculations, are likely to disproportionately affect a poor and vulnerable subset of the agricultural labor force. Results of the difference-in-differences analyses in table 2 confirm the sign and, for the analyses including all control counties, the statistical significance of the graphical outcomes. While both specifications (2) are negative, they are not statistically different from zero. Again, this is partly attributable to a significant reduction in the sample size in using only counties that receive nonzero weights in the synthetic control approach.

[28] The event studies using all available control counties show clear, statistically significant post-intervention dips in both high- and low-skill employment in both crop (see appendix figures D10 and D12) and ag (see appendix figures D14 and D16) sectors, with plausible pre-trends.

Table 3: Difference-in-Differences Estimates for Dust-Related Air Quality.

	PM 10 Days		PM 2.5 Days	
	(1)	(2)	(1)	(2)
Treatment Effect	0.6971***	0.9463	1.0241***	0.9757***
	(0.0000)	(2.3664)	(0.0000)	(0.0002)
Observations	1,876	264	1,069	105
Log-likelihood	-10,807.38	-3,095.025	-16,410.72	-900.2285

Notes: Difference-in-differences results for PM 10 and PM 2.5 Days using (1) all available control counties and (2) counties that receive nonzero weights in the synthetic control. Appendix tables D11 and D12 provide complete estimation results, including the list of control variables included in the analysis of each outcome variable. Summary statistics of the variables included in the analysis are in appendix tables C10 and C11. All models control for county and year fixed effects. Robust standard errors in parenthesis: *p<0.1; **p<0.05; ***p<0.01.

6.2.2 Environmental Externalities

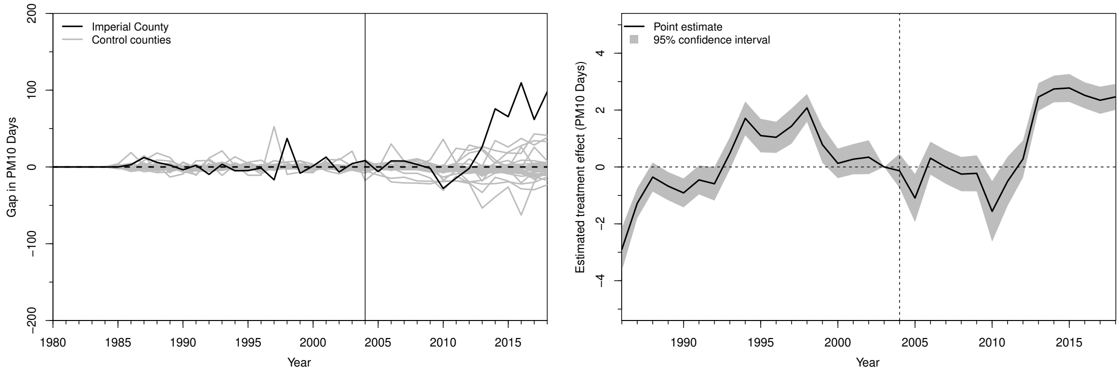
To understand the change in air pollution in Imperial County, we examine dust-related air pollutants PM 10 and PM 2.5. As shown in figure 2, accelerating decreases in Salton Sea elevation occurred starting in 2013 with implementation of on-farm and system efficiency programs. Between 2012 and 2018, exposed lakebed area went from aroun 8,000 acres to 20,911 acres (Formation Environmental, LLC, 2016, 2018). Figure 5 shows one key measure of air pollution, days per year a pollutant is above EPA standards, for PM 2.5 and PM 10. This measure increases dramatically around this same time period when more playa is exposed. The PM 10 gap plot shows that Imperial County has a larger divergence in 2014, and every subsequent year, relative to all other placebo counties. The PM 2.5 gap plot indicates that from 2014 on, Imperial County is among the counties with the largest positive divergence, although it is never the largest.

Difference-in-differences estimates from fixed-effects Poisson regressions are presented in table 3. Treatment effect coefficient estimates vary from 0.7 to 1.0 for PM 10 and are about 1.0 for PM 2.5, implying 2.01 to 2.72 times more days with PM 10 above EPA limits and about 2.72 times as many days above PM 2.5 limits. Given the changes in the timing of air pollution as a result of policy changes, the average treatment effect estimates of these regressions are lower than those from later years displayed in figure 5.[29]

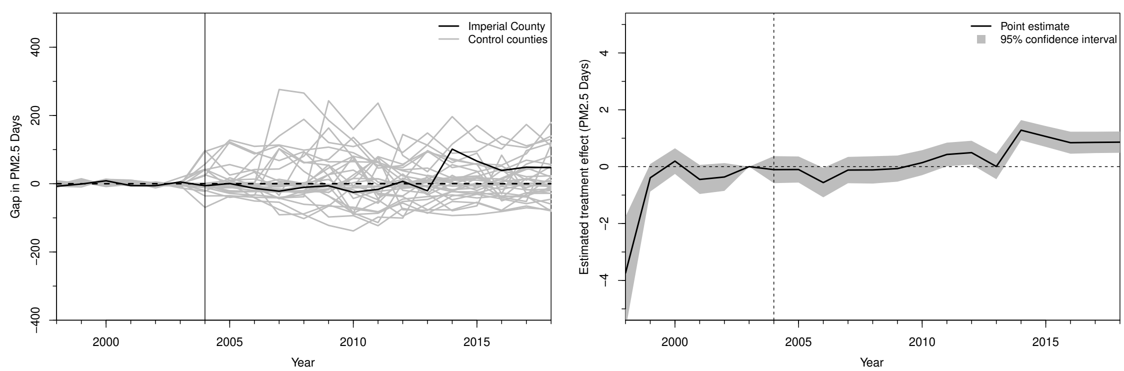
[29] We also perform analysis using EPA's annual mean PM 10 and PM 2.5 concentrations (μg/m^3). See synthetic control plots in appendix figures D27 and D29, event studies in appendix figures D28 and D30, and difference-in-differences results in appendix tables D15 and D16. For PM 2.5, we also examine satellite-based measures from van Donkelaar et al. (2021) on the county mean and max annual values. See synthetic control plots in appendix figures D31 and D33, event studies in appendix figures D32 and D34, and difference-in-differences results in appendix tables D17 and D18.

Figure 5: Imperial County Dust-Related Air Quality.

Panel A: PM 10 Days



Panel B: PM 2.5 Days



Notes: Panel A shows the graphical summary of synthetic control output (left) and the event study plot using counties that receive nonzero weights in the synthetic control (right) for PM 10 Days. Full results are shown in appendix figures D19 and D20 and table D11; summary statistics of the variables included in the analysis are in table C10. Panel B shows the graphical summary of synthetic control output (left) and the event study plot using counties that receive nonzero weights in the synthetic control (right) for PM 2.5 Days. Full results are shown in appendix figures D21 and D22 and table D12; summary statistics of the variables included in the analysis are in appendix table C11. All weights for synthetic controls are shown in appendix table E1 and RMSPE tests are shown in appendix table E2. In the falsification diagram we consider only control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit. Y-axis scales differ within panels.

To test the robustness of these results, we compare the dust-related pollutants to air pollutants attributable to other factors. Because our causal story is that the water transfer exposed additional lakebed playa, pollutants like ozone and NO_2 which are generated primarily through combustion, would not increase. The results in table 4 suggest that the placebo pollutants do not increase like PM 10 and PM 2.5. In fact, ozone and NO_2 days appear to decline. This provides evidence that the observed increases in PM 2.5 and PM 10 are not attributable to increased fossil fuel combustion, for instance as the result of increased economic activity.

Figure 6 shows that for non-dust pollutant days, synthetic control and event study plots see

Table 4: Difference-in-Differences Estimates for Air Quality Placebo Measures.

	Ozone Days		NO_2 Days	
	(1)	(2)	(1)	(2)
Treatment Effect	-0.1497***	0.1023***	-0.1027***	-0.1221
	(0.0000)	(0.0047)	(0.0000)	(0.1345)
Observations	1,276	150	1,276	100
Log-likelihood	-12,753.68	-3,048.978	-8,639.586	-612.4266

Notes: Difference-in-differences results for Ozone and NO_2 Days using (1) all available control counties and (2) counties that receive nonzero weights in the synthetic control. Appendix tables D13 and D14 provide complete estimation results, including the list of control variables included in the analysis of each outcome variable. Summary statistics of the variables included in the analysis are in appendix tables C12 and C13. All models control for county and year fixed effects. Robust standard errors in parenthesis: *p<0.1; **p<0.05; ***p<0.01.

large declines at the same time PM 2.5 and PM 10 increase. NO_2 is a precursor to ozone formation, which occurs through the combination of nitrogen oxides and volatile organic compounds (VOCs). The amount of ozone formed should follow that of the nitrogen oxides when they are the limiting reactant. Under the Clean Air Act, "The EPA designated Imperial County, California, as nonattainment for the 2008 ozone standards on May 21, 2012 (EPA, 2019). Following this designation, Imperial County made progress reducing ozone precursors, both nitrogen oxides and VOCs. From 2011 to 2017, total nitrogen oxide emissions decreased from 23.0 to 15.2 tons per day, primarily from reductions in on-road and off-road vehicle emissions (VOCs dropped from 19.5 to 13.5 tpd) (EPA, 2019, Table 5). These results suggest that absent the increase in dust pollution, PM 10 and PM 2.5 levels would likely have fallen during this time period.

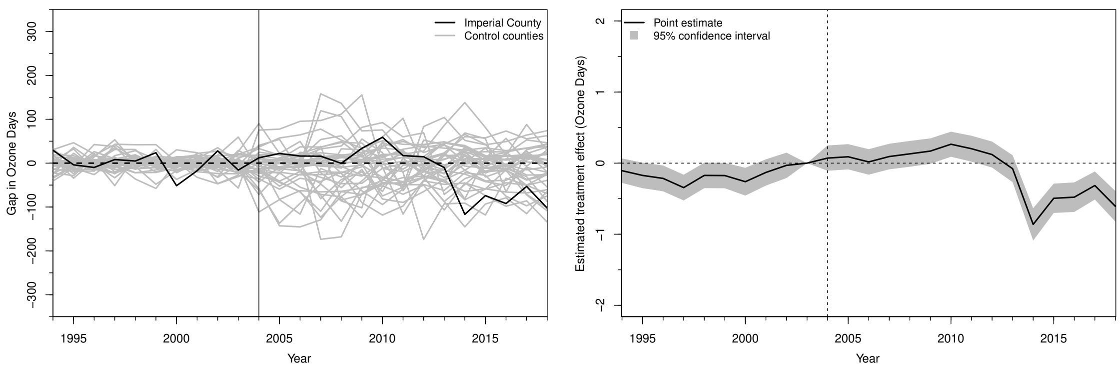
6.2.3 Health Costs

Exposure to particulate pollution causes a variety of adverse health effects, especially related to the heart and lungs. PM 10 are inhalable particles with diameters 10 micrometers and smaller; PM 2.5 are inhalable particles with diameters 2.5 micrometers or less. PM 2.5 particles can make their way deep into the lungs and even bloodstream, and pose the greatest risk to health. Because particles are defined according to their size, PM 10 measurements are inclusive of PM 2.5.

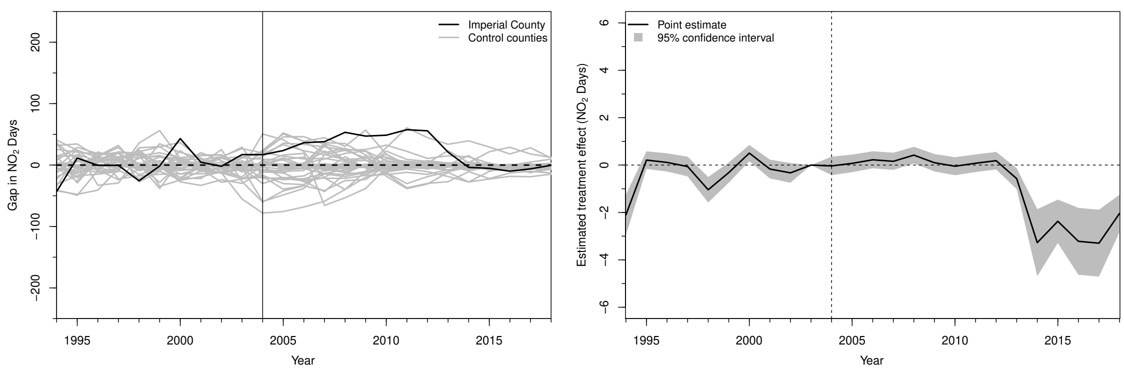
To estimate the health costs of increased particulate pollution, we perform a benefit transfer exercise using damage estimates from additional concentrations of PM 2.5 on elderly mortality from Deryugina et al. (2019) and infant mortality from Chay and Greenstone (2003). Although

Figure 6: Imperial County Air Quality Placebo Measures.

Panel A: Ozone Days



Panel B: NO_2 Days



Notes: Panel A shows the graphical summary of synthetic control output (left) and the event study plot using counties that receive nonzero weights in the synthetic control (right) for Ozone Days. Full results are shown in appendix figures D23 and D24 and table D13; summary statistics of the variables included in the analysis are in appendix table C12. Panel B shows the graphical summary of synthetic control output (left) and the event study plot using counties that receive nonzero weights in the synthetic control (right) for NO_2 Days. Full results are shown in appendix figures D25 and D26 and table D14; summary statistics of the variables included in the analysis are in appendix table C13. All weights for synthetic controls are shown in appendix table E1 and RMSPE tests are shown in appendix table E2. In the falsification diagram we consider only control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit. Y-axis scales differ within panels.

PM 2.5 is the particulate pollutant of primary concern, monitoring data for PM 2.5 in the pre-period is limited to five years. In a separate analysis, we estimate health costs based instead on additional PM 10 concentrations, for which monitoring data are available starting much earlier, using relationships from Jones et al. (2022).[30]

Health estimates are based on changes in the annual mean concentration of particulate matter. Post-treatment annual mean PM 2.5 levels increase 1.6 to 1.9μg/m^3 across the synthetic control

[30]Details of our health cost calculations are provided in appendix F.

and DID estimates, leading annually to 0.71 to 0.82 additional infant deaths, 36-42 lost life years among the elderly, and 32-38 additional ER visits. The total estimated cost of the PM 2.5 increase is between \$6.4 and \$7.5 million annually. Turning to the PM 10 approach, the synthetic control estimated annual mean increase of 15.1μg/m^3 is estimated to increase cardiovascular deaths by 10.6 annually and respiratory ER admissions by 25 visits.[31] Calculation details are documented in appendix table F1.

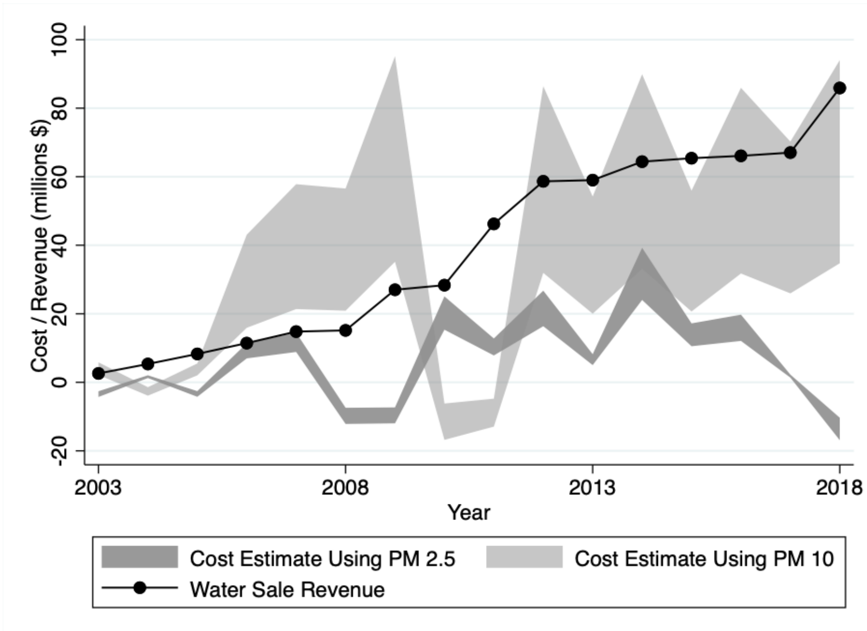
Our synthetic control approach also allows us to examine health cost estimates annually using the annual gap between the synthetic control and observed particulate levels. We use a VSL range of \$1.8-4.9 million to provide an upper and lower bound on this cost as shown in figure 7. The costs using the estimated annual increase in PM 2.5 are consistently lower than those modeled using PM 10. The figure also shows the total annual sale revenue of the water transfer. PM 10 estimates of health costs are of the same magnitude as the sale value. PM 2.5 estimates are less but still exceed \$20 million annually in several years. These costs suggest large externalities associated with the transfer. Because the approach for estimating PM 2.5 costs is more robust, and because PM 2.5 is the primary driver of particle health costs, these cost estimates are preferred.

7 Conclusion

This paper investigates the causal effect of the largest agriculture-to-urban water transfer in US history. A general-equilibrium representation of a regional economy with an ecosystem service sector is constructed to formalize economic intuition about the response of labor markets and ecosystem service provision in the exporting region. The model demonstrates that although water and labor are substitutes, the overall effect of trade is a decrease in production and job losses in the water exporting region. When water transfers lead to the intensification of consumptive water use, the ecosystems services sector is degraded. To test empirically whether these effects occur, we implement synthetic control, difference-in-differences, and event study analyses. Our results suggest an immediate loss of harvested acres, decreases in agricultural-sector employment, and increases in the skilled-unskilled wage gap. We also demonstrate a significant increase in dust-

[31] The DID estimates for PM 10 vary widely depending on what counterfactual counties are used, from a 7.5μg/m^3 decrease for the full sample to a 39.8μg/m^3 increase for the counterfactual sample using only counties with weights in the synthetic control.

Figure 7: Health Costs and Sales Revenue.



related air pollution, especially as more lake bed playa is exposed by transfers without mitigation mandates.

The distribution of the benefits from trade plays a key role in policy choice. While preserving the ecosystem services sector via a fallowing program with mitigation water for the Salton Sea provided broad public good benefits in terms of limiting dust-related air pollution, when this policy ended, a narrow set of benefits accrued to concentrated economic interests, especially farm-related businesses and agricultural labor. Thus, both the magnitude and distribution of these benefits are important factors to understanding the endogenous choice of water trade policy and its outcomes. Levers et al. (2019) suggest the low-cost approach to solving the problems of the Salton Sea is the purchase of additional water rights for environmental flows to preserve ecosystem service benefits. This water would likely come out of agriculture, increasing pecuniary externalities and political opposition.

This same political opposition stalled the original transfer, finally undertaken in the QSA, for over 20 years (Edwards and Libecap, 2015). Growing concerns about high rates of asthma around the Salton Sea and its continued decline suggest dust pollution from the desiccated lakebed will need to be addressed going forward via investment in mitigation or additional dedicated water inflows. Given the limited marginal value of water in irrigated agricultural production relative to urban consumption, addiitonal water transfers out of IID are likely to be initiated (Grafton et al., 2012). The challenge facing these and other water transfers is that environmental and pecuniary costs fall on parties who do not receive the gains from trade. Thus, large benefits accrue to those involved in the transfer while costs fall on those whose local economy is left in the dust.

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Appendix

A A Theory of a Rural-Urban Water Transfer

In this appendix, we develop a model of rural economy that sees a rural-urban water transfer. We start with a baseline general equilibrium model of a rural economy that transfers some of its water resource to an urban region. Then, we extend it to incorporate unemployment of some production factors, followed by policy implications and their empirical relevance.

A.1 Baseline Model

We develop a general equilibrium representation of a regional economy with three sectors: an agricultural sector (A), a manufacturing sector (M), and a water-based ecosystem (tourism) service sector (E). We derive a general set of results showing the changes in the originating rural region as a result of rural-urban water transfer.

Among the three sectors, the agricultural sector is the domain sector with the largest share of labor. Assume the rural water availability, W, follows the equation of motion:

$$\frac{dW}{dt} \equiv \dot{W} = \bar{\sigma} - \zeta W - W_A - W_M - W_T \tag{A1}$$

where $\bar{\sigma}$ is water inflow; ζW is water outflow, which is assumed to be a function of the amount of water with constant outflow rate ζ for simplicity; W_A and W_M are the amount of water used in the agricultural and manufacturing sectors, respectively; and $W_T \geq 0$ is the amount of water transferred.

The agricultural sector produces output using land, skilled labor, unskilled labor, and water, while the manufacturing sector uses skilled labor and water. The ecosystem service sector only uses unskilled labor and water that remains in the system. Production technologies are represented by the following production functions:

$$Q_A = Q_A(L_A, S_A, U_A, W_A) \tag{A2}$$
$$Q_M = Q_M(S_M, W_M) \tag{A3}$$
$$Q_E = U_E W \tag{A4}$$

where Q_j, S_j, U_j, and W_j are production quantity, skilled labor employed, unskilled labor employed, and water usage in sector $j = A, E, M$; respectively and when applicable, and L_A is land usage by agriculture. All the usual neoclassical assumptions are maintained for production functions in (A2) and (A3).

Skilled labor, unskilled labor, and water are assumed to be freely mobile across their respective sectors. We also maintain that all factors are fully employed. We will relax this latter assumption in the next subsection. Full employment implies that:

$$\alpha_{S_A} Q_A + \alpha_{S_M} Q_M = \bar{S} \tag{A5}$$
$$\alpha_{U_A} Q_A + \alpha_{U_E} Q_E = \bar{U} \tag{A6}$$
$$\alpha_{WA} Q_A + \alpha_{WM} Q_M = \bar{W} \tag{A7}$$
$$\alpha_{LA} Q_A = \bar{L} \tag{A8}$$

where $\bar{L}, \bar{S}$, and $\bar{U}$ are land, skilled labor, and unskilled labor amounts in this regional economy, respectively. The amount of water withdrawn from the ecological system for local use is $\bar{W}$. It directly follows from equation (A1) that the steady-state level of water in the system is $W^* = (\bar{\sigma} - \bar{W} - W_T)/\zeta$. Clearly, as expected, $\partial W^*/\partial W_T < 0$. Moreover, here and in the rest of the paper, we denote by α_{ij} the respective per-unit amount of factor $i = L, U, W$ in sector $j = A, M, S$ (e.g., $\alpha_{WA} \equiv W_A/Q_A$ is the water usage per unit of agricultural good). Cost minimization implies that:

$$\alpha_{ij} = C_{ij}(\gamma_L, \gamma_S, \gamma_U, \gamma_W) \tag{A9}$$

where γ_L, γ_S, γ_U, and γ_W are land price, skilled wage, unskilled wage, and water price respectively, for $i = L, S, U, W$ and $j = A, E, M$.

Assuming that all markets are perfectly competitive, the zero-profit conditions imply:

$$\alpha_{LA}\gamma_L + \alpha_{SA}\gamma_S + \alpha_{UA}\gamma_U + \alpha_{WA}\gamma_W = P_A \tag{A10}$$
$$\alpha_{SM}\gamma_S + \alpha_{WM}\gamma_W = P_M \tag{A11}$$
$$\alpha_{UE}\gamma_U = P_E \tag{A12}$$

where P_j denotes the price of good $j = A, E, M$. All good prices are exogenous due to our regional rural economy being small relative to the global economy.

By differentiating equations (A10)-(A12), where $\hat{x} \equiv \frac{dx}{x}$ denotes the proportional change in variable x, we obtain:

$$\theta_{LA}\hat{\gamma}_L + \theta_{SA}\hat{\gamma}_S + \theta_{UA}\hat{\gamma}_U + \theta_{WA}\hat{\gamma}_W = 0 \tag{A13}$$
$$\theta_{SM}\hat{\gamma}_S + \theta_{WM}\hat{\gamma}_W = 0 \tag{A14}$$
$$\hat{\gamma}_U = \hat{W}^* \tag{A15}$$

where θ_{ij} is the factor i's cost share in sector j (e.g., $\theta_{SA} \equiv \frac{\gamma_S \alpha_{SA}}{P_A}$ is cost share of skilled labor in agriculture).[32]

Equation (A15) relates changes in unskilled wage to the changes in the steady state level of water in the system, indicating that a rural-urban water transfer decreases wages for unskilled labor, ceteris paribus. Next, we differentiate $U_E = \alpha_{UE}W^*/\alpha_{WE}$ and manipulate the result to obtain $\hat{U}_E = \hat{\alpha}_{UE} - \hat{\alpha}_{WE} + \hat{W}^*$.[33] Note also that $\hat{\alpha}_{UE} - \hat{\alpha}_{WE} = -\sigma^E\hat{\gamma}_U$, where σ^E is the input elasticity of substitution in sector E, which amounts to unity due to its Cobb-Douglas production function, implying that:

$$\hat{U}_E = -\hat{\gamma}_U + \hat{W}^* = 0 \tag{A16}$$

where the last equality follows from equation (A15). On the one hand, since $\hat{U}_A = -\hat{U}_E$ due to the full employment of unskilled labor (i.e., (A6)), we conclude that $\hat{U}_A = 0$. On the other hand, a proportional change in unskilled labor demand is $\hat{U}_A = -\sigma^A_{UL}(\hat{\gamma}_U - \hat{\gamma}_L)$, where σ^A_{UL} is the substitution elasticity of unskilled labor and land in agriculture.[34] It follows that $\sigma^A_{UL}(\hat{\gamma}_U - \hat{\gamma}_L) = 0$, which implies that:

$$\hat{\gamma}_L = \hat{\gamma}_U \tag{A17}$$

[32]Note that we made use of $\hat{P}_j = 0, j = A, M, S$, due to our small open economy assumption and the fact that at any equilibrium we have $\theta_{LA}\hat{\alpha}_{LA} + \theta_{SA}\hat{\alpha}_{SA} + \theta_{UA}\hat{\alpha}_{UA} + \theta_{WA}\hat{\alpha}_{WA} = 0$ and $\theta_{SM}\hat{\alpha}_{SM} + \theta_{WM}\hat{\alpha}_{WM} = 0$.

[33]Recall that $U_E = \alpha_{UE}Q_E$ and $W^* = \alpha_{WE}Q_E$. Hence, we have $U_E = \alpha_{UE}W^*/\alpha_{WE}$.

[34]Recall that $\alpha_{iA} = i_A/Q_A, i = L, U$. Hence, $U_A = \alpha_{UA}\bar{L}/\alpha_{LA}$, where $L_A = \bar{L}$ due to the full employment of land. Differentiating this results in $\hat{U}_A = \hat{\alpha}_{UA} - \hat{\alpha}_{LA} = -\sigma^A_{UL}(\hat{\gamma}_U - \hat{\gamma}_L)$, where the last equality follows from the definition of elasticity of substitution between unskilled labor and land in agriculture.

That is, following (A15) and (A17), a reduction in steady-state water level reduces the price of land. Finally, substitute equation (A15) and A17 in equation (A11) and solve the system of equations (A13) and (A14) to obtain:

$$\hat{\gamma}_S = \frac{\omega_M(\theta_{LA} + \theta_{UA})}{\theta_{SA}(\omega_A - \omega_M)}\hat{W}^* \tag{A18}$$

$$\hat{\gamma}_W = -\frac{\gamma_S(\theta_{LA} + \theta_{UA})}{\gamma_W\theta_{SA}(\omega_A - \omega_M)}\hat{W}^* \tag{A19}$$

where $\omega_A \equiv W_A/S_A$ and $\omega_M \equiv W_M/S_M$ are water intensity ratios in the agriculture and manufacturing sectors, respectively. It is noteworthy from (A18) and (A19) that $\xi_S \equiv \omega_M(\theta_{LA} + \theta_{UA})/\theta_{SA}(\omega_A - \omega_M)$ and $\xi_W \equiv \gamma_S(\theta_{LA} + \theta_{UA})/\gamma_W\theta_{SA}(\omega_A - \omega_M)$ are water elasticities for skilled wage and water price, respectively. As it is evident from equation (A18)-(A19), the effects of water stock on skilled labor and water price crucially depend on water intensity ranking. We highlight this in the following proposition.

Proposition A1. *Water price (skilled labor wage) is decreasing (increasing) in steady-state level of water in the system if agriculture is more water intensive than manufacturing. Land price and the unskilled labor wage are increasing in steady-state water level regardless of water intensity rankings.*

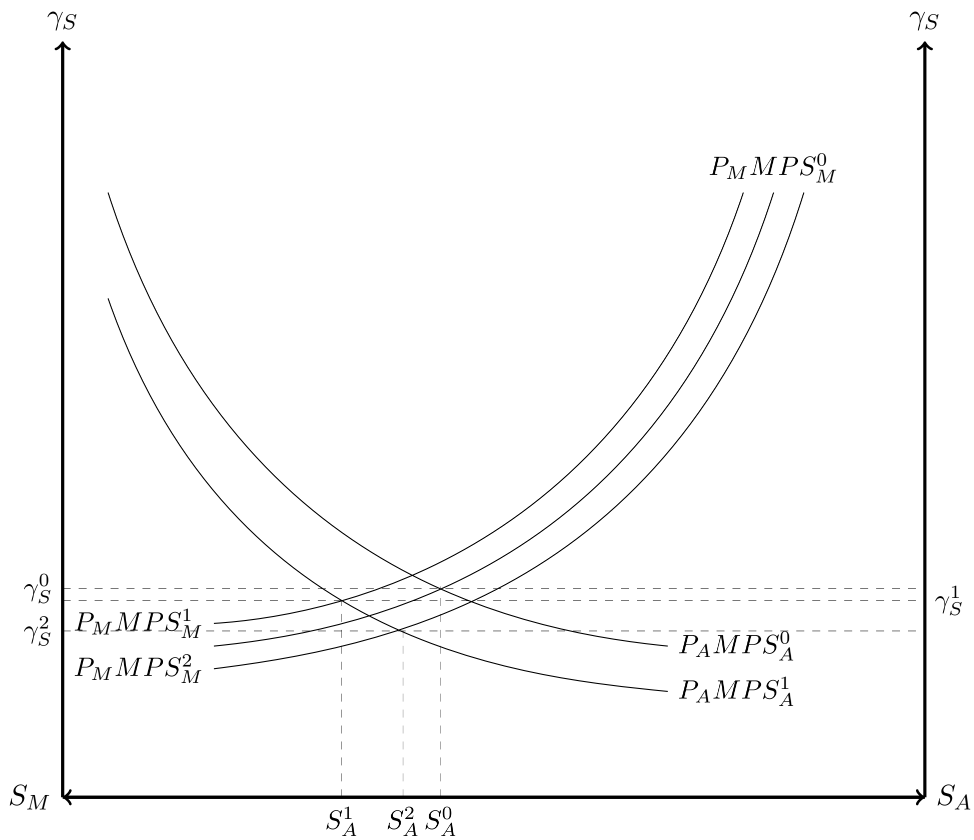
As it is the case for any general equilibrium analysis, there are many moving parts here. To grasp the intuition behind this result, consider a reduction in water stock. This directly reduces the marginal productivity of unskilled labor in the ecosystem service sector. We will show shortly in this appendix that the sectoral supply of unskilled labor does not change, resulting in a reduction in the unskilled wage rate the ecosystem service sector. Also, we will show shortly that water usage in the agricultural sector falls, reducing the marginal productivity of unskilled labor and land in this sector. Since land supply and sectoral supply of unskilled labor remain unchanged (as will be seen shortly), unskilled wages and land price must fall.

The effect on skilled wage is less straightforward, since the sectoral supply of skilled labor changes and water usage in agriculture and manufacturing may change differently. As we shall show shortly, water usage in agriculture falls unambiguously if the steady state level of water in the system falls. This will shift down the marginal productivity of skilled labor as well as its demand (i.e., $P_A MPS_A \equiv P_A\partial Q_A/\partial S_A$). In contrast, water usage in manufacturing may fall or rise. Hence, skilled labor demand in manufacturing may shift up or down. We depict two scenarios in Figure A1, where $P_M MPS_M^1$ denotes the skilled labor demand by manufacturing if its water usage goes up, while $P_M MPS_M^2$ denotes the skilled labor demand by this sector if its water usage falls as a result of a reduction in the steady state water level in the system. Note the width of the box measures the endowment of skilled labor and that skilled labor employment in agriculture (manufacturing) is measured from left to right (right to left). Under both scenarios skilled wages fall and skilled labor employment in manufacturing (agriculture) rises (falls). Despite the substitutablity of labor for water in the agricultural sector, both water usage and skilled labor employment fall in this sector. Because the water to skilled labor ratio must fall due to an increase in the land price to skilled wage ratio (i.e., γ_W/γ_S), the percentage decrease in water usage must be more than that of skilled labor employment.

We have established that a reduction in water lowers both skilled and unskilled wages, given that agriculture is water intensive. It is interesting to explore the effects of steady state level of water on the skilled-unskilled wage gap. Using equations (A18) and (A19), we obtain:

$$\hat{\gamma}_S - \hat{\gamma}_U = (\xi_S - 1)\hat{W}^* \tag{A20}$$

Figure A1: The effects of a reduction in the steady state water level in the system on skilled labor market.



where ξ_S is the water elasticity of skilled wages, as defined previously. The following results formally address the effects of water on wage inequality.

Proposition A2. *Assuming that agriculture is water intensive, the skilled-unskilled wage gap is decreasing in the steady state level of water if skilled wage is water inelastic (i.e., $\xi_S < 1$).*

To make a sense of this, note from equation (A15) that the water elasticity of unskilled wage is unity. Hence, proportional changes in skilled wages as a result of a change in the steady state level of water will fall short of those of unskilled wages when $\xi_S < 1$, resulting in an increase in the wage gap as a result of a decrease in steady state water level. It can also be shown with some algebraic manipulation that $\xi_S < 1$ if $\theta_{SA} > \omega_M/(\omega_A - \omega_M)$. When $\xi_S < 1$, a reduction in the steady state water level increases inequality given that the distributive share of skilled labor in agriculture (i.e., θ_{SA}) is sufficiently high, despite the fact that agriculture is water intensive. We expect that these conditions will be met in our test case.

Next, we explore the effects of a change in the steady state level of water in the system on sectoral employment and output. Since we have already established that the price of land is positively related to system water level, and a decrease in the price of land increases agricultural unit-land demand (i.e., α_{LA}), agricultural output must fall since $L_A = \bar{L}$ due to the full employment of land. In particular, we have $\hat{Q}_A = -\hat{\alpha}_{LA}$. Moreover, since we have established earlier that $\hat{U}_E = \hat{U}_A = 0$, it directly follows from (A4) that $\hat{Q}_E = \hat{W}^*$. Hence, as expected, production in sector E is increasing in the steady state water level. To explore the effects of W^* on Q_M and $\bar{W}$, differentiate (A5) and (A7) to obtain:

$$\lambda_{SA}\hat{Q}_A + \lambda_{SM}\hat{Q}_M + \lambda_{SA}\hat{\alpha}_{SA} + \lambda_{SM}\hat{\alpha}_{SM} = 0 \tag{A21}$$

$$\lambda_{WA}\hat{Q}_A + \lambda_{WM}\hat{Q}_M + \lambda_{WA}\hat{\alpha}_{WA} + \lambda_{WM}\hat{\alpha}_{WM} = \hat{\bar{W}} \tag{A22}$$

where λ_{ij} is the usage share of factor $i = S, M$ in sector $j = A, M$ (e.g., $\lambda_{SA} \equiv S_A/\bar{S}$). Also, recall that the substitution elasticity between water and skilled labor for sector $j = A, M$, is defined as $\sigma^j_{WS} \equiv (\hat{\alpha}_{Wj} - \hat{\alpha}_{Sj})/(\hat{\gamma}_S - \hat{\gamma}_W)$. Using these two equations (one for each of the two sectors) as well as (A18)-(A19) and (A21)-(A22), we can solve for proportional changes in the per-unit usage of skilled labor and of water as well as the change in manufacturing output. In particular, we obtain:

$$\hat{\alpha}_{SA} = \Omega - \theta_{WA}\Delta_A\hat{W}^* \tag{A23}$$

$$\hat{\alpha}_{SM} = -\theta_{WM}\Delta_M\hat{W}^* \tag{A24}$$

$$\hat{\alpha}_{WA} = \Omega_A + \theta_{SA}\Delta_A\hat{W}^* \tag{A25}$$

$$\hat{\alpha}_{WM} = \theta_{SM}\Delta_M\hat{W}^* \tag{A26}$$

$$\hat{Q}_M = -\frac{\lambda_{SA}}{\lambda_{SM}}\left(\hat{Q}_A + \Omega_A - \theta_{WA}\Delta_A\hat{W}^*\right) + \theta_{WM}\Delta_M\hat{W}^* \tag{A27}$$

where $\Omega \equiv -(\theta_{LA}\hat{\alpha}_{LA} + \theta_{UA}\hat{\alpha}_{UA})$ and $\Delta_j \equiv \sigma^j_{WS}(\xi_S + \xi_W) > 0, j = A, M$. Recall also that we have already established that a decrease in the steady state level of water increases per-unit unskilled labor employment and land usage as well as the agricultural output (i.e., $\hat{\alpha}_{LA}/\hat{W}^* < 0, \hat{\alpha}_{UA}/\hat{W}^* < 0$, and $\hat{Q}_A/\hat{W}^* > 0$). Hence, Ω is positive. Therefore, we conclude from (A24)-(A26) that α_{WA} and α_{WM} are increasing while α_{SM} is decreasing in the steady state level of water.

The effect of the steady state level of water on Q_M is generally ambiguous as it is evident from (A27). However, this effect of reduction in water on manufacturing output is negative if the share of skilled labor employment in agriculture is sufficiently small. To see this note that $\lim_{\lambda_{SA}\to 0}\hat{Q}_M = \theta_{WM}\Delta_M\hat{W}^*$, implying that a reduction in the steady state level of water reduces manufacturing output when the share of skilled labor employment in agriculture is very small. We highlight the effect on sectoral output by the following formal result.

Proposition A3. *Both agricultural and ecosystem production levels are increasing in the steady state level of water in the system. While the impact on manufacturing output is generally ambiguous, it is increasing in steady state level of water if the share of skilled labor employment in agriculture is sufficiently small.*

There is no straightforward way to infer the effects of the steady state level of water on its consumptive level unambiguously using the usual comparative static derivation we have employed so far, i.e., the solution for $\hat{\bar{W}}$ that one can obtain from the above system of equations (not presented here). Nevertheless, such a result can be derived, as highlighted by the following proposition and proof.

Proposition A4. *A reduction in the steady state level of water in the system reduces the consumptive level of water in the rural economy.*

Proof. We prove this result by negation. Assume by negation that $\hat{\bar{W}} \geq 0$ in response to $\hat{W}^* < 0$ (i.e., $\bar{W}$ is non-increasing in W^*). Since $\hat{\alpha}_{WA} < 0$ and $\hat{Q}_A < 0$, we conclude that:

$$\hat{W}_A < 0 \tag{A28}$$

It also directly follows from the definition of ω and equations (A23)-(A26) that:

$$\hat{\omega}_A = \Delta_A \hat{W}^* \tag{A29}$$

$$\hat{\omega}_M = \Delta_M \hat{W}^* \tag{A30}$$

where we have used $\hat{\omega}_j = \hat{\alpha}_{Wj} - \hat{\alpha}_{Sj}, j = A, M$. Hence, we conclude from these equations that in response to $\hat{W}^* < 0$, we have:

$$\hat{\omega}_A < 0 \tag{A31}$$

$$\hat{\omega}_M < 0 \tag{A32}$$

which is also intuitive as it states that water intensity ratios in both sectors fall if steady state water level falls. Next, recall our negation assumption that states:

$$\hat{\bar{W}} \equiv \hat{W}_A + \hat{W}_M \geq 0 \tag{A33}$$

which along with equation (A28) imply that:

$$\hat{W}_M > 0. \tag{A34}$$

Now, equation (A32) and (A34) imply that:

$$\hat{S}_M > 0 \tag{A35}$$

Note also that full employment of skilled labor implies that $\hat{S}_A = -\hat{S}_M$, which along with equation (A35) conclude that:

$$\hat{S}_A < 0 \tag{A36}$$

Now, on the one hand, equations (A28), (A31) and (A36) imply that:

$$|\hat{S}_A| < |\hat{W}_A| \tag{A37}$$

On the other hand, (A32), (A34) and (A35) imply that:

$$\hat{W}_M < \hat{S}_M \tag{A38}$$

Finally, (A37) and (A38) imply that:

$$\hat{W}_M < \hat{S}_M = |\hat{S}_A| < |\hat{W}_A|$$

that, is $\hat{W}_M < |\hat{W}_A|$, which in turn implies that $\hat{\bar{W}} < 0$, which contradicts our negation assumption. □

It is also interesting to explore the impact of a water transfer on aggregate income. Aggregate income, defined from the factor side, is $I \equiv \gamma_L L_A + \gamma_S(S_A + S_M) + \gamma_U(U_A + U_E) + \gamma_W(\bar{W} + W_T)$. Differentiating this equation, we obtain:

$$\hat{I} = \kappa_L \hat{\gamma}_L + \kappa_S \hat{\gamma}_S + \kappa_U \hat{\gamma}_U + \kappa_W \hat{\gamma}_W + \kappa_W \hat{\bar{W}} + \hat{W}_T$$

where κ_i is income share of factor $i = L, S, U, W$, e.g., $\kappa_L \equiv \gamma_L \bar{L}/I$. This equation implies that the effect of a change in water transfer is ambiguous since its first three terms and the fifth term are negative while the forth and the last terms are positive. Note that $\hat{L}_A = \hat{\bar{S}} = \hat{\bar{U}} = 0$ due to full employment of labor and land.

A.2 Water Transfer Policy Implications

A.2.1 Unrestricted-Transfer

Suppose the water transfer takes place without being tied to the water consumption level in the regional rural economy. We have $\hat{W}^* < 0$ under this scenario. Then, it follows from Propositions 1-3 that $\hat{\gamma}_L < 0$, $\hat{\gamma}_S < 0$, $\hat{\gamma}_U < 0$, $\hat{\gamma}_W > 0$. From these results, we make the following predictions:

(i) A water transfer raises the return to water in the water transferring region;

(ii) A water transfer reduces the returns to skilled and unskilled labor in the rural region;

(iii) A water transfer can increase wage inequality;

(iv) Land price falls;

(v) Agricultural output and ecosystem service output fall, while the effect on manufacturing is generally ambiguous.

If the predictions hold and the amount of water that remains in the system decreases, we expect an increase in water values—and therefore the marginal productivity of water—and a decrease in both skilled and unskilled labor in the agricultural sector. Furthermore, if water is transferred out of the system, the size of the resource providing the ecosystem service will decline.

Under the fallow-transfer policy, water is maintained in the ecosystem (by design), while the unrestricted-transfer policy leads to a decrease in system water (and thus ecosystem services). While both policies lead to reductions in agricultural employment, the unrestricted policy allows factor prices to change, leading to more water intensive production (i.e., a lower water-to-labor ratio) since wages fall for both types of labor. In this sense, the untied policy is less distortionary because there is no need for the displacement of labor.

A.2.2 Fallow-Transfer: the Restricted Transfer and Presence of Factor Unemployment

Now, we consider unemployment of unskilled labor due to a binding minimum wage when transfers are restricted via fallowing, which removes land from production and implies unemployment of land. Due to the existence of unskilled labor and land unemployment, unskilled labor and land markets are demand determined. Hence, we have to modify equations (A6) and (A8) to:

$$P_A \frac{\partial Q_A}{\partial U_A} = \bar{\gamma}_U = P_E \frac{\partial Q_E}{\partial U_E} \tag{A39}$$

$$P_A \frac{\partial Q_A}{\partial L_A} = \bar{\gamma}_L \tag{A40}$$

where $\bar{\gamma}_U$ is the binding minimum wage and $\bar{\gamma}_L$ is fixed land price due to infinitely elastic supply in the neighborhood of equilibrium due to land unemployment. In addition, these fixed factor prices must enter equations (A9), (A10), and (A12). We then, have $\hat{\gamma}_U = \hat{\gamma}_L = 0$. Finally, equations (A13) and (A14), change to:

$$\theta_{SA}\hat{\gamma}_S + \theta_{WA}\hat{\gamma}_W = 0 \tag{A41}$$

$$\theta_{SM}\hat{\gamma}_S + \theta_{WM}\hat{\gamma}_W = 0 \tag{A42}$$

which, in turn, imply that $\hat{\gamma}_S = \hat{\gamma}_W = 0$. We also maintain that $dW_T \leq -dW_A$ and $\hat{W}^* = 0$. Moreover, these results are consistent with the fact that factor prices are linked to the steady state level of water in our setup. Since the steady state level of water remains unchanged, marginal productivity of unskilled labor, and hence unskilled labor demand does not shift. This, in turn, implies that unskilled labor employment in sector E does not change since γ_U also does not change. We conclude that $\hat{Q}_E = 0$, as the steady state level of water and labor employment in sector E remain unchanged. However, a reduction in W_A, due to the rural-urban water transfer, reduces the marginal productivity of unskilled labor in agriculture, hence shifting down the unskilled labor demand. Given that the unskilled wage does not change, unskilled labor employment in agriculture falls. The unskilled agricultural workers who lose their jobs must join the pool of unemployed workers since we have established that $\hat{U}_E = 0$. The effects of the water transfer on agricultural land use will be similar to that of unskilled labor, i.e., land usage falls, resulting in more land unemployment (i.e., land fallowing).

The effect on the skilled labor market is different due to its full employment. The lowered water usage in agriculture lowers the marginal productivity of skilled labor in agriculture and hence its demand. With this direct effect, at the initial equilibrium, the marginal productivity of skilled labor would be higher in manufacturing than in agriculture, which results in movement of skilled labor from the latter to the former. As factor intensities in both sectors remain unchanged due to the rigidity of factor prices, some water must also move from agriculture to manufacturing to keep ω_M unchanged. This will also lead to an increase in productivity of skilled labor in manufacturing, which shifts up its demand for skilled workers. All in all, the employment of skilled workers in manufacturing (agriculture) goes up (down). We depict this in figure A2, where superscript 1 denotes post-transfer. Without ambiguity, agricultural (manufacturing) production falls (rises) since both skilled and unskilled labor employment and water and land usage (skilled labor and water usage) in agriculture (manufacturing) fall (rise). Production in the ecosystem service sector does not change since both its employment and the steady state level of water do not change.

Under the fallow-transfer policy, water transfers must be removed directly from consumptive use in agriculture, so that overall water in the system remains unchanged, i.e., land is fallowed and conserved water is exported, less some amount to maintain the amount of water that remains in the system. This implies that $\hat{W}^* = 0$. It follows from preceding analysis that $\hat{\gamma}_U = \hat{\gamma}_S = \hat{\gamma}_W = \hat{\gamma}_L = 0$, i.e., factor prices do not change. It also follows that under this policy, $dW_M > 0$. Moreover, from our analysis of the previous subsection that employment of skilled and unskilled labor in agriculture falls, unskilled workers who lose their jobs in agriculture must join the pool of unemployed, while skilled workers move to manufacturing. The effects of this policy on regional aggregate income are negative. To see this, note that in this case we have $\hat{\bar{W}} = \hat{W}_T$ since $\hat{W}^* = 0$. Therefore, $\hat{I} = \kappa_L \hat{L}_A + \kappa_U \hat{U}_A$ since all factor price do not change and $\hat{\bar{S}} = 0$. Regional income falls due to the lost labor and land income as a result of their underemployment.

All in all, the consequences in factor markets would lead to a decrease agricultural output and increase in manufacturing output. Unemployment also rises. Since the steady state water level and employment in the service sector remain unchanged, sector output also remains unchanged. Hence, an increase in the water trade under the fallow-transfer policy will cause:

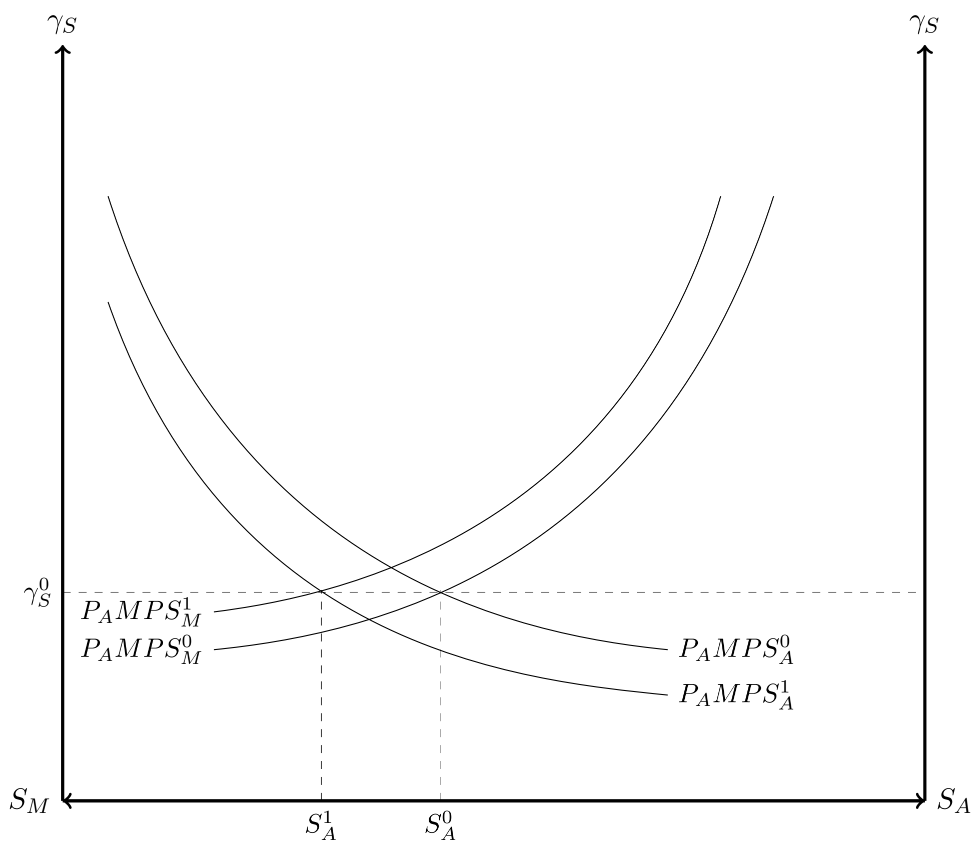
(i) a decrease in agricultural output;

(ii) a decrease in the employment of skilled and unskilled workers;

(iii) an increase in manufacturing output;

(iv) a decrease in aggregate income.

Figure A2: The effects of a restricted rural-urban water transfer on skilled labor market.



B Data Description

Table B1: Variable Descriptions and Sources.

Outcome Variables	Source	Period	Notes
Harvested acreage	USDA	1980-2018	Data from annual crop report compiled by the California County Agricultural Commissioners (CCAC) providing detailed annual agricultural production data at the county level. https://www.nass.usda.gov/Statistics_by_State/California/Publications/AgComm/index.php
Per capita income	BEA	1980-2018	
Skilled labor employment	Census Bureau	1992-2018	Quarterly employment is the estimate of the number of jobs that are held on both the first and last day of the quarter with the same employer. Our measure is the mean of the four quarters in a year.
Unskilled labor employment	Census Bureau	1992-2018	Quarterly employment is the estimate of the number of jobs that are held on both the first and last day of the quarter with the same employer. Our measure is the mean of the four quarters in a year.
Crop high-skill earnings	Census Bureau	1992-2018	Yearly average of four quarters' average monthly earnings (in dollars) of college or higher degree employees with stable jobs in NAICS111 subsector.
Crop low-skill earnings	Census Bureau	1992-2018	Yearly average of four quarters' average monthly earnings (in dollars) of high school or lower degree employees with stable jobs in NAICS111 subsector.
Air pollutant days	EPA	PM10: 1980-2018 PM2.5: 1998-2018 Ozone and NO_2: 1994-2018	NAAQS standards in our data are based on the current AQI breakpoints, regardless of year and are as follows: PM2.5: 35µg/m^3; PM10: 24-hour concentration exceeds 150µg/m^3; NO_2: 1-hour concentration exceeds 100ppb; Ozone: 8-hour concentration exceeds 0.07ppm. https://www.epa.gov/criteria-air-pollutants/naaqs-table
PM10 annual mean	EPA	1990-2018	The weighted annual mean (mean weighted by calendar quarter) for the year (in µg/m^3).
PM2.5 annual mean	EPA	2000-2018	The weighted annual mean (mean weighted by calendar quarter) for the year (in µg/m^3).
Satellite-Based PM2.5	van Donkelaar et al. (2021)	2000-2018	Mean and max annual global satellite-based fine particulate matter concentration estimates (in µg/m^3).
Predictors	**Source**	**Periods**	**Notes**
Farm proprietors' income	BEA	1980-2018	Income (in $ millions) received by sole proprietorships and partnerships that operate farms (excludes income received by corporate farms).

Table B1: (*Continued*).

Predictors	Source	Periods	Notes
Farm proprietors' employment	BEA	1980-2018	Employment of sole proprietors and non-corporate partners in the farm industry in thousands of jobs.
Wage and salary employment	BEA	1980-2018	Average annual number of full-time and part-time jobs (thousands of jobs).
Wage and salary	BEA	1980-2018	Aggregation of county wages and salaries (in billions of dollars).
Proprietors' employment	BEA	1980-2018	Proprietors' income is the current-production income (including income in kind) of sole proprietorships, partnerships, and tax-exempt cooperatives. Includes farm proprietors' and nonfarm proprietors' employment (in number of jobs).
Proprietors' income	BEA	1980-2018	The proprietor's income is in billions of dollars. https://apps.bea.gov/regional/histdata/releases/1117lapi/index.cfm
White ag labor ratio	Census Bureau	1992-2018	Author calculation using LEHD number of stable jobs in agricultural sector, white employees over total employment.
Male ag labor ratio	Census Bureau	1992-2018	Male employees over total employment.
Hispanic ag labor ratio	Census Bureau	1992-2018	Hispanic employees over total employment.
High school or higher ag labor ratio	Census Bureau	1992-2018	Employees with high school degree or higher over total employment.
Annual cattle values	USDA	1980-2018	Data from annual crop report compiled by the California County Agricultural Commissioners (CCAC) providing detailed annual agricultural production data at the county level.
Annual alfalfa hay values	USDA	1980-2018	Data from annual crop report compiled by the California County Agricultural Commissioners (CCAC) providing detailed annual agricultural production data at the county level.
Annual lettuce values	USDA	1980-2018	Data from annual crop report compiled by the California County Agricultural Commissioners (CCAC) providing detailed annual agricultural production data at the county level.
Annual melons values	USDA	1980-2018	Data from annual crop report compiled by the California County Agricultural Commissioners (CCAC) providing detailed annual agricultural production data at the county level.
Annual other vegetable values	USDA	1980-2018	Data from annual crop report compiled by the California County Agricultural Commissioners (CCAC) providing detailed annual agricultural production data at the county level.

C Summary Statistics of Variables Used in Each Outcome Variable Analysis

Table C1: Summary Statistics for Variables Used in the Analysis of Log Harvested Acres.

Variable	Sample	Mean	Std. Dev.
Log Harvested Acres	1,555	10.94	1.9
Farm Proprietors' Income	1,555	119.20	223.43
Farm Proprietors' Employment	1,555	1.44	1.52
Wage and Salary Employment	1,555	222.99	498.23
Wage and Salary	1,555	8,542.49	19,204.46
Proprietors' Employment	1,555	52.67	100.84
Proprietors' Income	1,555	1,523.13	2,773.80
Annual Cattle Values	1,555	44,888.45	93,886.92
Annual Alfalfa Hay Values	1,555	22,449.45	45,380.42
Annual Vegetable Values	1,555	119,730.20	342,839.10

Notes: (Unbalanced) data includes observations for 51 counties (the treatment county and 50 control counties) for 1980-2018. Omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. All the variables, except Log Harvested Acres, are in thousands.

Table C2: Summary Statistics for Variables Used in the Analysis of Harvested Acres.

Variable	Sample	Mean	Std. Dev.
Harvested Acres	1,555	188.68	265.08
Farm Proprietors' Income	1,555	119.20	223.43
Farm Proprietors' Employment	1,555	1.44	1.52
Wage and Salary Employment	1,555	222.99	498.23
Wage and Salary	1,555	8,542.49	19,204.46
Proprietors' Employment	1,555	52.67	100.84
Proprietors' Income	1,555	1,523.13	2,773.80
Annual Cattle Values	1,555	44,888.45	93,886.92
Annual Alfalfa Hay Values	1,555	22,449.45	45,380.42
Annual Vegetable Values	1,555	119,730.20	342,839.10

Notes: (Unbalanced) data includes observations for 51 counties (the treatment county and 50 control counties) for 1980-2018. Omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. All the variables are in thousands.

Table C3: Summary Statistics for Variables Used in the Analysis of Log Hay Alfalfa Acres.

Variable	Sample	Mean	Std. Dev.
Log Hay Alfalfa Acres	1,834	8.93	2.02
Farm Proprietors' Income	1,834	105.71	211.98
Farm Proprietors' Employment	1,834	1.31	1.45
Wage and Salary Employment	1,834	239.5	623.38
Wage and Salary	1,834	9,557.37	27,303.80
Proprietors' Employment	1,834	59.65	156.6
Proprietors' Income	1,834	1,819.15	5,465.98
Annual Alfalfa Hay Values	1,834	19,527.83	42,386.85

Notes: (Unbalanced) data includes observations for 52 counties (the treatment county and 51 control counties) for 1980-2018. Omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. All the variables, except Log Hay Alfalfa Acres, are in thousands.

Table C4: Summary Statistics for Variables Used in the Analysis of Per Capita Income.

Variable	Sample	Mean	Std. Dev.
Per Capita Income	2,106	29.32	16.68
Farm Proprietors' Income	2,106	96.56	201.27
Farm Proprietors' Employment	2,106	1.22	1.39
Wage and Salary Employment	2,106	253.32	626.78
Wage and Salary	2,106	10,511.04	28,889.29
Proprietors' Employment	2,106	64.02	163.89
Proprietors' Income	2,106	2,051.00	5,909.85

Notes: (Unbalanced) data includes observations for 54 counties (the treatment county and 53 control counties) for 1980-2018. Omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. All the variables are in thousands.

Table C5: Summary Statistics for Variables Used in the Analysis of Crop High-Skill Labor Employment (NAICS=111).

Variable	Sample	Mean	Std. Dev.
Crop High Skill Labor Employment	1,008	687.40	889.37
Farm Proprietors' Income	1,008	151.08	262.31
Farm Proprietors' Employment	1,008	1.42	1.44
Wage and Salary Employment	1,008	225.66	412.64
Wage and Salary	1,008	10,616.88	20,934.10
Proprietors' Employment	1,008	59.08	99.56
Proprietors' Income	1,008	1,978.46	3,067.70
White Ag Labor Ratio	1,008	0.84	0.04
Male Ag Labor Ratio	1,008	0.70	0.07
Hispanic Ag Labor Ratio	1,008	0.50	0.14
High School or Higher Ag Labor Ratio	1,008	0.53	0.09
Annual Cattle Values	1,008	56,513.84	111,275.20
Annual Alfalfa Hay Values	1,008	27,007.97	51,994.56
Annual Vegetable Values	1,008	155,902.30	411,021.80

Notes: (Unbalanced) data includes observations for 48 counties (the treatment county and 47 control counties) for 1992-2018. Omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. All the variables, except Crop High Skill Labor Employment, White Ag Labor Ratio, Male Ag Labor Ratio, Hispanic Ag Labor Ratio, and High School or Higher Ag Labor Ratio, are in thousands.

Table C6: Summary Statistics for Variables Used in the Analysis of Crop Low-Skill Labor Employment (NAICS=111).

Variable	Sample	Mean	Std. Dev.
Crop Low Skill Labor Employment	1,029	1,468.99	2,045.55
Farm Proprietors' Income	1,029	148.07	260.46
Farm Proprietors' Employment	1,029	1.40	1.43
Wage and Salary Employment	1,029	221.25	409.55
Wage and Salary	1,029	10,406.86	20,770.27
Proprietors' Employment	1,029	57.98	98.84
Proprietors' Income	1,029	1,940.81	3,047.41
White Ag Labor Ratio	1,029	0.85	0.04
Male Ag Labor Ratio	1,029	0.70	0.07
Hispanic Ag Labor Ratio	1,029	0.50	0.15
High School or Higher Ag Labor Ratio	1,029	0.53	0.09
Annual Cattle Values	1,029	55,585.80	110,323.20
Annual Alfalfa Hay Values	1,029	26,516.94	51,577.75
Annual Vegetable Values	1,029	152,728.60	407,396.30

Notes: (Unbalanced) data includes observations for 49 counties (the treatment county and 48 control counties) for 1992-2018. Omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. All the variables, except Crop Low Skill Labor Employment, White Ag Labor Ratio, Male Ag Labor Ratio, Hispanic Ag Labor Ratio, and High School or Higher Ag Labor Ratio, are in thousands.

Table C7: Summary Statistics for Variables Used in the Analysis of Ag High-Skill Labor Employment (NAICS=11).

Variable	Sample	Mean	Std. Dev.
Ag High Skill Labor Employment	1,050	1,398.96	2,135.29
Farm Proprietors' Income	1,050	145.17	258.64
Farm Proprietors' Employment	1,050	1.37	1.43
Wage and Salary Employment	1,050	217	406.52
Wage and Salary	1,050	10,205.03	20,609.87
Proprietors' Employment	1,050	56.89	98.14
Proprietors' Income	1,050	1,904.59	3,027.42
White Ag Labor Ratio	1,050	0.85	0.04
Male Ag Labor Ratio	1,050	0.70	0.07
Hispanic Ag Labor Ratio	1,050	0.49	0.15
High School or Higher Ag Labor Ratio	1,050	0.53	0.09
Annual Cattle Values	1,050	54,654.46	109,409.30
Annual Alfalfa Hay Values	1,050	26,059.64	51,161.19
Annual Vegetable Values	1,050	149,702.70	403,854.40

Notes: (Unbalanced) data includes observations for 49 counties (the treatment county and 48 control counties) for 1992-2018. Omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. All the variables, except Ag High Skill Labor Employment, White Ag Labor Ratio, Male Ag Labor Ratio, Hispanic Ag Labor Ratio, and High School or Higher Ag Labor Ratio, are in thousands.

Table C8: Summary Statistics for Variables Used in the Analysis of Ag Low-Skill Labor Employment (NAICS=11).

Variable	Sample	Mean	Std. Dev.
Ag Low Skill Labor Employment	1,049	2,856.66	4,443.42
Farm Proprietors' Income	1,049	145.3	258.72
Farm Proprietors' Employment	1,049	1.37	1.43
Wage and Salary Employment	1,049	217.2	406.66
Wage and Salary	1,049	10,214.64	20,617.34
Proprietors' Employment	1,049	56.94	98.17
Proprietors' Income	1,049	1,906.36	3,028.32
White Ag Labor Ratio	1,049	0.85	0.04
Male Ag Labor Ratio	1,049	0.70	0.07
Hispanic Ag Labor Ratio	1,049	0.49	0.15
High School or Higher Ag Labor Ratio	1,049	0.53	0.09
Annual Cattle Values	1,049	54,703.48	109,450.00
Annual Alfalfa Hay Values	1,049	26,084.40	51,179.29
Annual Vegetable Values	1,049	149,845.40	404,020.50

Notes: (Unbalanced) data includes observations for 49 counties (the treatment county and 48 control counties) for 1992-2018. Omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. All the variables, except Ag Low Skill Labor Employment, White Ag Labor Ratio, Male Ag Labor Ratio, Hispanic Ag Labor Ratio, and High School or Higher Ag Labor Ratio, are in thousands.

Table C9: Summary Statistics for Variables Used in the Analysis of Crop High-Skill Earnings/Crop Low-Skill Earnings.

Variable	Sample	Mean	Std. Dev.
Crop High-Skill Earn/Crop Low-Skill Earn	1,350	1.33	0.24
Farm Proprietors' Income	1,350	124.03	237.91
Farm Proprietors' Employment	1,350	1.23	1.32
Wage and Salary Employment	1,350	290.47	662.09
Wage and Salary	1,350	14,116.63	34,215.60
Proprietors' Employment	1,350	80.11	191.14
Proprietors' Income	1,350	2,867.61	7,149.11

Notes: (Unbalanced) data includes observations for 53 counties (the treatment county and 52 control counties) for 1980-2018. Omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. All the variables, except Crop High-Skill Earnings/Crop Low-Skill Earnings, are in thousands.

Table C10: Summary Statistics for Variables Used in the Analysis of PM10 Days.

Variable	Sample	Mean	Std. Dev.
PM10 Days	1,876	12.81	33.65
Days with AQI	1,876	334.62	80.13
Median AQI	1,876	48.54	21.53
Farm Proprietors' Income	1,876	107.37	210.63
Farm Proprietors' Employment	1,876	1.32	1.43
Wage and Salary Employment	1,876	283.48	657.8
Wage and Salary	1,876	11,782.76	30,366.88
Proprietors' Employment	1,876	71.55	172.14
Proprietors' Income	1,876	2,297.81	6,217.10

Notes: (Unbalanced) data includes observations for 54 counties (the treatment county and 53 control counties) for 1980-2018. Omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. All the variables, except PM10 Days, Days with AQI, and Median AQI, are in thousands.

Table C11: Summary Statistics for Variables Used in the Analysis of PM2.5 Days.

Variable	Sample	Mean	Std. Dev.
PM2.5 Days	1,069	83.46	74.02
Days with AQI	1,069	343.73	69.67
Median AQI	1,069	47.60	18.27
Farm Proprietors' Income	1,069	135.89	258.48
Farm Proprietors' Employment	1,069	1.14	1.20
Wage and Salary Employment	1,069	294.78	670.70
Wage and Salary	1,069	15,596.14	36,842.41
Proprietors' Employment	1,069	83.92	201.75
Proprietors' Income	1,069	3,208.93	7,788.22

Notes: (Unbalanced) data includes observations for 54 counties (the treatment county and 53 control counties) for 1998-2018. Omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. All the variables, except PM2.5 Days, Days with AQI, and Median AQI, are in thousands.

Table C12: Summary Statistics for Variables Used in the Analysis of Ozone Days.

Variable	Sample	Mean	Std. Dev.
Ozone Days	1,276	227.11	101.21
Days with AQI	1,276	341.68	73.15
Median AQI	1,276	47.30	18.31
Farm Proprietors' Income	1,276	124.86	242.79
Farm Proprietors' Employment	1,276	1.19	1.28
Wage and Salary Employment	1,276	287.71	660.73
Wage and Salary	1,276	14,361.13	34,802.35
Proprietors' Employment	1,276	80.22	193.24
Proprietors' Income	1,276	2,935.39	7,303.44

Notes: (Unbalanced) data includes observations for 54 counties (the treatment county and 53 control counties) for 1994-2018. Omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. All the variables, except Ozone Days, Days with AQI, and Median AQI, are in thousands.

Table C13: Summary Statistics for Variables Used in the Analysis of NO_2 Days.

Variable	Sample	Mean	Std. Dev.
NO_2 Days	1,276	26.42	45.47
Days with AQI	1,276	341.68	73.15
Median AQI	1,276	47.30	18.31
Farm Proprietors' Income	1,276	124.86	242.79
Farm Proprietors' Employment	1,276	1.19	1.28
Wage and Salary Employment	1,276	287.71	660.73
Wage and Salary	1,276	14,361.13	34,802.35
Proprietors' Employment	1,276	80.22	193.24
Proprietors' Income	1,276	2,935.39	7,303.44

Notes: (Unbalanced) data includes observations for 54 counties (the treatment county and 53 control counties) for 1994-2018. Omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. All the variables, except NO_2 Days, Days with AQI, and Median AQI, are in thousands.

Table C14: Summary Statistics for Variables Used in the Analysis of PM10 Annual Mean.

Variable	Sample	Mean	Std. Dev.
PM10 Annual Mean	1,160	29.4	15.27
Days with AQI	1,160	351.5	53.36
Median AQI	1,160	49.75	19.46
Farm Proprietors' Income	1,160	139.05	248.8
Farm Proprietors' Employment	1,160	1.39	1.44
Wage and Salary Employment	1,160	342.9	724.39
Wage and Salary	1,160	15,965.13	36,480.61
Proprietors' Employment	1,160	92.39	205.96
Proprietors' Income	1,160	3,189.44	7,608.04

Notes: (Unbalanced) data includes observations for 50 counties (the treatment county and 49 control counties) for 1990-2018. Omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. All the variables, except PM10 Annual Mean, Days with AQI, and Median AQI, are in thousands.

Table C15: Summary Statistics for Variables Used in the Analysis of PM2.5 Annual Mean.

Variable	Sample	Mean	Std. Dev.
PM2.5 Annual Mean	612	10.62	4.14
Days with AQI	612	360.57	30.98
Median AQI	612	51.58	17.05
Farm Proprietors' Income	612	201.12	314.45
Farm Proprietors' Employment	612	1.25	1.20
Wage and Salary Employment	612	392.6	753.78
Wage and Salary	612	22,151.29	43,448.74
Proprietors' Employment	612	114.6	235.98
Proprietors' Income	612	4,496.36	9,193.49

Notes: (Unbalanced) data includes observations for 43 counties (the treatment county and 42 control counties) for 2002-2018. Omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. All the variables, except PM2.5 Annual Mean, Days with AQI, and Median AQI, are in thousands.

Table C16: Summary Statistics for Variables Used in the Analysis of Satellite-Based PM2.5 Mean.

Variable	Sample	Mean	Std. Dev.
Satellite-Based PM2.5 Mean	963	6.72	2.46
Days with AQI	963	345.62	65.75
Median AQI	963	47.76	18.08
Farm Proprietors' Income	963	144.28	267.95
Farm Proprietors' Employment	963	1.11	1.14
Wage and Salary Employment	963	297.9	674.29
Wage and Salary	963	16,235.79	37,919.28
Proprietors' Employment	963	86.00	206.32
Proprietors' Income	963	3,347.24	8,046.33

Notes: (Unbalanced) data includes observations for 54 counties (the treatment county and 53 control counties) for 2000-2018. Omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. All the variables, except Satellite-Based PM2.5 Mean, Days with AQI, and Median AQI, are in thousands.

Table C17: Summary Statistics for Variables Used in the Analysis of Satellite-Based PM2.5 Max.

Variable	Sample	Mean	Std. Dev.
Satellite-Based PM2.5 Max	963	12.24	3.62
Days with AQI	963	345.62	65.75
Median AQI	963	47.76	18.08
Farm Proprietors' Income	963	144.28	267.95
Farm Proprietors' Employment	963	1.11	1.14
Wage and Salary Employment	963	297.9	674.29
Wage and Salary	963	16,235.79	37,919.28
Proprietors' Employment	963	86.00	206.32
Proprietors' Income	963	3,347.24	8,046.33

Notes: (Unbalanced) data includes observations for 54 counties (the treatment county and 53 control counties) for 2000-2018. Omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. All the variables, except Satellite-Based PM2.5 Max, Days with AQI, and Median AQI, are in thousands.

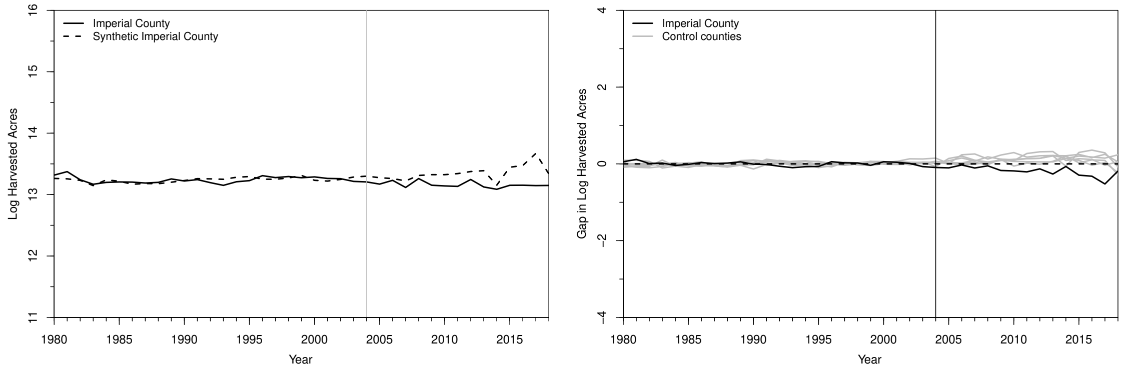
D Complete/Additional Empirical Results

Table D1: Estimated Annual Treatment Effects from Synthetic Control Analysis.

	Mean	Min	Max
Log Harvested Acres	-0.18	-0.52	-0.03
Harvested Acres (in thousands)	-57.84	-251.53	-10.41
Per Capita Income (in thousands)	-0.95	-3.12	0.45
Crop High-Skill Labor Employment	-279.26	-381.39	-196.77
Crop Low-Skill Labor Employment	-628.40	-954.27	-347.97
Ag High-Skill Labor Employment	-493.46	-605.79	-250.15
Ag Low-Skill Labor Employment	-1,372.08	-1,806.62	-836.88
Crop High-Skill Earn/Crop Low-Skill Earn	0.22	0.10	0.38
PM10 Days	27.45	-27.90	109.61
PM2.5 Days	12.61	-25.08	101.37
Ozone Days	-17.25	-116.83	58.99
NO_2 Days	24.86	-9.96	57.59
PM10 Annual Mean (μg/m^3)	15.11	-4.79	28.55
PM2.5 Annual Mean (μg/m^3)	1.64	-3.11	7.22

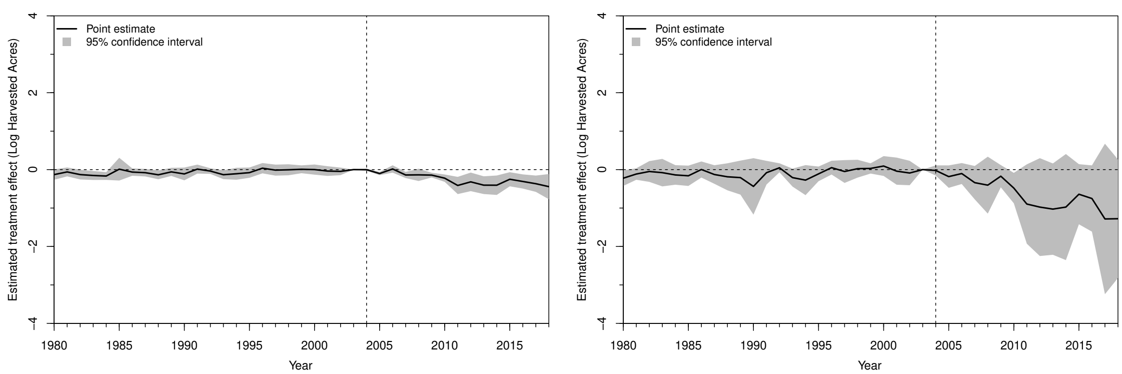
Notes: Mean/min/max annual treatment effect is obtained by taking the average/minimum/maximum of differences between the treatment outcome and its synthetic counterpart (i.e., measured treatment effect) for the post-intervention period (2004-2018).

Figure D1: Synthetic Control Analysis for Log Harvested Acres.



Notes: Graphical summary of synthetic control output for Log Harvested Acres. Right panel shows the time path realized by Imperial County and the synthetic Imperial County. Left panel shows the falsification test results of the estimated treatment effect for Imperial County along with placebo effects for control units. Donor pool for Harvested Acres consists of 29 control counties. See appendix C for the list of control variables included in the analysis. To refine inferences from falsification tests, we consider control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit (Abadie et al., 2010). The vertical line represents the QSA effective year.

Figure D2: Event Study Analysis for Log Harvested Acres.



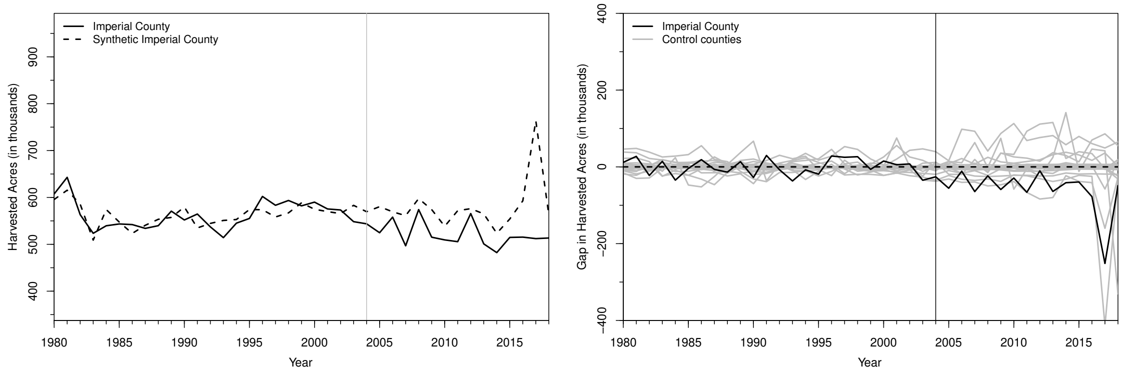
Notes: Event study analysis for Log Harvested Acres. Right panel shows the estimated treatment effect for Imperial County using all available (50) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Left panel shows the estimated treatment effect for Imperial County using only control counties that receive nonzero weight in the synthetic control analysis (see table E1). See appendix C for the list of control variables included in the analysis. Both models control for county and year fixed effects. The confidence bounds are obtained using robust standard errors. The vertical line represents the QSA effective year.

Table D2: Difference-in-Differences Analysis for Log Harvested Acres.

	(1)	(2)
1(Imperial)×1(Post-intervention)	-0.1403**	-0.1840
	(0.0621)	(0.1311)
Farm Proprietors' Income	0.0001	0.0001
	(0.0001)	(0.0002)
Farm Proprietors' Employment	-0.0204	-0.0029
	(0.0534)	(0.0660)
Wage and Salary Employment	-0.0002	0.0055
	(0.0005)	(0.0066)
Wage and Salary	-0.000004*	0.00002
	(0.0000)	(0.0001)
Proprietors' Employment	-0.0009	0.0074
	(0.0010)	(0.0146)
Proprietors' Income	0.000001	-0.0002
	(0.0000)	(0.0001)
Annual Cattle Values	0.00000002	0.0000003
	(0.0000)	(0.0000)
Annual Alfalfa Hay Values	0.000001	0.000001
	(0.0000)	(0.0000)
Annual Vegetable Values	0.0000001***	0.0000002
	(0.0000)	(0.0000)
Observations	1,555	195
R^2	0.0713	0.2168
F Statistic	11.1777***	3.9308***

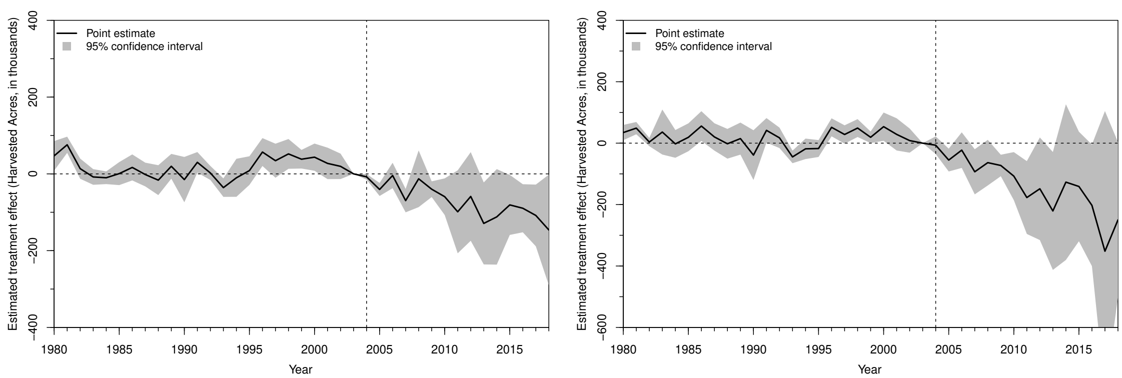
Notes: Model 1 uses all available (50) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Model 2 uses only control counties that receive nonzero weight in the synthetic control analysis (see table E1). Both models control for county and year fixed effects. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Figure D3: Synthetic Control Analysis for Harvested Acres.



Notes: Graphical summary of synthetic control output for Harvested Acres. Right panel shows the time path realized by Imperial County and the synthetic Imperial County. Left panel shows the falsification test results of the estimated treatment effect for Imperial County along with placebo effects for control units. Donor pool for Harvested Acres consists of 29 control counties. See appendix C for the list of control variables included in the analysis. To refine inferences from falsification tests, we consider control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit (Abadie et al., 2010). The vertical line represents the QSA effective year.

Figure D4: Event Study Analysis for Harvested Acres.



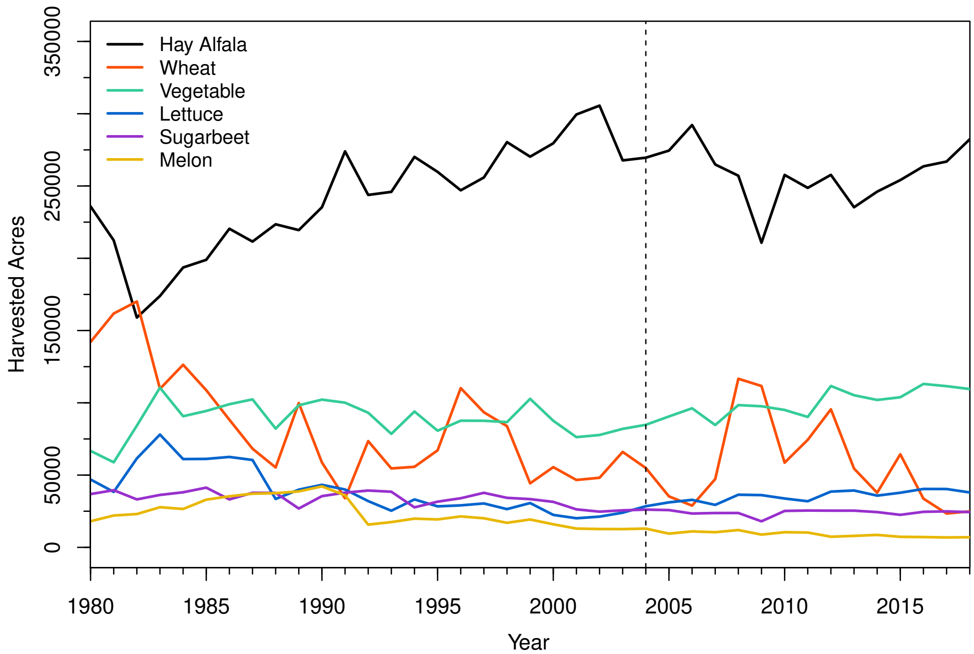
Notes: Event study analysis for Harvested Acres. Right panel shows the estimated treatment effect for Imperial County using all available (50) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Left panel shows the estimated treatment effect for Imperial County using only control counties that receive nonzero weight in the synthetic control analysis (see table E1). See appendix C for the list of control variables included in the analysis. Both models control for county and year fixed effects. The confidence bounds are obtained using robust standard errors. The vertical line represents the QSA effective year.

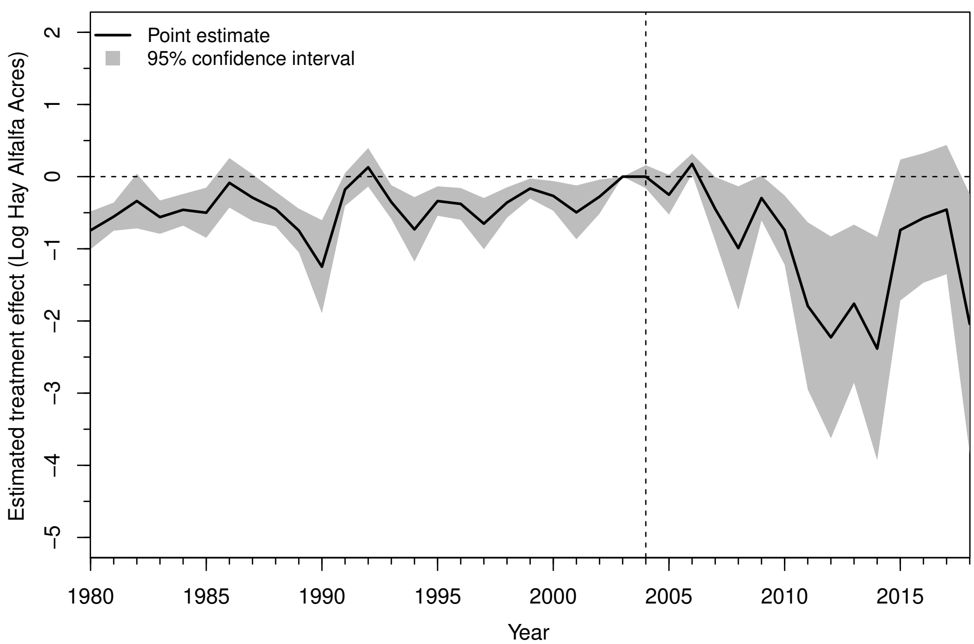
Table D3: Difference-in-Differences Analysis for Harvested Acres.

	(1)	(2)
1(Imperial)×1(Post-intervention)	-75.5588***	-101.5805***
	(23.8476)	(33.9260)
Farm Proprietors' Income	-0.0129	-0.0353
	(0.0349)	(0.0760)
Farm Proprietors' Employment	12.2460	-40.9849***
	(20.6599)	(12.9161)
Wage and Salary Employment	-0.0418	2.2353**
	(0.0416)	(1.0953)
Wage and Salary	0.0001	-0.0401*
	(0.0002)	(0.0206)
Proprietors' Employment	0.0113	0.1774
	(0.0777)	(2.6029)
Proprietors' Income	-0.00005	0.0135
	(0.0014)	(0.0525)
Annual Cattle Values	0.0001	0.0002
	(0.0002)	(0.0001)
Annual Alfalfa Hay Values	0.0001	0.00001
	(0.0002)	(0.0002)
Annual Vegetable Values	0.00003*	0.0001***
	(0.00002)	(0.00002)
Observations	1,555	234
R^2	0.0324	0.1947
F Statistic	4.8697***	4.3512***

Notes: Harvested Acres is measured in thousands. Model 1 uses all available (50) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Model 2 uses only control counties that receive nonzero weight in the synthetic control analysis (see table E1). Both models control for county and year fixed effects. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Figure D5: Harvested Acres by Crop Type in Imperial County.





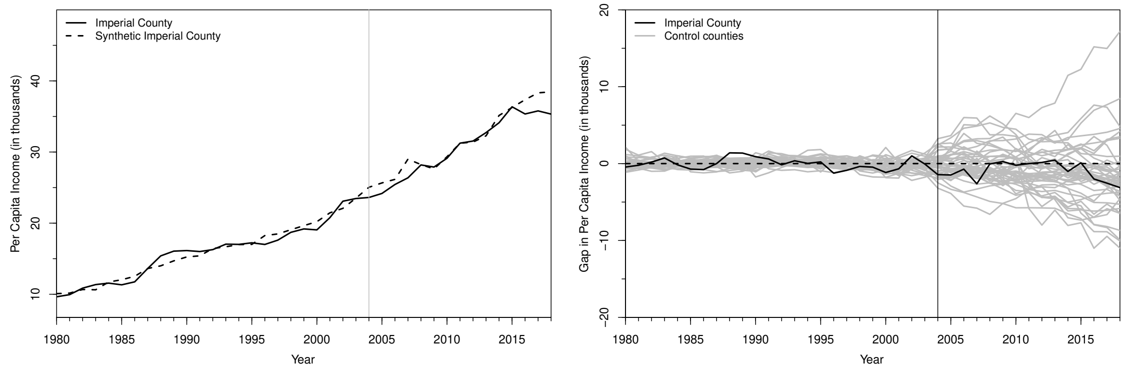
Notes: Top panel uses data from annual crop report compiled by the California County Agricultural Commissioners (CCAC). Bottom panel shows event study analysis for Log Harvested Hay Alfalfa Acres using all available (51) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. See appendix C for the list of control variables included in the analysis. The model controls for county and year fixed effects. The confidence bounds are obtained using robust standard errors. The vertical line represents the QSA effective year.

Table D4: Difference-in-Differences Analysis for Hay Alfalfa Acres.

	(1)	(2)
1(Imperial)×1(Post-intervention)	-14.7916^{*}	-48.1613^{***}
	(7.8049)	(3.6182)
Farm Proprietors' Income	-0.0226^{***}	-0.0597^{***}
	(0.0081)	(0.0016)
Farm Proprietors' Employment	-1.1685	10.1109^{***}
	(3.4083)	(2.3190)
Wage and Salary Employment	-0.0189	-0.7917^{***}
	(0.0137)	(0.0162)
Wage and Salary	0.0001	0.0228^{***}
	(0.0001)	(0.00003)
Proprietors' Employment	-0.0090	-5.0185^{***}
	(0.0288)	(0.1206)
Proprietors' Income	-0.0001	0.0024^{***}
	(0.0005)	(0.0002)
Annual Alfalfa Hay Values	0.0004^{***}	0.0004^{***}
	(0.0001)	(0.00001)
Observations	1,834	78
R^2	0.2117	0.7932
F Statistic	58.2751^{***}	14.3866^{***}

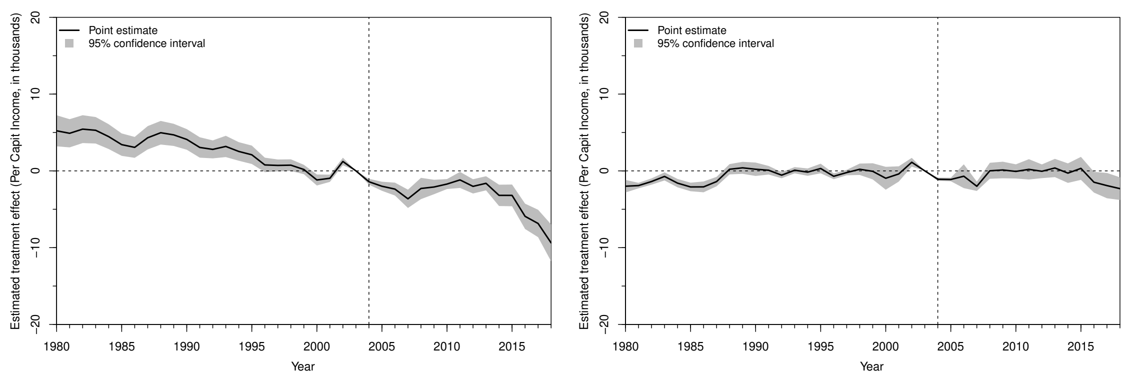
Notes: Hay Alfalfa Acres is measured in thousands. Model 1 uses all available (51) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Model 2 uses only control counties that receive nonzero weight in the synthetic control analysis (see table E1). Both models control for county and year fixed effects. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Figure D6: Synthetic Control Analysis for Per Capita Income.



Notes: Graphical summary of synthetic control output for Per Capita Income. Right panel shows the time path realized by Imperial County and the synthetic Imperial County. Left panel shows the falsification test results of the estimated treatment effect for Imperial County along with placebo effects for control units. Donor pool for Per Capita Income consists of 53 control counties. See appendix C for the list of control variables included in the analysis. To refine inferences from falsification tests, we consider control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit (Abadie et al., 2010). The vertical line represents the QSA effective year.

Figure D7: Event Study Analysis for Per Capita Income.



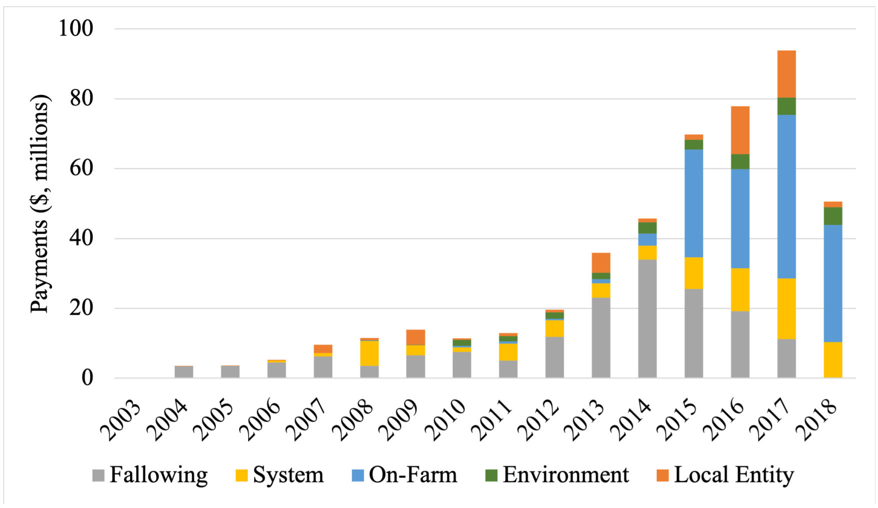
Notes: Event study analysis for Per Capita Income. Right panel shows the estimated treatment effect for Imperial County using all available (53) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Left panel shows the estimated treatment effect for Imperial County using only control counties that receive nonzero weight in the synthetic control analysis (see table E1). See appendix C for the list of control variables included in the analysis. Both models control for county and year fixed effects. The confidence bounds are obtained using robust standard errors. The vertical line represents the QSA effective year.

Table D5: Difference-in-Differences Analysis for Per Capita Income.

	(1)	(2)
1(Imperial)×1(Post-intervention)	-5.9623***	0.0483
	(0.8793)	(0.3862)
Farm Proprietors' Income	-0.003	-0.0011
	(0.0022)	(0.0016)
Farm Proprietors' Employment	3.7007***	0.9202***
	(0.8948)	(0.2182)
Wage and Salary Employment	-0.0017	-0.0529***
	(0.0074)	(0.0202)
Wage and Salary	0.0005***	0.0015***
	(0.0001)	(0.0002)
Proprietors' Employment	-0.1589***	0.1701*
	(0.0461)	(0.1033)
Proprietors' Income	0.0013*	0.0022**
	(0.0007)	(0.0011)
Observations	2,106	195
R^2	0.3728	0.897
F Statistic	170.4042***	180.4013***

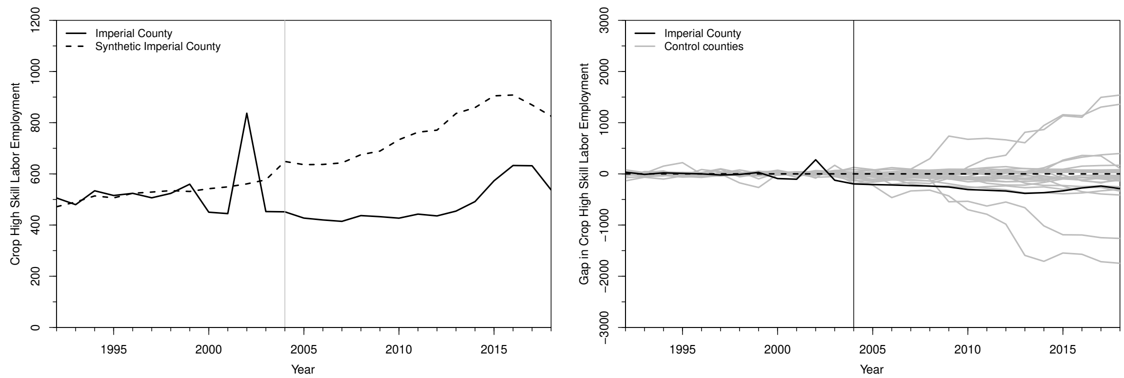
Notes: Per Capita Income is measured in thousands. Model 1 uses all available (53) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Model 2 uses only control counties that receive nonzero weight in the synthetic control analysis (see table E1). Both models control for county and year fixed effects. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Figure D8: Transfer Payments.



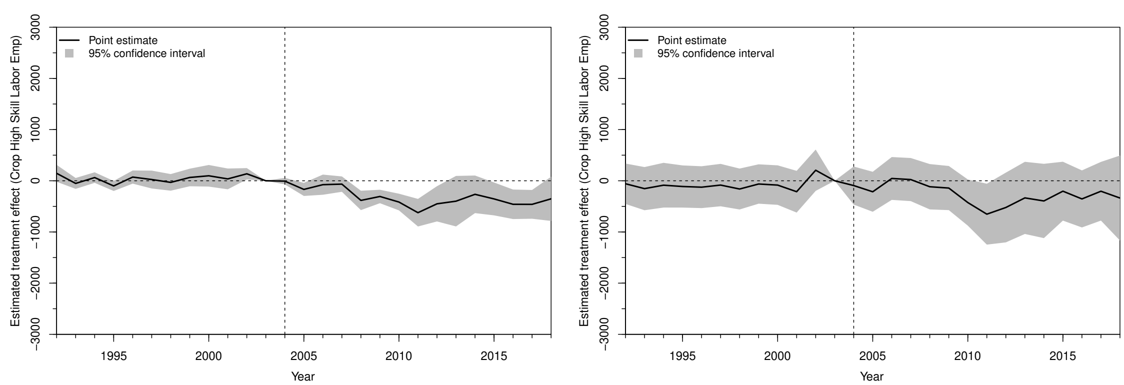
Source: QSA Annual Reports from Imperial Irrigation District digitized by the authors available at `www.iid.com/water/library/qsa-water-transfer/qsa-annual-reports`.

Figure D9: Synthetic Control Analysis for Crop High-Skill Labor Employment.



Notes: Graphical summary of synthetic control output for Crop High-Skill Employment. Employment measure is for the crop sector (NAICS=111). Right panel shows the time path realized by Imperial County and the synthetic Imperial County. Left panel shows the falsification test results of the estimated treatment effect for Imperial County along with placebo effects for control units. Donor pool for Crop High-Skill Employment consists of 29 control counties. See appendix C for the list of control variables included in the analysis. To refine inferences from falsification tests, we consider control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit (Abadie et al., 2010). The vertical line represents the QSA effective year.

Figure D10: Event Study Analysis for Crop High-Skill Labor Employment.



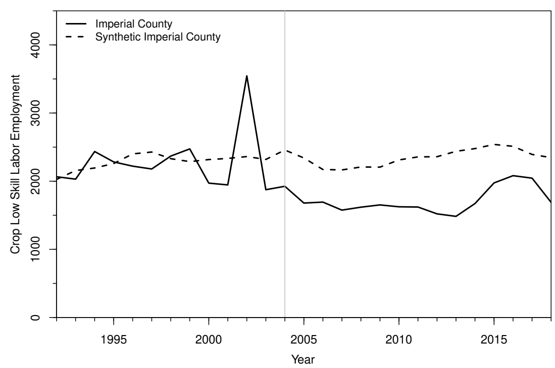
Notes: Event study analysis for Crop High-Skill Labor Employment. Employment measure is for the crop sector (NAICS=111). Right panel shows the estimated treatment effect for Imperial County using all available (47) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Left panel shows the estimated treatment effect for Imperial County using only control counties that receive nonzero weight in the synthetic control analysis (see table E1). See appendix C for the list of control variables included in the analysis. Both models control for county and year fixed effects. The confidence bounds are obtained using robust standard errors. The vertical line represents the QSA effective year.

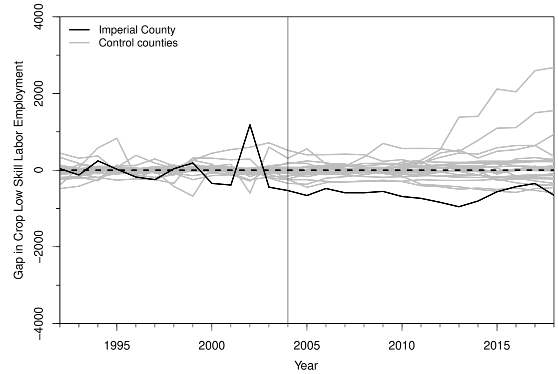
Table D6: Difference-in-Differences Analysis for Crop High-Skill Labor Employment.

	(1)	(2)
1(Imperial)×1(Post-intervention)	-320.0928***	-67.9849
	(119.5283)	(56.4572)
Farm Proprietors' Income	0.6911*	0.2257
	(0.3871)	(0.2664)
Farm Proprietors' Employment	134.4385	101.3437**
	(131.6754)	(42.6406)
Wage and Salary Employment	1.9767**	-20.6808***
	(0.9502)	(2.7785)
Wage and Salary	-0.0058**	0.4844***
	(0.0025)	(0.1227)
Proprietors' Employment	-0.7314	50.1366***
	(1.2684)	(14.1521)
Proprietors' Income	-0.0055	-0.1041
	(0.0193)	(0.2022)
White Ag Labor Ratio	-1,658.2800***	1,776.1150
	(576.6743)	(1,392.5900)
Male Ag Labor Ratio	-488.4528	-3,008.2560***
	(522.5314)	(1,015.9870)
Hispanic Ag Labor Ratio	-216.5619	2,850.9250**
	(502.1189)	(1,300.1720)
High School or Higher Ag Labor Ratio	895.6604	2,471.6420
	(990.6768)	(2,160.7160)
Annual Cattle Values	-0.0007	-0.0008*
	(0.0008)	(0.0004)
Annual Alfalfa Hay Values	-0.0002	-0.0002
	(0.0008)	(0.0003)
Annual Vegetable Values	0.0009***	0.0005***
	(0.0003)	(0.0001)
Observations	1,008	135
R^2	0.4357	0.9344
F Statistic	50.7392***	91.5996***

Notes: Employment measure is for the crop sector (NAICS=111). Model 1 uses all available (47) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Model 2 uses only control counties that receive nonzero weight in the synthetic control analysis (see table E1). Both models control for county and year fixed effects. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

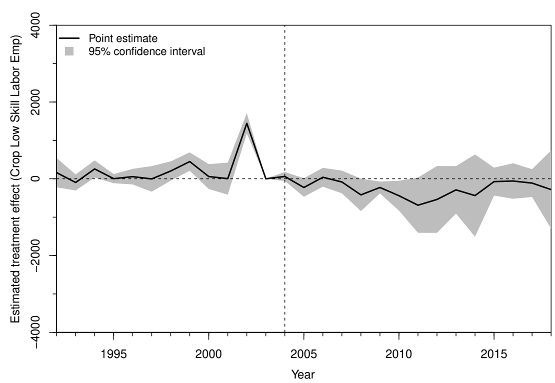
Figure D11: Synthetic Control Analysis for Crop Low-Skill Labor Employment.

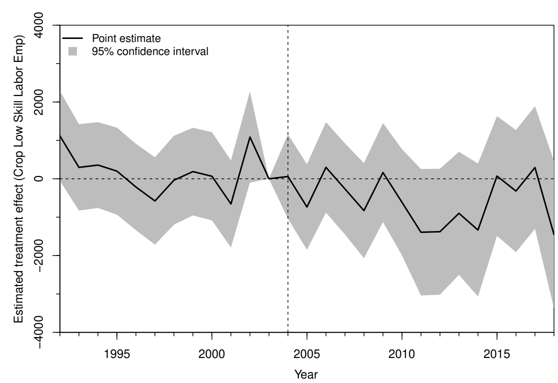




Notes: Graphical summary of synthetic control output for Crop Low-Skill Employment. Employment measure is for the crop sector (NAICS=111). Right panel shows the time path realized by Imperial County and the synthetic Imperial County. Left panel shows the falsification test results of the estimated treatment effect for Imperial County along with placebo effects for control units. Donor pool for Crop Low-Skill Employment consists of 29 control counties. See appendix C for the list of control variables included in the analysis. To refine inferences from falsification tests, we consider control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit (Abadie et al., 2010). The vertical line represents the QSA effective year.

Figure D12: Event Study Analysis for Crop Low-Skill Labor Employment.





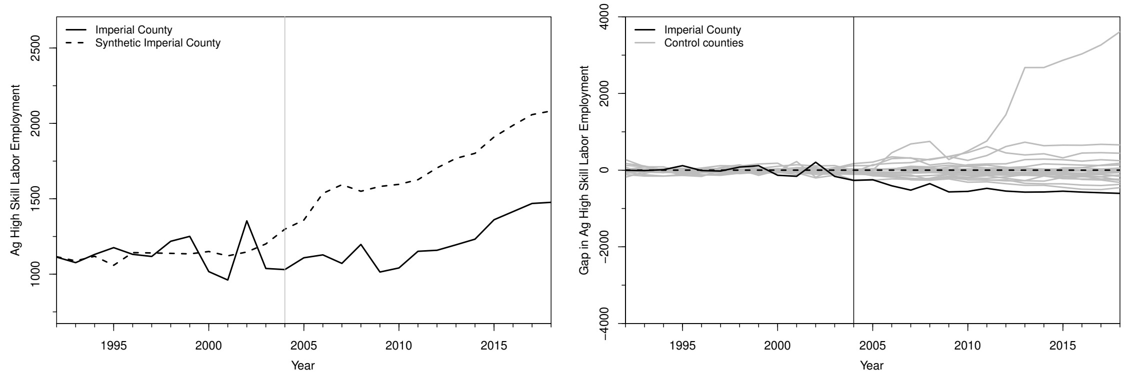
Notes: Event study analysis for Crop Low-Skill Labor Employment. Employment measure is for the crop sector (NAICS=111). Right panel shows the estimated treatment effect for Imperial County using all available (48) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Left panel shows the estimated treatment effect for Imperial County using only control counties that receive nonzero weight in the synthetic control analysis (see table E1). See appendix C for the list of control variables included in the analysis. Both models control for county and year fixed effects. The confidence bounds are obtained using robust standard errors. The vertical line represents the QSA effective year.

Table D7: Difference-in-Differences Analysis for Crop Low-Skill Labor Employment.

	(1)	(2)
1(Imperial)×1(Post-intervention)	-438.2687***	-283.5757
	(139.5125)	(284.9373)
Farm Proprietors' Income	0.7666	-1.2171**
	(0.5543)	(0.4775)
Farm Proprietors' Employment	663.2295***	316.9246*
	(215.0754)	(176.6794)
Wage and Salary Employment	2.7993***	7.8799
	(0.9868)	(13.7148)
Wage and Salary	-0.0107***	-0.0112
	(0.0023)	(0.1929)
Proprietors' Employment	-0.4435	-138.8576***
	(1.3554)	(50.3148)
Proprietors' Income	-0.0225	0.5034
	(0.0267)	(0.3829)
White Ag Labor Ratio	-1,125.7700*	-2,812.7910
	(619.8188)	(6,668.7190)
Male Ag Labor Ratio	-430.6889	-11,240.4400***
	(583.9036)	(4,266.9500)
Hispanic Ag Labor Ratio	426.8016	9,121.5260*
	(686.8160)	(4,689.3630)
High School or Higher Ag Labor Ratio	379.5046	6,653.9970
	(1,124.4850)	(7,907.4080)
Annual Cattle Values	-0.0020**	-0.0013
	(0.0009)	(0.0008)
Annual Alfalfa Hay Values	0.0006	0.0036***
	(0.0020)	(0.0014)
Annual Vegetable Values	0.0006*	0.0020***
	(0.0004)	(0.0004)
Observations	1,029	135
R^2	0.4268	0.7533
F Statistic	49.9867***	19.6349***

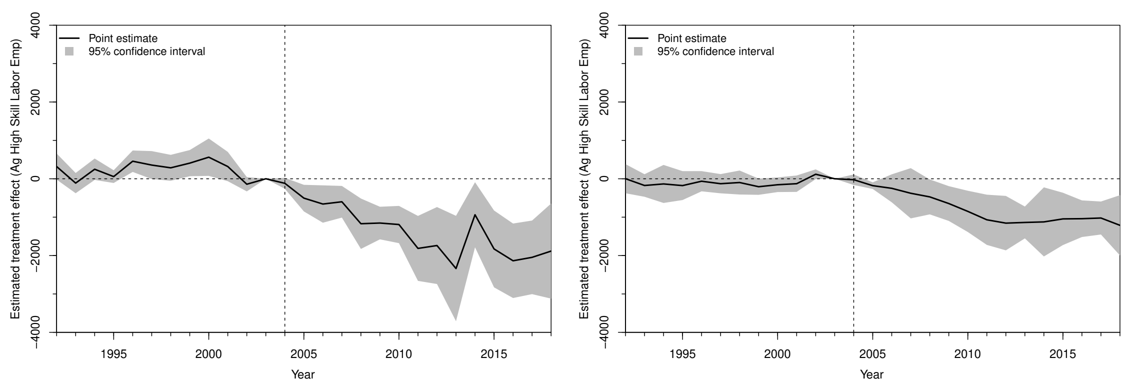
Notes: Employment measure is for the crop sector (NAICS=111). Model 1 uses all available (48) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Model 2 uses only control counties that receive nonzero weight in the synthetic control analysis (see table E1). Both models control for county and year fixed effects. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Figure D13: Synthetic Control Analysis for Ag High-Skill Labor Employment.



Notes: Graphical summary of synthetic control output for Ag High-Skill Labor Employment. Employment measure is for the ag sector (NAICS=11). Right panel shows the time path realized by Imperial County and the synthetic Imperial County. Left panel shows the falsification test results of the estimated treatment effect for Imperial County along with placebo effects for control units. Donor pool for Ag High-Skill Labor Employment consists of 30 control counties. See appendix C for the list of control variables included in the analysis. To refine inferences from falsification tests, we consider control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit (Abadie et al., 2010). The vertical line represents the QSA effective year.

Figure D14: Event Study Analysis for Ag High-Skill Labor Employment.



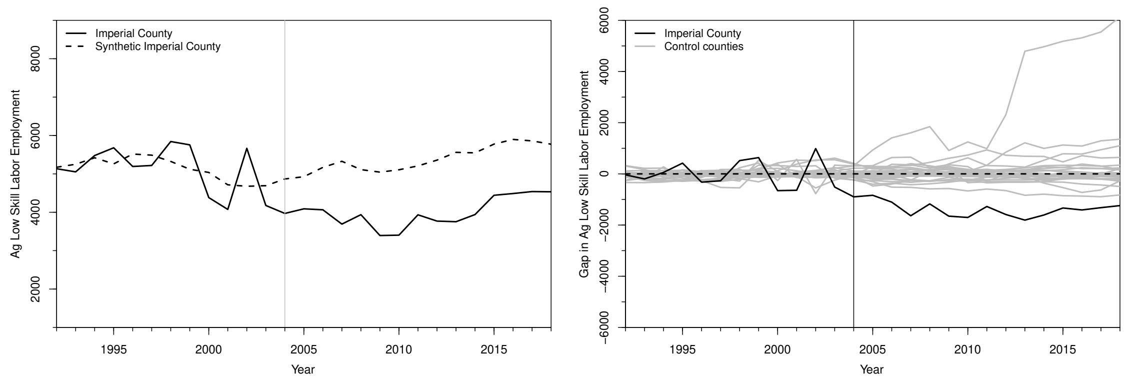
Notes: Event study analysis for Ag High-Skill Labor Employment. Employment measure is for the ag sector (NAICS=11). Right panel shows the estimated treatment effect for Imperial County using all available (48) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Left panel shows the estimated treatment effect for Imperial County using only control counties that receive nonzero weight in the synthetic control analysis (see table E1). See appendix C for the list of control variables included in the analysis. The model controls for county and year fixed effects. The confidence bounds are obtained using robust standard errors. The vertical line represents the QSA effective year.

Table D8: Difference-in-Differences Analysis for Ag High-Skill Labor Employment.

	(1)	(2)
1(Imperial)×1(Post-intervention)	-1,367.0360***	86.9032
	(391.3947)	(93.7862)
Farm Proprietors' Income	1.7902**	1.1420***
	(0.8163)	(0.0637)
Farm Proprietors' Employment	149.8136	-692.1584***
	(384.4494)	(183.9810)
Wage and Salary Employment	3.4769	14.4508
	(2.2658)	(10.0252)
Wage and Salary	-0.0107**	-0.0291
	(0.0052)	(0.1491)
Proprietors' Employment	-5.3897*	49.7737*
	(3.0171)	(26.4864)
Proprietors' Income	0.0076	-0.8106***
	(0.0389)	(0.1285)
White Ag Labor Ratio	-2,303.4760**	-9,837.8240**
	(1,013.6630)	(4,380.8940)
Male Ag Labor Ratio	-656.3264	-3,452.4110***
	(930.0653)	(939.5769)
Hispanic Ag Labor Ratio	-979.6626	7,358.6510***
	(873.4222)	(2,314.2420)
High School or Higher Ag Labor Ratio	2,023.6130	9,280.2650**
	(1,396.6070)	(4,204.5420)
Annual Cattle Values	0.0028*	-0.0011***
	(0.0017)	(0.0003)
Annual Alfalfa Hay Values	-0.0018	0.0001
	(0.0019)	(0.0007)
Annual Vegetable Values	0.0023***	0.0003*
	(0.0008)	(0.0002)
Observations	1,050	108
R^2	0.5986	0.9076
F Statistic	102.3863***	44.9236***

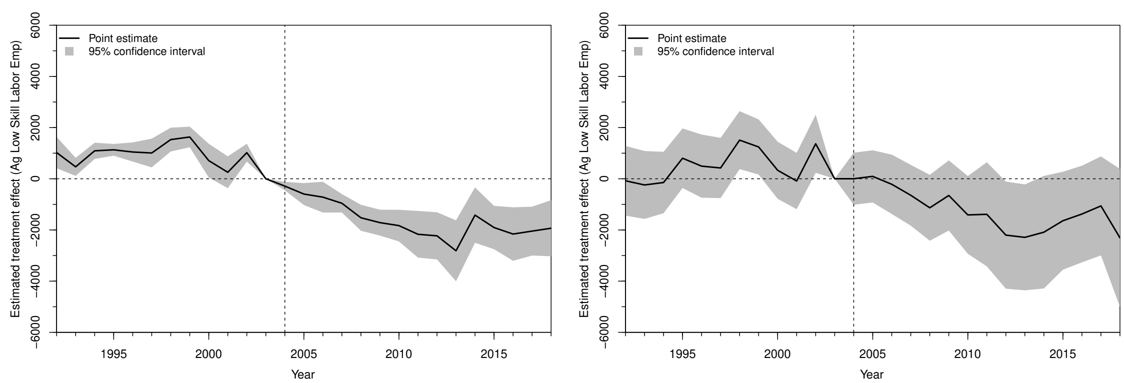
Notes: Employment measure is for the ag sector (NAICS=11). Model 1 uses all available (48) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Model 2 uses only control counties that receive nonzero weight in the synthetic control analysis (see table E1). Both models control for county and year fixed effects. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Figure D15: Synthetic Control Analysis for Ag Low-Skill Labor Employment.



Notes: Graphical summary of synthetic control output for Ag Low-Skill Labor Employment. Employment measure is for the ag sector (NAICS=11). Right panel shows the time path realized by Imperial County and the synthetic Imperial County. Left panel shows the falsification test results of the estimated treatment effect for Imperial County along with placebo effects for control units. Donor pool for Ag Low-Skill Labor Employment consists of 30 control counties. See appendix C for the list of control variables included in the analysis. To refine inferences from falsification tests, we consider control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit (Abadie et al., 2010). The vertical line represents the QSA effective year.

Figure D16: Event Study Analysis for Ag Low-Skill Labor Employment.



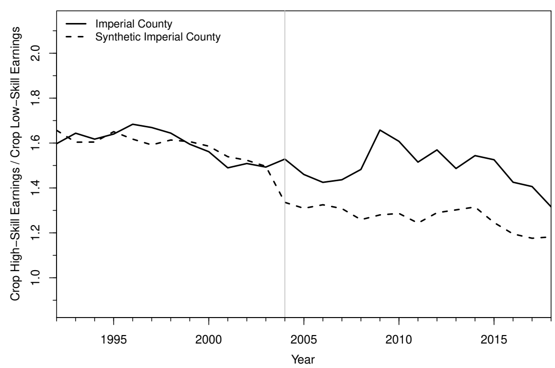
Notes: Event study analysis for Ag Low-Skill Labor Employment. Employment measure is for the ag sector (NAICS=11). Right panel shows the estimated treatment effect for Imperial County using all available (48) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Left panel shows the estimated treatment effect for Imperial County using only control counties that receive nonzero weight in the synthetic control analysis (see table E1). See appendix C for the list of control variables included in the analysis. Both models control for county and year fixed effects. The confidence bounds are obtained using robust standard errors. The vertical line represents the QSA effective year.

Table D9: Difference-in-Differences Analysis for Ag Low-Skill Labor Employment.

	(1)	(2)
1(Imperial)×1(Post-intervention)	-2,323.6270***	-769.1221***
	(361.6651)	(185.9512)
Farm Proprietors' Income	2.2219**	1.6630***
	(0.9720)	(0.5251)
Farm Proprietors' Employment	876.8601	238.4546
	(551.9801)	(152.5152)
Wage and Salary Employment	4.1706	47.7105***
	(2.7683)	(12.5571)
Wage and Salary	-0.0149**	-1.1076***
	(0.0062)	(0.1641)
Proprietors' Employment	-7.0656*	282.3479***
	(3.6523)	(19.2937)
Proprietors' Income	0.0055	-0.5685
	(0.0485)	(0.4475)
White Ag Labor Ratio	-1,597.3660	-33,550.5000***
	(1,127.8540)	(3,360.5480)
Male Ag Labor Ratio	-1,470.3720	-10,910.6400*
	(974.4953)	(5,763.6920)
Hispanic Ag Labor Ratio	-29.5041	22,865.2700***
	(981.3061)	(3,628.1840)
High School or Higher Ag Labor Ratio	2,262.3560	15,344.5700***
	(1,825.9140)	(5,393.1060)
Annual Cattle Values	0.0023	-0.0015
	(0.0020)	(0.0011)
Annual Alfalfa Hay Values	-0.0012	0.0008
	(0.0028)	(0.0005)
Annual Vegetable Values	0.0021*	-0.0010**
	(0.0011)	(0.0004)
Observations	1,049	108
R^2	0.4487	0.8421
F Statistic	55.8084***	24.3877***

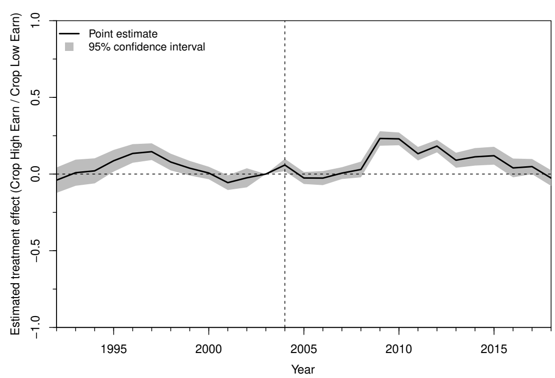
Notes: Employment measure is for the ag sector (NAICS=11). Model 1 uses all available (48) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Model 2 uses only control counties that receive nonzero weight in the synthetic control analysis (see table E1). Both models control for county and year fixed effects. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Figure D17: Synthetic Control Analysis for Crop High-Skill Earnings/Crop Low-Skill Earnings.



Notes: Graphical summary of synthetic control output for Crop High-Skill Earnings/Crop Low-Skill Earnings. Right panel shows the time path realized by Imperial County and the synthetic Imperial County. Left panel shows the falsification test results of the estimated treatment effect for Imperial County along with placebo effects for control units. Donor pool for Crop High-Skill Earnings/Crop Low-Skill Earnings consists of 45 control counties. See appendix C for the list of control variables included in the analysis. To refine inferences from falsification tests, we consider control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit (Abadie et al., 2010). The vertical line represents the QSA effective year.

Figure D18: Event Study Analysis for Crop High-Skill Earnings/Crop Low-Skill Earnings.



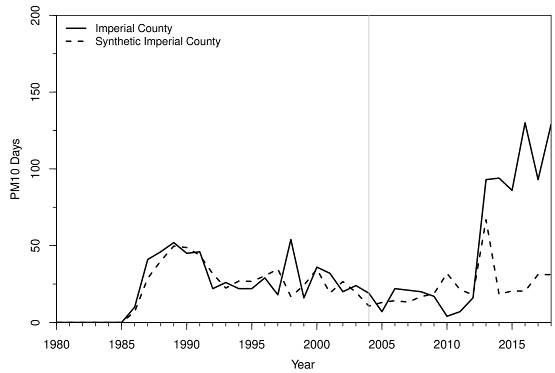
Notes: Event study analysis for Crop High-Skill Earnings/Crop Low-Skill Earnings. Right panel shows the estimated treatment effect for Imperial County using all available (52) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Left panel shows the estimated treatment effect for Imperial County using only control counties that receive nonzero weight in the synthetic control analysis (see table E1). See appendix C for the list of control variables included in the analysis. Both models control for county and year fixed effects. The confidence bounds are obtained using robust standard errors. The vertical line represents the QSA effective year.

Table D10: Difference-in-Differences Analysis for Crop High-Skill Earnings/Crop Low-Skill Earnings.

	(1)	(2)
1(Imperial)×1(Post-intervention)	0.0468*	0.1057
	(0.0240)	(0.0829)
Farm Proprietors' Income	-0.00002	-0.0002
	(0.00005)	(0.0002)
Farm Proprietors' Employment	-0.0029	-0.4684**
	(0.0200)	(0.1904)
Wage and Salary Employment	-0.0004	0.0065
	(0.0003)	(0.0049)
Wage and Salary	0.000002	-0.0001
	(0.000002)	(0.0001)
Proprietors' Employment	-0.0008*	0.0002
	(0.0004)	(0.0182)
Proprietors' Income	0.000003	0.0001**
	(0.000004)	(0.0001)
Observations	1,350	135
R^2	0.0205	0.2514
F Statistic	3.7791***	4.6539***

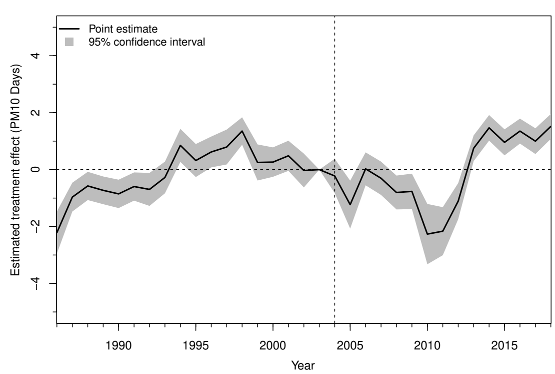
Notes: Model 1 uses all available (52) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Model 2 uses only control counties that receive nonzero weight in the synthetic control analysis (see table E1). Both models control for county and year fixed effects. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Figure D19: Synthetic Control Analysis for PM10 Days.



Notes: Graphical summary of synthetic control output for PM10 Days. Right panel shows the time path realized by Imperial County and the synthetic Imperial County. Left panel shows the falsification test results of the estimated treatment effect for Imperial County along with placebo effects for control units. Donor pool for PM10 Days consists of 35 control counties. See appendix C for the list of control variables included in the analysis. To refine inferences from falsification tests, we consider control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit (Abadie et al., 2010). The vertical line represents the QSA effective year.

Figure D20: Event Study Analysis for PM10 Days (Fixed Effects Poisson Regression).



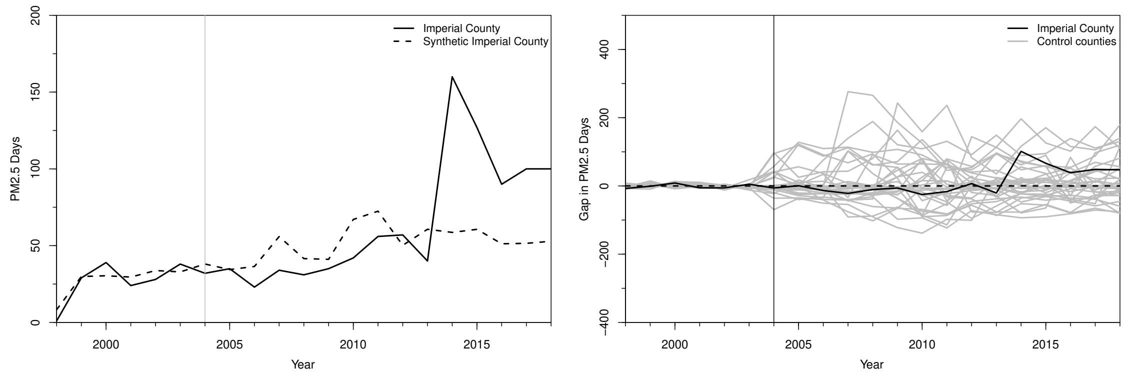
Notes: Event study analysis for PM10 Days using a fixed effects Poisson regression. Right panel shows the estimated treatment effect for Imperial County using all available (53) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Left panel shows the estimated treatment effect for Imperial County using only control counties that receive nonzero weight in the synthetic control analysis (see table E1). See appendix C for the list of control variables included in the analysis. Both models control for county and year fixed effects. The confidence bounds are obtained using robust standard errors. The vertical line represents the QSA effective year.

Table D11: Difference-in-Differences Analysis for PM10 Days (Fixed Effects Poisson Regression).

	(1)	(2)
1(Imperial)×1(Post-intervention)	0.6971***	0.9463
	(0.0000)	(2.3664)
Days with AQI	0.0003	0.0012
	(0.0013)	(0.0060)
Median AQI	-0.0437***	-0.0502*
	(0.0135)	(0.0243)
Farm Proprietors' Income	0.0014***	0.0021
	(0.0004)	(0.0073)
Farm Proprietors' Employment	0.7180***	0.6606
	(0.0000)	(0.9997)
Wage and Salary Employment	0.0011	0.0174
	(0.0018)	(0.5060)
Wage and Salary	0.0000	0.0004
	(0.0000)	(0.0057)
Proprietors' Employment	0.0121**	-0.0515
	(0.0053)	(0.2799)
Proprietors' Income	-0.0002**	-0.0021
	(0.0001)	(0.0037)
Observations	1,876	264
Log-likelihood	-10,807.38	-3,095.025

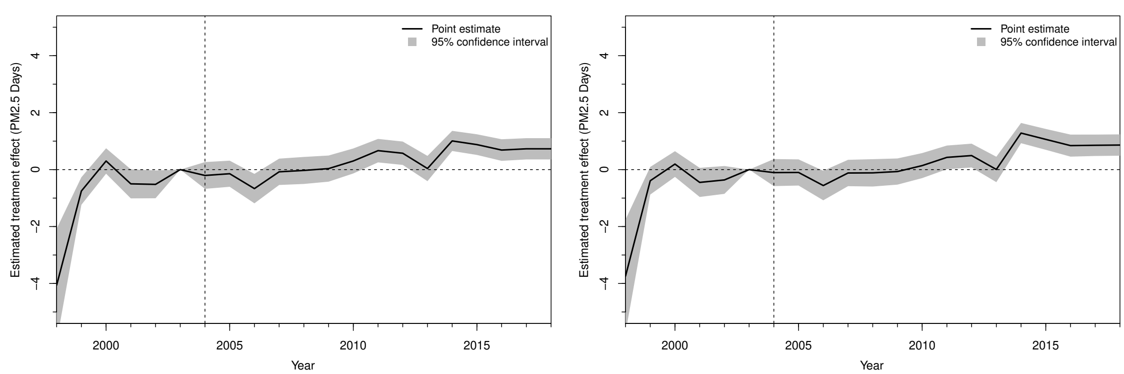
Notes: Model 1 uses all available (53) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Model 2 uses only control counties that receive nonzero weight in the synthetic control analysis (see table E1). Both models control for county and year fixed effects. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Figure D21: Synthetic Control Analysis for PM2.5 Days.



Notes: Graphical summary of synthetic control output for PM2.5 Days. Right panel shows the time path realized by Imperial County and the synthetic Imperial County. Left panel shows the falsification test results of the estimated treatment effect for Imperial County along with placebo effects for control units. Donor pool for PM2.5 Days consists of 49 control counties. See appendix C for the list of control variables included in the analysis. To refine inferences from falsification tests, we consider control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit (Abadie et al., 2010). The vertical line represents the QSA effective year.

Figure D22: Event Study Analysis for PM2.5 Days (Fixed Effects Poisson Regression).



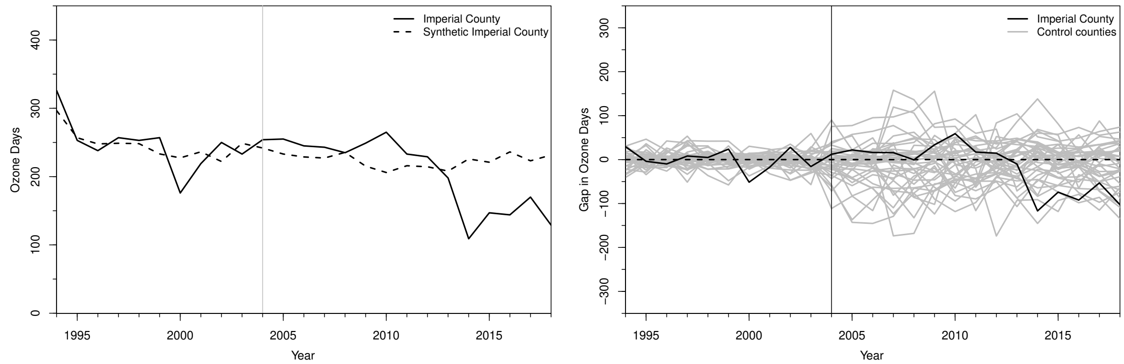
Notes: Event study analysis for PM2.5 Days using a fixed effects Poisson regression. Right panel shows the estimated treatment effect for Imperial County using all available (53) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Left panel shows the estimated treatment effect for Imperial County using only control counties that receive nonzero weight in the synthetic control analysis (see table E1). See appendix C for the list of control variables included in the analysis. Both models control for county and year fixed effects. The confidence bounds are obtained using robust standard errors. The vertical line represents the QSA effective year.

Table D12: Difference-in-Differences Analysis for PM2.5 Days (Fixed Effects Poisson Regression).

	(1)	(2)
1(Imperial)×1(Post-intervention)	1.0241***	0.9757***
	(0.0000)	(0.0002)
Days with AQI	0.0017***	-0.0764***
	(0.0006)	(0.0006)
Median AQI	0.0438***	0.0183*
	(0.0065)	(0.0101)
Farm Proprietors' Income	0.0004*	-0.0003
	(0.0003)	(0.0012)
Farm Proprietors' Employment	-0.9694***	-0.0570***
	(0.0000)	(0.0020)
Wage and Salary Employment	-0.0020***	-0.0199
	(0.0006)	(0.0290)
Wage and Salary	0.0000***	0.0003
	(0.0000)	(0.0005)
Proprietors' Employment	0.0009	-0.0067
	(0.0008)	(0.0481)
Proprietors' Income	0.0000	0.0004
	(0.0000)	(0.0005)
Observations	1,069	105
Log-likelihood	-16,410.72	-900.2285

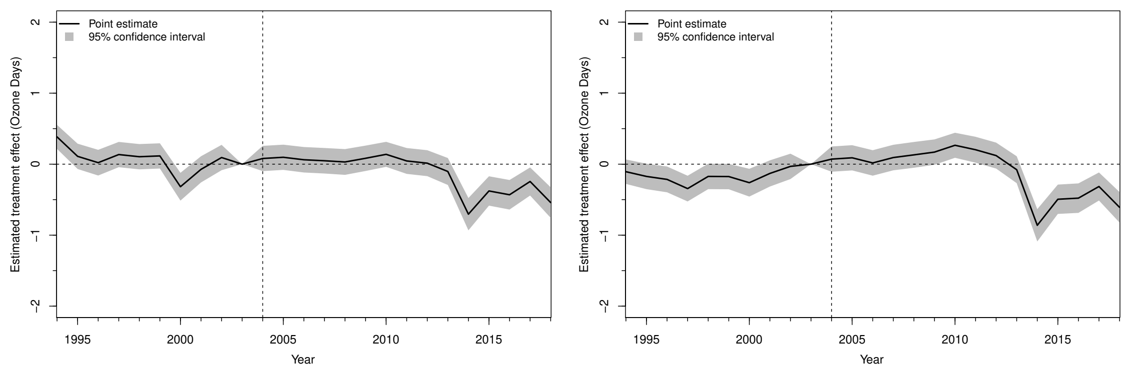
Notes: Model 1 uses all available (53) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Model 2 uses only control counties that receive nonzero weight in the synthetic control analysis (see table E1). Both models control for county and year fixed effects. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Figure D23: Synthetic Control Analysis for Ozone Days.



Notes: Graphical summary of synthetic control output for Ozone Days. Right panel shows the time path realized by Imperial County and the synthetic Imperial County. Left panel shows the falsification test results of the estimated treatment effect for Imperial County along with placebo effects for control units. Donor pool for Ozone Days consists of 48 control counties. See appendix C for the list of control variables included in the analysis. To refine inferences from falsification tests, we consider control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit (Abadie et al., 2010). The vertical line represents the QSA effective year.

Figure D24: Event Study Analysis for Ozone Days (Fixed Effects Poisson Regression).



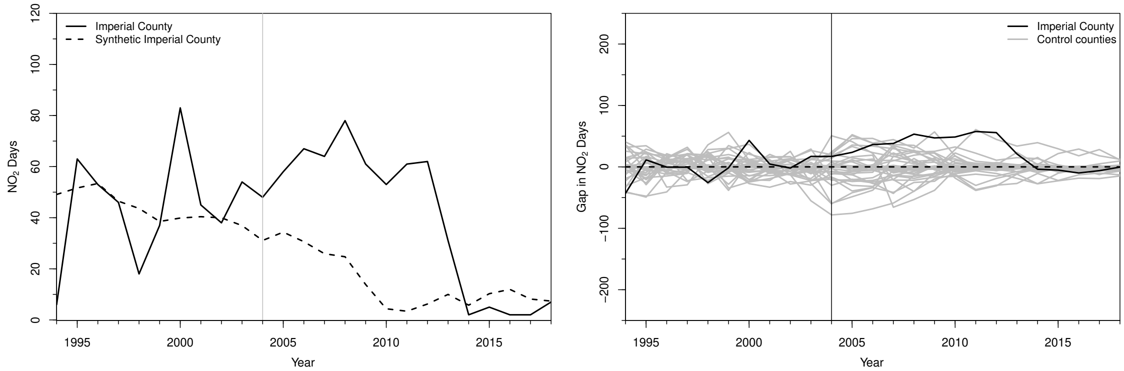
Notes: Event study analysis for Ozone Days using a fixed effects Poisson regression. Right panel shows the estimated treatment effect for Imperial County using all available (53) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Left panel shows the estimated treatment effect for Imperial County using only control counties that receive nonzero weight in the synthetic control analysis (see table E1). See appendix C for the list of control variables included in the analysis. Both models control for county and year fixed effects. The confidence bounds are obtained using robust standard errors. The vertical line represents the QSA effective year.

Table D13: Difference-in-Differences Analysis for Ozone Days (Fixed Effects Poisson Regression).

	(1)	(2)
1(Imperial)×1(Post-intervention)	-0.1497***	0.1023***
	(0.0000)	(0.0047)
Days with AQI	0.0083***	0.0150
	(0.0019)	(0.0602)
Median AQI	-0.0020	0.0183*
	(0.0034)	(0.0103)
Farm Proprietors' Income	-0.0002**	0.0003
	(0.0001)	(0.0023)
Farm Proprietors' Employment	0.0717***	0.3530***
	(0.0000)	(0.0006)
Wage and Salary Employment	0.0002	-0.0068
	(0.0002)	(0.1151)
Wage and Salary	0.0000	0.0000
	(0.0000)	(0.0016)
Proprietors' Employment	-0.0004	0.0383
	(0.0004)	(0.2193)
Proprietors' Income	0.0000*	-0.0002
	(0.0000)	(0.0010)
Observations	1,276	150
Log-likelihood	-12,753.68	-3,048.978

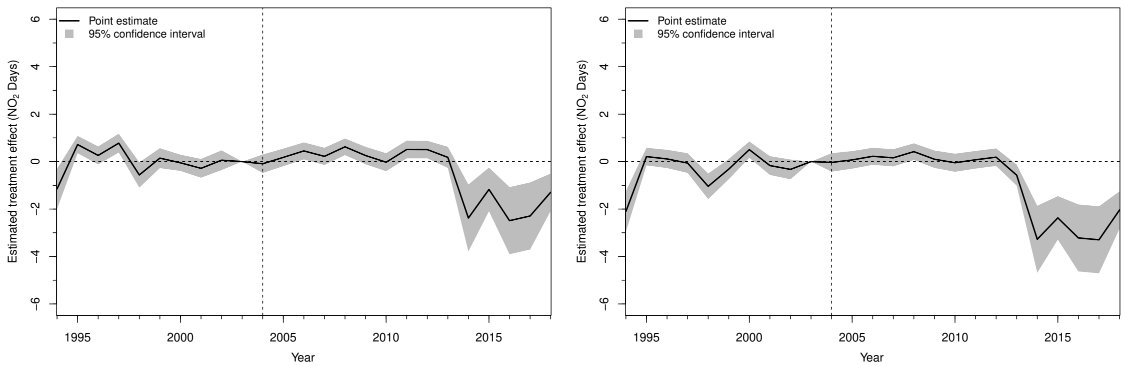
Notes: Model 1 uses all available (53) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Model 2 uses only control counties that receive nonzero weight in the synthetic control analysis (see table E1). Both models control for county and year fixed effects. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Figure D25: Synthetic Control Analysis for NO_2 Days.



Notes: Graphical summary of synthetic control output for NO_2 Days. Right panel shows the time path realized by Imperial County and the synthetic Imperial County. Left panel shows the falsification test results of the estimated treatment effect for Imperial County along with placebo effects for control units. Donor pool for NO_2 Days consists of 48 control counties. See appendix C for the list of control variables included in the analysis. To refine inferences from falsification tests, we consider control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit (Abadie et al., 2010). The vertical line represents the QSA effective year.

Figure D26: Event Study Analysis for NO_2 Days (Fixed Effects Poisson Regression).



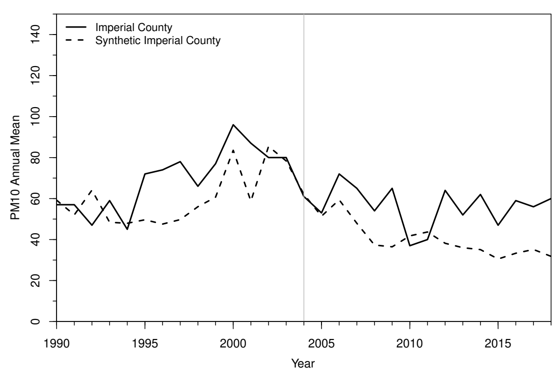
Notes: Event study analysis for NO_2 Days using a fixed effects Poisson regression. Right panel shows the estimated treatment effect for Imperial County using all available (53) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Left panel shows the estimated treatment effect for Imperial County using only control counties that receive nonzero weight in the synthetic control analysis (see table E1). See appendix C for the list of control variables included in the analysis. Both models control for county and year fixed effects. The confidence bounds are obtained using robust standard errors. The vertical line represents the QSA effective year.

Table D14: Difference-in-Differences Analysis for NO_2 Days (Fixed Effects Poisson Regression).

	(1)	(2)
1(Imperial)×1(Post-intervention)	-0.1027***	-0.1221
	(0.0000)	(0.1345)
Days with AQI	0.0057***	-0.0782
	(0.0021)	(8.6883)
Median AQI	-0.0548***	-0.0580
	(0.0117)	(0.1632)
Farm Proprietors' Income	-0.0024***	-0.0011
	(0.0006)	(0.0032)
Farm Proprietors' Employment	0.9390***	1.6944***
	(0.0001)	(0.0648)
Wage and Salary Employment	0.0007	0.0116
	(0.0013)	(0.1369)
Wage and Salary	0.0000***	0.0000
	(0.0000)	(0.0034)
Proprietors' Employment	-0.0001	-0.0417
	(0.0043)	(0.4127)
Proprietors' Income	0.0000	-0.0002
	(0.0000)	(0.0016)
Observations	1,276	100
Log-likelihood	-8,639.586	-612.4266

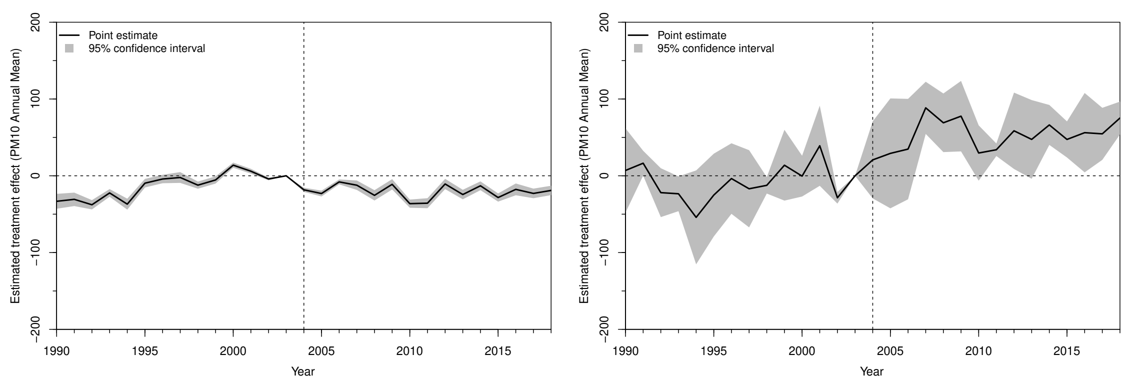
Notes: Model 1 uses all available (53) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Model 2 uses only control counties that receive nonzero weight in the synthetic control analysis (see table E1). Both models control for county and year fixed effects. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Figure D27: Synthetic Control Analysis for PM10 Annual Mean (µg/m^3).



Notes: Graphical summary of synthetic control output for PM10 Annual Mean. Right panel shows the time path realized by Imperial County and the synthetic Imperial County. Left panel shows the falsification test results of the estimated treatment effect for Imperial County along with placebo effects for control units. Donor pool for PM10 Annual Mean consists of 12 control counties. See appendix C for the list of control variables included in the analysis. To refine inferences from falsification tests, we consider control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit (Abadie et al., 2010). The vertical line represents the QSA effective year.

Figure D28: Event Study Analysis for PM10 Annual Mean (µg/m^3).



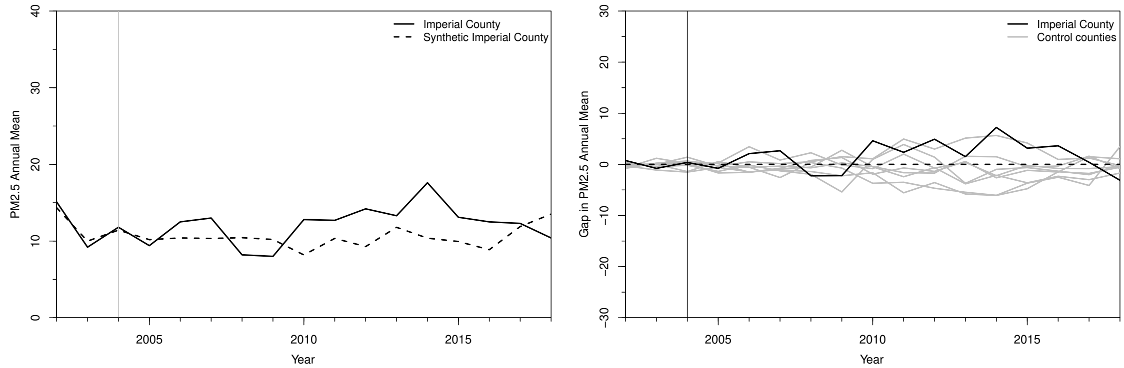
Notes: Event study analysis for PM10 Annual Mean (µg/m^3). Right panel shows the estimated treatment effect for Imperial County using all available (49) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Left panel shows the estimated treatment effect for Imperial County using only control counties that receive nonzero weight in the synthetic control analysis (see table E1). See appendix C for the list of control variables included in the analysis. Both models control for county and year fixed effects. The confidence bounds are obtained using robust standard errors. The vertical line represents the QSA effective year.

Table D15: Difference-in-Differences Analysis for PM10 Annual Mean (µg/m^3).

	(1)	(2)
1(Imperial)×1(Post-intervention)	-7.4623***	39.8011
	(1.8371)	(24.3608)
Days with AQI	0.0226	-0.0161
	(0.0204)	(0.0462)
Median AQI	0.0339	0.7414***
	(0.1210)	(0.1888)
Farm Proprietors' Income	0.0016	0.0631***
	(0.0039)	(0.0131)
Farm Proprietors' Employment	2.1874**	146.4164**
	(0.9877)	(65.8332)
Wage and Salary Employment	-0.0082	0.3374
	(0.0106)	(0.4400)
Wage and Salary	-0.00002	-0.0078
	(0.00005)	(0.0062)
Proprietors' Employment	0.0050	2.3607**
	(0.0244)	(0.9612)
Proprietors' Income	-0.0001	-0.0124
	(0.0003)	(0.0084)
Observations	1,160	87
R^2	0.0345	0.5099
F Statistic	4.2665***	5.4335***

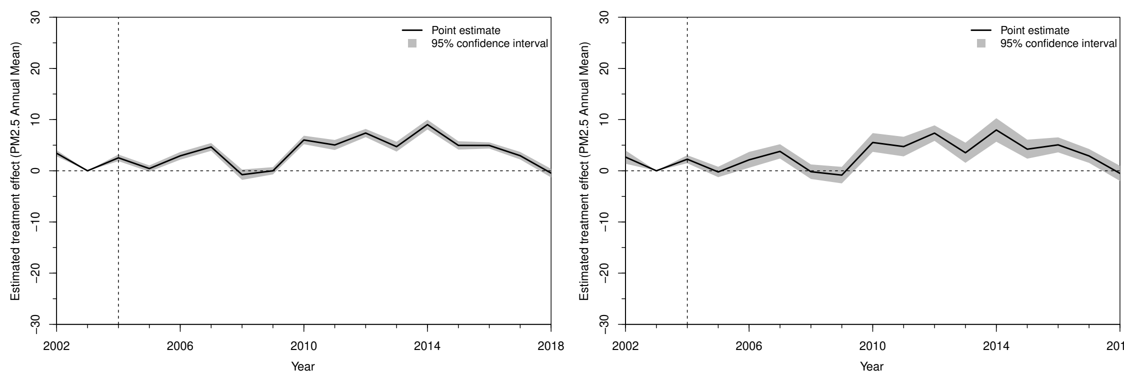
Notes: Model 1 uses all available (49) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Model 2 uses only control counties that receive nonzero weight in the synthetic control analysis (see table E1). Both models control for county and year fixed effects. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Figure D29: Synthetic Control Analysis for PM2.5 Annual Mean (µg/m^3).



Notes: Graphical summary of synthetic control output for PM2.5 Annual Mean. Right panel shows the time path realized by Imperial County and the synthetic Imperial County. Left panel shows the falsification test results of the estimated treatment effect for Imperial County along with placebo effects for control units. Donor pool for PM2.5 Annual Mean consists of 13 control counties. See appendix C for the list of control variables included in the analysis. To refine inferences from falsification tests, we consider control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit (Abadie et al., 2010). The vertical line represents the QSA effective year.

Figure D30: Event Study Analysis for PM2.5 Annual Mean (µg/m^3).



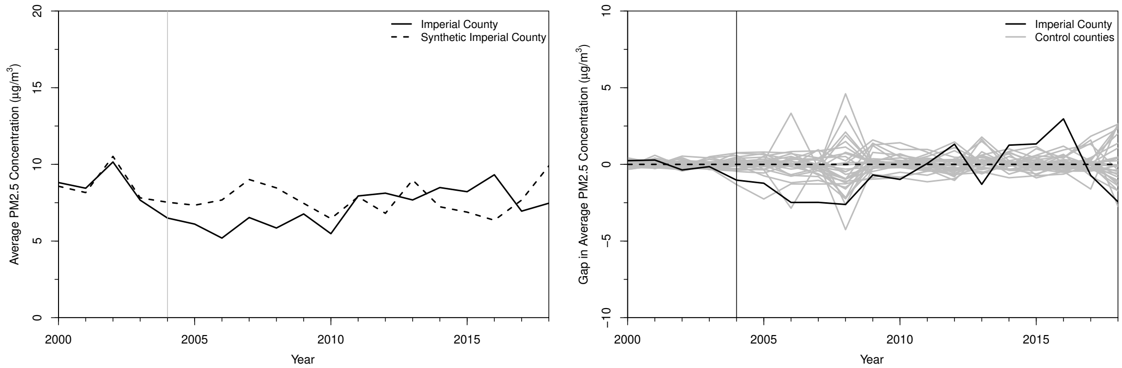
Notes: Event study analysis for PM2.5 Annual Mean (µg/m^3). Right panel shows the estimated treatment effect for Imperial County using all available (42) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Left panel shows the estimated treatment effect for Imperial County using only control counties that receive nonzero weight in the synthetic control analysis (see table E1). See appendix C for the list of control variables included in the analysis. Both models control for county and year fixed effects. The confidence bounds are obtained using robust standard errors. The vertical line represents the QSA effective year.

Table D16: Difference-in-Differences Analysis for PM2.5 Annual Mean (μg/m^3).

	(1)	(2)
1(Imperial)×1(Post-intervention)	1.9111***	1.7372**
	(0.2943)	(0.6775)
Days with AQI	-0.0018	-1.9016*
	(0.0033)	(1.0018)
Median AQI	0.0829***	0.1100***
	(0.0196)	(0.0272)
Farm Proprietors' Income	0.0001	-0.0009
	(0.0005)	(0.0006)
Farm Proprietors' Employment	1.3591***	-0.1805
	(0.4423)	(0.5174)
Wage and Salary Employment	0.0045*	0.0193
	(0.0024)	(0.0131)
Wage and Salary	-0.00001	-0.0001*
	(0.00001)	(0.00003)
Proprietors' Employment	-0.0151*	0.0044
	(0.0084)	(0.0152)
Proprietors' Income	0.0001	-0.00002
	(0.0001)	(0.0002)
Observations	612	204
R^2	0.1900	0.2028
F Statistic	14.1772***	4.7194***

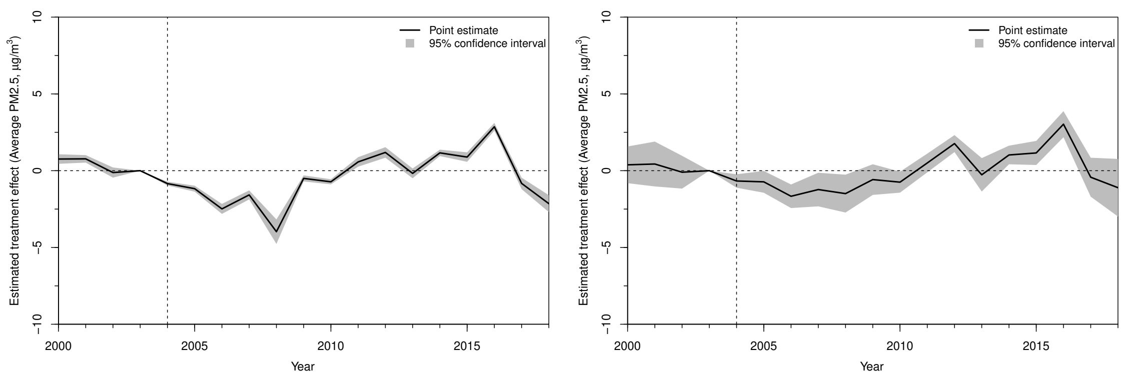
Notes: Model 1 uses all available (42) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Model 2 uses only control counties that receive nonzero weight in the synthetic control analysis (see table E1). Both models control for county and year fixed effects. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Figure D31: Synthetic Control Analysis for Satellite-Based PM2.5 Mean (µg/m^3).



Notes: Graphical summary of synthetic control output for Satellite-Based PM2.5 Mean. Right panel shows the time path realized by Imperial County and the synthetic Imperial County. Left panel shows the falsification test results of the estimated treatment effect for Imperial County along with placebo effects for control units. Donor pool for Satellite-Based PM2.5 Mean consists of 49 control counties. See appendix C for the list of control variables included in the analysis. To refine inferences from falsification tests, we consider control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit (Abadie et al., 2010). The vertical line represents the QSA effective year.

Figure D32: Event Study Analysis for Satellite-Based PM2.5 Mean (µg/m^3).



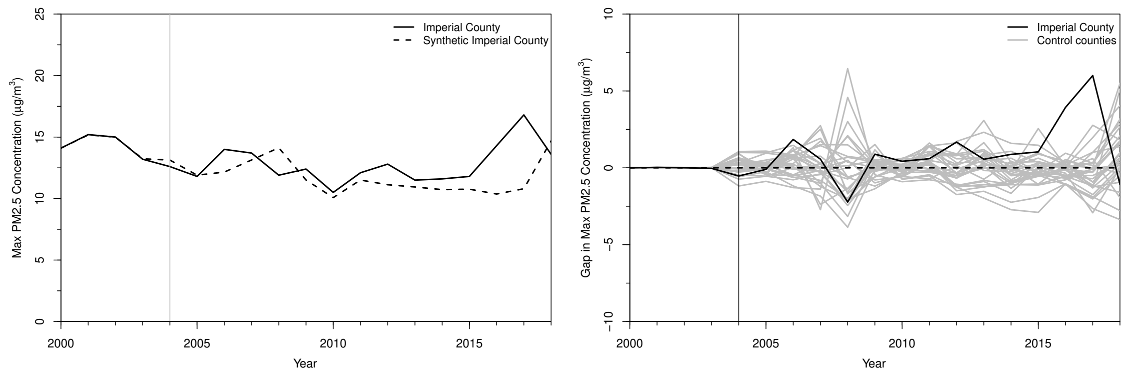
Notes: Event study analysis for Satellite-Based PM2.5 Mean (µg/m^3). Right panel shows the estimated treatment effect for Imperial County using all available (53) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Left panel shows the estimated treatment effect for Imperial County using only control counties that receive nonzero weight in the synthetic control analysis (see table E1). See appendix C for the list of control variables included in the analysis. Both models control for county and year fixed effects. The confidence bounds are obtained using robust standard errors. The vertical line represents the QSA effective year.

Table D17: Difference-in-Differences Analysis for Satellite-Based PM2.5 Mean (μg/m^3).

	(1)	(2)
1(Imperial)×1(Post-intervention)	-0.8762***	-0.3355
	(0.1480)	(0.4419)
Days with AQI	-0.0001	-0.0192
	(0.0012)	(0.0496)
Median AQI	0.0122**	0.0372***
	(0.0055)	(0.0134)
Farm Proprietors' Income	0.0002	0.0017
	(0.0003)	(0.0015)
Farm Proprietors' Employment	0.4653	3.5003
	(0.3449)	(2.9764)
Wage and Salary Employment	-0.0002	0.0020
	(0.0008)	(0.0031)
Wage and Salary	-0.00001	0.00004
	(0.00001)	(0.00003)
Proprietors' Employment	-0.0079**	-0.0271***
	(0.0034)	(0.0037)
Proprietors' Income	0.0001**	-0.0001
	(0.00004)	(0.0001)
Observations	963	133
R^2	0.0722	0.3539
F Statistic	7.6213***	6.0245***

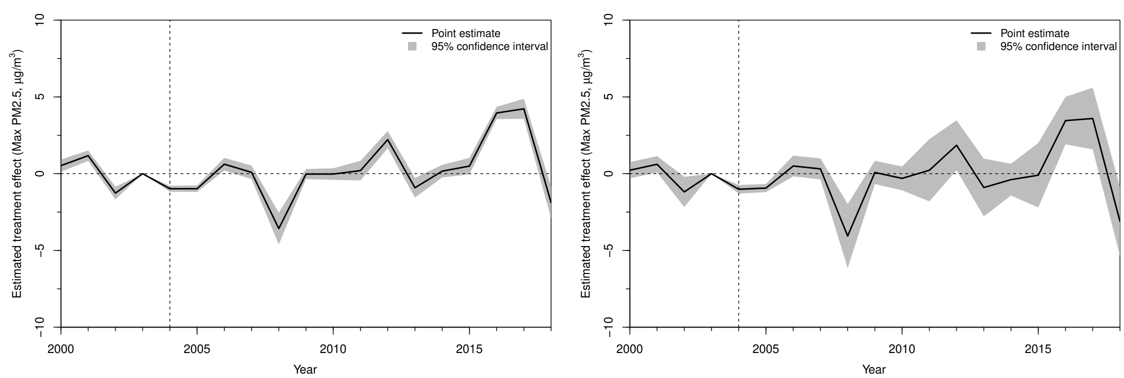
Notes: Model 1 uses all available (53) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Model 2 uses only control counties that receive nonzero weight in the synthetic control analysis (see table E1). Both models control for county and year fixed effects. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

Figure D33: Synthetic Control Analysis for Satellite-Based PM2.5 Max (µg/m^3).



Notes: Graphical summary of synthetic control output for Satellite-Based PM2.5 Max. Right panel shows the time path realized by Imperial County and the synthetic Imperial County. Left panel shows the falsification test results of the estimated treatment effect for Imperial County along with placebo effects for control units. Donor pool for Satellite-Based PM2.5 Max consists of 49 control counties. See appendix C for the list of control variables included in the analysis. To refine inferences from falsification tests, we consider control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit (Abadie et al., 2010). The vertical line represents the QSA effective year.

Figure D34: Event Study Analysis for Satellite-Based PM2.5 Max (µg/m^3).



Notes: Event study analysis for Satellite-Based PM2.5 Max (µg/m^3). Right panel shows the estimated treatment effect for Imperial County using all available (53) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Left panel shows the estimated treatment effect for Imperial County using only control counties that receive nonzero weight in the synthetic control analysis (see table E1). See appendix C for the list of control variables included in the analysis. Both models control for county and year fixed effects. The confidence bounds are obtained using robust standard errors. The vertical line represents the QSA effective year.

Table D18: Difference-in-Differences Analysis for Satellite-Based PM2.5 Max (μg/m^3).

	(1)	(2)
1(Imperial)×1(Post-intervention)	0.1239	-0.0389
	(0.2454)	(0.5511)
Days with AQI	0.0012	-0.0027*
	(0.0021)	(0.0015)
Median AQI	0.0266**	0.0433**
	(0.0109)	(0.0217)
Farm Proprietors' Income	-0.0009	-0.0005
	(0.0006)	(0.0027)
Farm Proprietors' Employment	0.9954**	0.1423
	(0.4628)	(0.8242)
Wage and Salary Employment	-0.0003	-0.0005
	(0.0053)	(0.0070)
Wage and Salary	-0.000001	-0.00001
	(0.00003)	(0.00005)
Proprietors' Employment	-0.0211***	-0.0196**
	(0.0061)	(0.0094)
Proprietors' Income	0.0002***	0.0002**
	(0.0001)	(0.0001)
Observations	963	437
R^2	0.1574	0.1955
F Statistic	18.3090***	10.4478***

Notes: Model 1 uses all available (53) control counties, where omitted counties include those with missing observations and/or significant water transfer (due to other policy/agreements) during the study period. Model 2 uses only control counties that receive nonzero weight in the synthetic control analysis (see table E1). Both models control for county and year fixed effects. Robust standard errors in parenthesis. *p<0.1; **p<0.05; ***p<0.01.

E Additional Results for Synthetic Control Analysis

Table E1: Donor County Weights for Each Outcome Variable Analysis.

Donor	Weight	Donor	Weight
Log Harvested Acres		*NO_2 Days*	
Tulare	0.780	Inyo	0.640
Siskiyou	0.109	San Bernardino	0.301
Monterey	0.104	Marin	0.058
Kings	0.006		
		Ozone Days	
Harvested Acres		Inyo	0.542
Kern	0.346	Kern	0.156
Siskiyou	0.224	Monterey	0.116
Tulare	0.197	Del Norte	0.114
Monterey	0.142	Mono	0.072
Kings	0.091		
		PM10 Annual Mean	
Per Capita Income		San Bernardino	0.645
Tulare	0.405	Inyo	0.354
Merced	0.342		
Kings	0.190	*PM2.5 Annual Mean*	
Monterey	0.064	Solano	0.841
		Alameda	0.022
Crop High Skill Labor Employment		Kern	0.021
Lassen	0.542	Kings	0.020
Merced	0.222	Sacramento	0.019
Kings	0.124	Ventura	0.019
Monterey	0.112	Contra Costa	0.017
		Santa Clara	0.016
Crop Low Skill Labor Employment		San Luis Obispo	0.014
Colusa	0.705	Fresno	0.009
Monterey	0.191	Placer	0.001
Merced	0.078		
Tulare	0.026	*Satellite-Based PM2.5 Mean*	
		Mariposa	0.545
Ag High Skill Labor Employment		Inyo	0.207
Kings	0.516	Kings	0.185
Merced	0.270	Kern	0.045
Colusa	0.215	Orange	0.016
		San Francisco	0.002
Ag Low Skill Labor Employment			
Kings	0.530	*Satellite-Based PM2.5 Max*	
Merced	0.324	Colusa	0.318
Fresno	0.146	San Diego	0.313
		Plumas	0.179
Crop High-Skill Earn/Crop Low-Skill Earn		San Bernardino	0.167
Yolo	0.463	Butte	0.001
Monterey	0.316	Calaveras	0.001
Del Norte	0.127	Del Norte	0.001
San Benito	0.094	Glenn	0.001
		Lake	0.001
PM10 Days		Los Angeles	0.001
Mendocino	0.314	Mariposa	0.001
Glenn	0.259	Nevada	0.001
Butte	0.234	San Francisco	0.001
Colusa	0.116	San Luis Obispo	0.001
Mono	0.040	San Mateo	0.001
Kern	0.028	Santa Barbara	0.001
Kings	0.007	Siskiyou	0.001
		Sonoma	0.001
PM2.5 Days		Sutter	0.001
Inyo	0.662	Tehama	0.001
Fresno	0.220	Trinity	0.001
Monterey	0.057	Yolo	0.001
San Bernardino	0.057		

Notes: County weights are obtained by performing synthetic control analysis separately for each outcome variable of interest. Reported counties are those that receive nonzero weights in the analysis.

E.1 The RMSPE test

An alternative technique to evaluate the statistical significance of the measured treatment effect is by the ratio of the post-intervention root mean square prediction error (RMSPE) to the pre-intervention RMSPE (Abadie et al., 2010; Abadie, 2021). Given that the control units are not exposed to treatment, the post-intervention RMSPE (i.e., the square root of average discrepancy between actual and synthetic outcomes for the post-intervention period) for control units should, in theory, be similar to the pre-intervention RMSPE (i.e., the square root of average discrepancy between actual and synthetic outcomes for the pre-intervention period), thus producing a relatively small ratio. On the other hand, for the treatment unit, the difference between actual and synthetic outcomes will be more pronounced during the post-intervention period if a treatment effect is truly present, thus producing a larger post-intervention RMSPE and, in turn, a larger overall ratio. As such, the estimated treatment effect for the treatment county ($\hat{\delta}_{1t}$, for $t > T_0$) is considered statistically significant if the treatment county has one of the few large post/pre RMSPE ratios. In particular, a treatment unit with a significant treatment effect would appear at or near the top when all post/pre RMSPE ratios were listed in descending order.

The disadvantage of RMSPE test is that it does not distinguish between positive and negative deviations in the post-intervention period when ranking post/pre RMSPE ratios of the treatment and placebo units. So, for instance, a treatment unit may present a large negative effect in the post-intervention period (i.e., placebo units do not produce similar negative effect), but such effect may not necessarily be found to be significant according to RMSPE test (i.e., post-pre RMSPE ratio of the treatment unit may not appear at or near the top of the ranking) if there are placebo counties that produce large (cumulative) positive effect in the post-intervention period. Hence, a caution should be exercised when interpreting RMSPE test results. The RMSPE test results corresponding to our analysis are reported in table E2.

Table E2: RMSPE Tests.

Outcome Variable	Post/Pre RMSPE Ratio	Max / Min	Treatment Unit Rank / # of All Valid Units
Log Harvested Acres	4.30	4.30 / 2.27	1 / 7
Harvested Acres	3.79	4.01 / 0.48	3 / 22
Per Capita Income	2.05	19.08 / 1.19	40 / 45
Crop High Skill Labor Employment	2.92	40.80 / 1.23	24 / 27
Crop Low Skill Labor Employment	1.56	11.28 / 0.52	18 / 26
Ag High Skill Labor Employment	4.57	19.46 / 1.02	7 /23
Ag Low Skill Labor Employment	2.73	10.95 / 0.42	10 / 28
Crop High-Skill Earn/Crop Low-Skill Earn	5.72	5.72 / 0.87	1 / 15
PM10 Days	5.06	10.91 / 0.64	8 / 33
PM2.5 Days	6.49	1,786.54 / 2.69	25 / 32
Ozone Days	2.37	13.44 / 0.61	26 / 39
NO_2 Days	1.58	64,478,918.91 / 0.17	13 / 46
PM10 Annual Mean	1.15	0.83 / 4.70	11 / 12
PM2.5 Annual Mean	4.25	96,621.55 / 2.24	7 / 9
Satellite-Based PM2.5 Mean	6.43	44.81 / 0.88	9 / 32
Satellite-Based PM2.5 Max	95.53	2,734,941.00 / 15.72	29 / 31

Notes: Post/Pre RMSPE ratio indicates the ratio of the post-intervention RMSPE to the pre-intervention RMSPE for the treatment unit. Max/Min indicates the maximum/minimum ratio of the post-intervention RMSPE to the pre-intervention RMSPE from among treatment and control units. Treatment unit rank is the rank of the ratio of the post-intervention RMSPE to the pre-intervention RMSPE for the treatment unit when all the ratios (both for treatment and control units) are ordered in descending order. To refine inferences from falsification tests, we consider control counties with pre-intervention RMSPEs that are less than or equal to twice that of a treatment unit (Abadie et al., 2010).

F Health Cost Estimation

F.1 PM2.5 Cost Estimate

To find elderly morbidity and mortality health cost estimates as a result of estimated increases in PM2.5, we perform a benefit transfer exercise using results from Deryugina et al. (2019). For mortality, the authors estimate that a 1µg/m^3 increase in PM2.5 for one day causes 0.69 additional deaths per million elderly. Rather than using the standard VSL measures—which tend to overestimate economic costs when the population who die as a result of pollution exposure are elderly—the authors instead estimate the lost life years. A 1µg/m^3 increase in PM2.5 for one day results in 2.99 lost life-years per million medicare beneficiaries, with life years estimated to be worth $100,000 (Cutler, 2005).

For morbidity estimates, Deryugina et al. (2019) estimate that a 1µg/m^3 increase in PM2.5 exposure for on day leads to 2.7 additional ER visits and increases spending by $16,400 per million medicare beneficiaries. Imperial County has an estimated population over 65 of 13.4%, which given an overall population of 180,000 leads to an impacted population of 24,000.

To find infant mortality we use estimates from Chay and Greenstone (2003) who find that a 1µg/m^3 reduction in total suspended particles is associated with 4-7 fewer infant deaths per 100,000 live births. Imperial County has 90 births per 1,000 women per year, and a female population estimated at 87,000.

F.2 PM10 Cost Estimate

Jones et al. (2022) use estimates for the effect of PM10 exposure on health to estimate the cost of cardiovascular mortality and respiratory hospital admissions. While focused on PM10, these estimates have the benefit of being more specifically tailored to Imperial County. They start with baseline estimates of cardiovascular mortality of 134.15 per 100,000 and respiratory-related hospital admissions of 569.1 per 100,000 from the California Department of Public Health and Christensen et al. (2009). A 1µg/m^3 reduction in PM10 is scaled to increase respiratory hospital admissions using results from Schwartz (1996) and cardiovascular mortality using results from Ostro et al. (2000). Jones et al. (2022) use a log-linear health impact function according to the following relationship:

$$H_t = b\left(1 - \frac{1}{e^{\beta \cdot \Delta PM10_t}}\right)$$

where H is the health outcome, b is the baseline estimate, and β is the damage coefficient of increased PM10. We scale the estimates to 180,000 people, the population of Imperial County. We modify their cost assumptions by assuming the lower bound for VSL is $1.8 million (Agarwal et al., 2010) and the upper bound is $4.9 million, which is the high estimate for the oldest age group in Aldy and Viscusi (2007). We continue to use their estimate for the cost of $38,660 from the US Environmental Protection Agency for the cost of a cardiovascular hospital admission.

F.3 Changes in Air Pollution

We apply the above health cost estimates to the results from our synthetic control and difference-in-differences models for mean annual PM2.5 and PM10. Appendix table F1 shows the results for the average treatment effect over the post-treatment period for the synthetic control results found in appendix table D1 and the difference-in-differences results found in appendix tables D16 and D15. For this table, we use the average of the high and low VSL estimates. In addition, we use the yearly difference between the synthetic control estimate and observed Imperial County air pollution values to estimate an annual high and low cost as shown in table F2. High and low cost estimates differ in the VSL estimate used.

Table F1: Health Cost Estimates.

Panel A: PM 2.5								
	Coefficient	Elderly Mortality		Elderly Morbidity		Infant Mortality		
	μg/m^3	Lost Years	Cost	Visits	Cost	Deaths (Avg)	Cost	Total
Synthetic Control	1.64	35.85	3,584,698	32.37	196,619	0.71	2,654,820	6,436,137.10
DID (model 1)	1.91	41.71	4,171,358	37.67	228,797	0.82	3,089,300	7,489,454.70
DID (model 2)	1.74	37.92	3,791,786	34.24	207,978	0.75	2,808,190	6,807,953.90

Panel B: PM 10						
	Coefficient	Cardiovascular		Respiratory Morbidity		
	μg/m^3	Deaths	Cost	Admissions	Cost	Total
Synthetic Control	15.11	10.55	35,185,482	24.95	964,656	36,150,138
DID (model 1)	-7.46	-5.39	(17,960,568)	-12.55	(485,128)	(18,445,695)
DID (model 2)	39.80	26.80	89,381,433	64.41	2,490,042	91,871,474

Table F2: Annual Health Cost Estimates.

	PM2.5 Estimated Cost			PM10 Estimated Cost		
Year	Δμg/m^3	Low Cost (mil$)	High Cost (mil$)	Δμg/m^3	Low Cost (mil$)	High Cost (mil$)
2003	-0.79	-4.27	-2.62	1.68	2.15	5.82
2004	0.38	1.25	2.04	-1.12	-3.89	-1.44
2005	-0.78	-4.23	-2.59	1.58	2.03	5.49
2006	2.10	6.98	11.39	12.62	15.91	43.06
2007	2.66	8.86	14.47	17.05	21.37	57.81
2008	-2.24	-12.15	-7.44	16.67	20.90	56.55
2009	-2.20	-11.97	-7.33	28.55	35.17	95.15
2010	4.61	15.35	25.06	-4.80	-16.80	-6.21
2011	2.36	7.84	12.79	-3.70	-12.93	-4.78
2012	4.92	16.37	26.73	25.81	31.93	86.38
2013	1.51	5.02	8.19	15.96	20.03	54.20
2014	7.22	24.03	39.24	26.90	33.22	89.88
2015	3.16	10.52	17.19	16.48	20.67	55.92
2016	3.63	12.08	19.73	25.67	31.76	85.93
2017	0.41	1.37	2.23	20.84	25.96	70.24
2018	-3.11	-16.90	-10.35	28.19	34.75	94.02