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How much potable water is saved by wastewater recycling? Quasi-experimental evidence from California

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ABSTRACT

Recently, California has made large investments in wastewater recycling to replace applications that use potable water. It may be expected that the use of recycled water reduces potable water use, but such an equivalency is not assured. The addition of recycled water infrastructure in a large Californian water district creates a natural experiment where this work tests how recycled water usage affects primary potable water. This is done using econometric methods for causal inference in an observational setting that mirror a randomized control trial (RCT). From 2001 to 2014, a number of public parks were given recycled water infrastructure, while others in those regions remained exclusively on potable supply. A two-way fixed effects regression is used to produce a difference-in-differences estimate of the average treatment effect of recycled water on total and potable water usage. The results indicate that potable water usage is reduced significantly when a park is connected to the recycled water supply. The estimated rate of displacement in the study period is 81.7%, meaning each unit of recycled water use avoided 0.817 units of potable water usage, which implies the connection of parks to recycled water supply increases total water use. The analysis provides, to the best of our knowledge, the first empirical estimate of the water savings claimed by urban water recycling programs, and the first empirical estimate of displacement using quasi-experimental methods. The methodology can be utilized to evaluate the effectiveness of recycling programs around the world.

1. Introduction

The reuse of treated wastewater, or water recycling, traces back to ancient civilizations in the dry areas of the world. Angelakis et al. (2005) place the earliest uses of wastewater for agricultural irrigation in the Minoan civilization, more than a millennium before the Christian era. Today, wastewater recycling is a common practice in water stressed areas, with the Middle East and North Africa and various island nationshaving the highest levels of water reuse per capita in the world (Jimenez and Asano, 2008; Jones et al. 2021). As climate change progresses, droughts are expected to increase in frequency and severity in many parts of the world (Dai, 2013; Guneralp et al., 2015). The potential future risks of climate change, as well as increasing demand for water resources, has led to increased investment in wastewater recycling as a means of decreasing reliance on ground and surface water sources (Palazzo et al., 2017). For wastewater recycling to mitigate risk or decrease demand on primary supply, the use of recycled water must decrease the consumption of primary water supply. At first glance, this might seem to be a trivial point. Certainly, the nuance has been overlooked by many suppliers. For instance, in water districts with active water recycling programs, promotional material states the amount of primary water saved is equivalent to the amount of recycled wastewater supplied to customers (Goleta Water District, 2018; Horticulture Australia Limited, 2011). But this relationship is implicitly assumed and need not be the case. There is no theoretical reason that consumption of recycled water must happen in place of primary supply and an empirical estimate of this equivalency is lacking in the literature.

The consumption of units of recycled wastewater may not replace consumption of primary sources on a one-to-one basis. Why might recycled wastewater usage not avoid primary water usage? For one, recycled water is not currently suitable for all uses. Some uses such as direct consumption (drinking) remain best served by primary potable water infrastructure. In the case of direct consumption, there are technical and economic limitations of treating water to a level of sanitation required to meet human health and safety regulations (Tang et al. 2018). As a result, the introduction of recycled water infrastructure often occurs

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Table 1
An overview of the two study regions including the number of control and treatment sites, the mean number of observations for the treatment and control sites, and the mean monthly water usage for treatment and control sites in cubic meters (cu m) during the period before any site is connected to recycled water.

Region	Control Sites	Treated Sites	Mean control observations	Mean treatment observations	Mean pre-treatment monthly water usage for controls (cu m/site/month)	Mean pre-treatment monthly water usage for treated (cu m/site/month)
R1	5	5	168	129	3937	1933
R2	4	5	168	136	770	604

as a supplement to the already existing potable water network. Since recycled water is generally non-potable, 'potable' and 'primary' are used interchangeably here. When recycled water infrastructure exists alongside potable water infrastructure it need not be the case that the use of recycled water avoids the use of potable water. For instance, if recycled water is cheaper, less healthy or considered to be more environmentally friendly, it may be used in ways that differ from its potable counterpart. To this end, the introduction of recycled water infrastructure has an unclear effect on potable (and total) water usage. As a point of clarity, the effect on potable and total water usage are related, since total water usage is equal to potable usage plus recycled water usage. As a result, the observation that total water usage is *unaffected* by recycled water treatment implies that potable water usage is avoided by recycled water usage on a 1:1 basis. To what extent does the introduction of recycled water change the overall demand for water and, in particular, the demand for potable water? To shed light on this question, data from a California water district is examined that recently introduced treated wastewater into its supply.

In general, characterizing the environmental benefits that arise from recycling activity is a topic of great interest to the industrial ecology community (Ekvall, 2000; Frischknecht, 2010; Koffler and Finkbeiner, 2018). The environmental benefits are driven by the degree to which recycled materials substitute for their primary equivalents on the material market, a phenomenon referred to as displacement (Geyer et al., 2015; Yang, 2016; Zink and Geyer, 2018). When displacement is incomplete, i.e. recycled materials do not substitute for primary materials on a one-to-one basis, increases in recycling are not completely offset by decreases in primary production or usage. Such a scenario results in the increase of total material use and a decrease in the environmental benefits of the recycling activity. In recent research, authors have shown that paper consumption may increase when users are aware of its recycled content (Catlin and Wang, 2013) and that the complete substitution of recycled aluminum for primary aluminum on the U.S. material market is unlikely (Zink et al., 2017). It has also been shown that resource consumption may increase when recycling is added as a disposal option, in comparison to scenarios where trashing is the only disposal option (Sun and Trudel, 2017). These studies provide evidence that recycling may not displace primary production, leading to increases in total resource consumption, a phenomenon known as circular economy rebound (Zink and Geyer, 2017). The relationship between primary and secondary material use can be complex, driven by economic, behavioral, or other contextual factors. As a result, estimating the rate of displacement is an empirical challenge. One recent paper outlines how displacement can be estimated using quasi-experimental approaches such as difference-in-differences (DID), where data are divided into treatment and control groups (Palazzo et al., 2019). Such a strategy has yet to be executed in the literature. We direct readers to Palazzo et al. (2019) for a thorough treatment of the benefits and limitations quasi-experimental methods more generally.

Water recycling presents a compelling case study because water is used, recycled, and reused in a localized system with data that are regularly tracked at the level of the individual user. Furthermore, recycled water is often delivered for non-potable applications in which the usage data of potable and recycled water are metered separately. In this research, data was collected on recycled and potable water use over time to conduct the first quasi-experimental estimation of the effect of wastewater recycling on total and potable water usage. A two-way fixed effects regression is used to produce a difference-in-differences (DID) estimate of the effect of recycled water conversions on total and potable water usage, and the estimated treatment effect is used to estimate the displacement ratio. The paper proceeds as follows. First, the difference-in-differences estimator is revisited and the assumptions that qualify the use of the two-way fixed effects model are discussed. Second, the estimation of the displacement ratio is discussed. Third, the two-way fixed effects model is applied to a panel of nineteen properties in two regions of a specific water district. The estimated effects of access to recycled water on total water usage are presented, as well as estimates of the displacement ratio. The research concludes with a discussion of the limitations of the approach, future research directions, and the implications of the findings for water resources management.

2. Data and methods

Section 2 presents a discussion of the data source used, followed by a discussion of the methods employed. For readers less familiar with the difference-in-differences (DID) framework, the estimation framework is presented in detail along with a discussion of DID estimation in a general two-period case. After the two-period case, the multiple-period, staggered adoption case is presented. The section concludes with a discussion of statistical inference and the estimation of the displacement ratio from the average treatment effect.

2.1. Data source

To examine the effect of water recycling on total water use, and in turn displacement, primary data was collected (2016-2018) of site-level water usage from the East Bay Municipal Utility District (EBMUD), a large water district (more than 1 million customers) in California. These data consist of monthly observations of water usage from public recreational properties, also known as parks. These parks consist of green open spaces, trails and walking paths, and in some instances sport fields, however the specific uses of each park were anonymized by the data provider. For each site, a minimum of 120 observations were collected at the monthly level. Data were collected from a total of 19 sites that are divided into two small regions within EBMUD. A site is considered "treated" once it has been connected to the infrastructure that supplies recycled wastewater. Sites that are never connected to the infrastructure serve as controls. The proximity of treatment and control properties to each other allows for the isolation of the effect of the addition of recycled water infrastructure from the myriad other factors that determine water usage (Arbués et al., 2003; DeOliver, 1999; Gilbertson et al., 2011; Martinez-Espineira, 2002). Additional information regarding the data collection process, and sample statistics for each site are presented in Appendix A.4, including dates of data collection, site specific means and number of observations, and site treatment information.

Table 1 gives a summary of the data set used in the analysis. EBMUD supplied the water usage data without site-specific identifiers. Thus, the exact location and size of all properties is unknown as well as additional details regarding site specific differences such as vegetation. Such differences are accounted for using site specific fixed effects, as discussed in section 2.2.3. However, it is assumed that given their geographic proximity, the treatment and control groups are robust matches in predictors of water usage, such as rainfall and temperature. The connection to recycled water is staggered over time, with some sites connected later than others. We account for this staggered adoption in our estimated model. Notably, two potential control sites, one from each region, were excluded due to data anomalies noticed and indicated as anomalies by the data provider. In addition, the unit price of water of both potable and recycled water faced by the parks is observed, both of which increase over the data collection period. The price of each type of water in a given year is the same across all sites. In all but one year (2010), the price of potable water is exactly 1.2 times the price of recycled water, nearly constant across our sample. In 2010, the price of potable water was 1.08 times the price of recycled water. Furthermore, the public recreational properties do not pay a tiered water rate based on usage.

Table 1 compares average water use in the pre-treatment period for the sites that eventually are treated and those that serve as corresponding controls. A more intuitive comparison of the changes associated with a treatment can be made when the average water use is comparable across the two groups. This is true in Region 2, where the average usage in control sites, 770, is close in magnitude to the average usage in the sites selected for treatment, 604. In Region 1, however, the average usage in control sites, 3,937, is much larger than the average usage in sites selected for treatment, 1,933. It could be that in Region 1, smaller parks are located closer to the source of recycled water, and so are more likely to be treated. As long as this differential usage pattern does not change over time (either in levels or percentage terms) it can be accounted for with site specific effects and the comparison of treatment and control groups remains valid. In Section 2.2.2 it is discussed why this difference is likely random with respect to selection into recycled water conversion, and thus does not threaten the identification of the effect of recycled water conversion on total and potable water usage.

2.2. Empirical Approach

To estimate the effect of introducing recycled water infrastructure on total water demand a difference-in-differences (DID) estimation framework is employed, which Palazzo et al. (2019) propose as a method to analyze the effect of recycling on total and primary resource usage at treated parks. The difference-in-differences is estimated using the two-way fixed effects estimator, an estimator commonly employed when there are multiple time periods and multiple units that are treated over time. Before describing the two-way fixed effects estimator, the DID estimation framework is presented, alongside a detailed case that describes DID estimation in a two-period case designed to aid the intuitive understanding of the reader. This section concludes with a discussion of the estimation of the rate of displacement.

2.2.1. Estimation framework

The identification of causal effects using the difference-in-differences approach depends on several key assumptions. Let Y_{it} measure total water usage at park i in period t. Y_{it} can be measured either in levels (measured in volume) or in logs (used to represent percentage changes in volume); which measure is more appropriate is discussed below alongside the discussion of the parallel trends assumption. For each park in each time period, there are two *potential* outcomes: $Y_{it}(1)$, if the park is connected to the recycled water network in period t; and $Y_{it}(0)$, if the park is not connected to the recycled water network in period t. Let D_{it} indicate treatment, that is, $D_{it} = 1$ if park i is connected to the recycled water network in period t and is observed in the treatment state, otherwise $D_{it} = 0$ and the park is observed in the control state.

The treatment, or causal, effect is

$$\tau_{it} = Y_{it}(1) - Y_{it}(0).$$

τ_{it} represents the change in total water usage in park i in time period t caused by connection to the recycled water network. These effects can differ over parks and time periods and thus capture all possible heterogeneous treatment effects. Because both of the potential outcomes for park i in period t can never be simultaneously observed, the treatment effect τ_{it} is unobservable. If treatment effects do not vary by park or over time, then $\tau_{it} = \tau$, a quantity that can be estimated directly from the data. In some instances it is more plausible that treatment effects differ over parks and over time. When the treatment effects for parks vary over parks and over time, estimation focuses on the average treatment effect among parks that are treated (ATT):

$$E[\tau_{it}|D_{it} = 1] = E[Y_{it}(1) - Y_{it}(0)|D_{it} = 1].$$

The ATT can be thought of as the effect of the treatment at the water district level. That is, the effect of the treatment could be different for each park: one park could increase water usage after being connected to the recycled water network because of pent-up demand or simply a belief that recycled water is more plentiful; another park could decrease water usage because of new found concerns regarding water usage. The average water use across treated parks provides an aggregate measure of these effects at the water district level. If the ATT is zero, then total water usage at the district level is unchanged as a result of connection to the recycled water network. In such a case, the used recycled water has simply replaced previous usage of potable water and the displacement ratio is 1. If, instead, total water usage increases, then 1 unit of recycled water replaces less than 1 unit of potable water and the displacement ratio is less than 1. The next two sections discuss the general framework for the estimation of the treatment effect, first in a two-period case, followed by a multiple period case in which we introduce the two-way fixed effects estimator. Once estimation and inference of the treatment effect has been discussed, the estimation of the displacement ratio using the estimated treatment effect is discussed.

2.2.2. Two periods

To aid the reader in the intuition of a difference-in-differences estimation, a general two-period case is presented. Suppose first that we compare only two periods, a pre-treatment period denoted $t=0$ and a post-treatment period denoted $t=1$. The logic is that none of the parks are treated in the pretreatment period, so $D_{i0} = 0$ for all parks, while some, but not all of the parks are treated in the post-treatment period. To be able to estimate the ATT, it must be the case that the treatment is randomly assigned. Here, random assignment means that there is no tendency to assign parks to treatment based on their change in water use over time. Mathematically, the parks that are in the control group have $D_{i1} = 0$, so their expected change in water use over the two periods is

$$E[Y_{i1}(0) - Y_{i0}(0)|D_{i1} = 0].$$

This needs to be equal to the expected change in water use over the two periods for the parks in the treatment group, if those parks had not been treated, which is

$$E[Y_{i1}(0) - Y_{i0}(0)|D_{i1} = 1].$$

If these two quantities are equal, then the treatment and control groups would have similar paths of water usage, apart from assignment to treatment. It is important to note that this allows for parks that are treated to be systematically different from parks that are not treated in their water usage in the pre-treatment period. For example, if the parks that were treated had lower water usage in the pre-treatment period, the estimation method accounts for this. What must be true is that the *change* in water usage – the trend – be similar across all parks. This assumption is often termed the parallel trends assumption. The assumption would be threatened if, for example, there was another major change that occurred in the treated parks simultaneously with their conversion to recycled water. Moreover, the parallel trends assumption is sensitive to scaling of the outcome of interest when the baseline levels between control and treatment groups are not equivalent, which is the case here as seen in Table 1. Since the baseline levels of water usage are different across the control and treatment groups pre-treatment, the parallel trends assumption cannot hold in both levels and logs. For instance, when the control and treatment group both

Table 2
The mean monthly water usage (in logs) for pre- and post-treatment observations in the treated and control groups when using the difference-in-differences regression model in Eq. (1).

	Pre-treatment mean	Post-treatment mean
Treated	$\mu+\delta$	$\mu+\delta+\rho+\theta$
Control	μ	$\mu+\rho$

experience a ten percent increase in water usage, they violate the parallel trends assumption in terms of water usage level (since 10% of the 3937 is not equal to 10% of 1933). As such the research must choose whether to consider the outcome variable in levels or logs. Here, it is assumed that external forces have similar percentage change effects on park water usage, due to the lack of data on park size. As a result, we consider the log of total water usage as the outcome variable, with a discussion of the estimation in the case of levels left to Appendix A.1. The parallel trends assumption is discussed further in Section 2.2.3.

Still, is the parallel trends assumption (in logs) reasonable for the case at hand? The assumption is that the decision to connect a park to the recycled water network is not based on the change in water usage at that park over time. Understanding the decision to treat can help justify the parallel trends assumption. From conversations with the utility district, parks were connected to the recycled water network based on a set of factors that is not directly tied to the evolution of their water usage. A park was more likely to be connected to the recycled water network if it was: closer to the treatment plant that recycled water, closer to the main recycled water pipeline, and if there were fewer sites served along the pipeline closest to the park. Within EBMUD, main recycled water pipelines are constructed in an alignment that enables recycled water to reach an "anchor" customer such as a golf course or large industrial user. The pipeline going from the treatment plant to the anchor customer is configured such that the maximum number of smaller irrigation customers, such as the parks observed in the data, can be reached at the lowest cost. Because the main driver of the decision to connect a park to the recycled water network is that park's proximity to an anchor customer, and because there is no reason to believe that the trend in water usage at parks is correlated with proximity to anchor customers, there is no reason to believe that the parallel assumption is violated in treatment assignment.

To express the estimation equation, let $\{TREAT_i=1\}$ be a variable that indicates the parks that are treated in any period and let $\{t=1\}$ be a variable that indicates the post-treatment period. Thus for a treated park in the post treatment period, both of these variables equal 1, hence $D_{it} = \{TREAT_i=1\} * \{t=1\}$. The estimating equation is

$$Y_{it} = \mu + \delta\{TREAT_i=1\} + \rho\{t=1\} + \theta D_{it} + \varepsilon_{it}. \quad (1)$$

Where μ is the mean value across all sites and ε_{it} is the error term. Since, the water usage is measured in logs, Y_{it} is the log of total water use in site i at time t. To understand how the parameters of the estimating equation correspond to measurements of total water usage by park, first note that the equation is designed to fit average water usage. Average water usage in the pre-treatment period for parks that will not be treated is

$$E\left[Y_{it}|t=0, TREAT_i=0\right] = \mu.$$

In corresponding fashion, average water use in the pre-treatment period for parks that will be treated is $E\left[Y_{it}|t=0, TREAT_i=1\right] = \mu+\delta$, so that δ is the difference in average water use, before treatment begins, between parks that will be treated and those that will not be treated. From the information in Table 1, we anticipate that the estimate of δ will be negative. Table 2 lays out these relations and the corresponding relations for average water use in the post-treatment period.

From Table 2 we see that the change in water use over time for the parks that are not treated is ρ, so the parallel trends assumption implies that if the treated parks had not been treated, their water use over time would also have changed by ρ. Thus, if there is no effect of the treatment on total water usage, then average water usage in the treated parks post treatment is simply $\mu+\delta+\rho$, and θ would equal 0. If, however, θ does not equal 0, then the treatment has affected total water usage and θ captures the magnitude of the effect. Since the dependent variable, Y_{it}, is in logs, the treatment effect, θ, is a percentage change in water usage. The estimator from this equation is termed the difference-in-differences estimator because $\left\{\left[\underline{Y}_{post,treated} - \underline{Y}_{pre,treated}\right] - \left[\underline{Y}_{post,control} - \underline{Y}_{pre,control}\right]\right\}$ $\{[\mu+\delta+\rho+\theta-\mu-\delta] - [\mu+\rho-\mu]\} = \theta$. The coefficient θ represents the difference between pre-and post-treatment means in the treatment group, minus the difference between pre-and post-treatment means in the control group.

Note that it is extremely important to include the variables $\{TREAT_i=1\}$ and $\{t=1\}$ in the estimation equation, where $\{TREAT_i=1\}$ and $\{t=1\}$are indicator variables for the treatment group and the post-treatment period, respectively. In essence, these terms are controls for the quasi-experiment represented by this model. It is likely that mean monthly water usage levels are systematically different in the treatment and control groups throughout the entire study period, regardless of the exposure of the treatment group to recycled water. The coefficient δ captures this difference in means, and including the term in the regression addresses potential bias in the estimate of the treatment effect. This bias would arise because the previously existing difference in

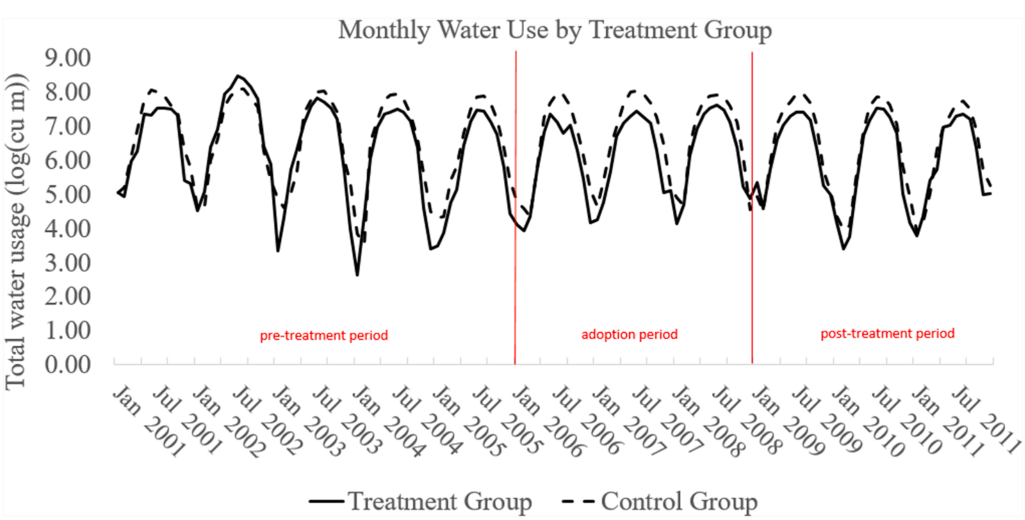

Fig. 1. Monthly water usage in log(cu m) averaged across treated sites (solid line) and control sites (dashed line) during the period where all sites report data. The staggered treatment adoption is indicated with labels the number of treated sites at the beginning of each year where new treated sites are introduced. The all-sites period is broken into three parts, one before any site is treated (per-treatment), a second during the staggered adoption period (adoption period), and a third once all sites are treated (all-treated).

Table 3
Two-way fixed effects results with log total water usage as the dependent variable, using cluster-robust standard errors and wild bootstrap critical values. Actual clusters, effective clusters, number of observations, critical values, 95% confidence intervals, and sample restrictions are also shown. Each column corresponds to a specific sample restriction described in the final row of the table.

Model	(1)	(2)	(3)	(4)	(5)
$\hat{\pi}$ (%) (S.E)	9.65 (16.0)	-0.24 (28.8)	-1.21 (14.6)	21.0 (28.7)	-5.10 (16.8)
N	2,707	2,175	1,458	1,249	946
Actual Clusters	19	19	10	9	19
Effective Clusters	16.9	13.0	8.17	8.94	16.9
Bootstrap critical values	[-1.97, 2.15]	[-2.10, 2.36]	[-2.51, 2.06]	[-2.33, 2.34]	[-2.48, 1.67]
Bootstrap 95% CI (%)	[-21.9,44.1]	[-60.8,67.9]	[-38.0,28.9]	[-46.0,88.2]	[-36.5,33.2]
Restrictions	None	1-year post	Region 1	Region 2	Peak only

Table 4
Estimated mean monthly percentage change in total water usage ($\hat{\theta}$), total recycled water usage, total water usage after treatment, displacement, and bootstrap 95% confidence intervals for displacement across all sample restrictions. Each column corresponds to a specific sample restriction described in the final row of the table.

Model	(1)	(2)	(3)	(4)	(5)
$\hat{\pi}$ (S.E)	9.65 (16.0)	-0.24 (28.8)	-1.21 (14.6)	21.0 (28.7)	-5.10 (16.8)
Total recycled water usage (cu m)	756217	137823	567207	249009	471221
Total water usage by treated units (cu m)	1565720	933064	1107308	458412	1101772
Treated observations	681	120	326	355	232
Displacement	81.7%	102%	102%	68%	113%
Bootstrap 95% CI (%)	[36.6,158]	[-174,1150]	[57.3,220]	[18.4,257]	[41.7,216]
Restrictions	None	1-year post	Region 1	Region 2	Peak only

water usage levels between the treatment and control groups would be absorbed into the estimate $\hat{\theta}$. Similarly, ρ captures a change in mean water usage that arises in both the treatment and control groups in the post-treatment period. Including this term in the regression addresses potential bias in the estimate of the treatment effect that arises from time trends that exist across both treatment and control groups. Such time trends are not attributable to the treatment itself. With these controls in place, under the parallel trends assumption, θ is identified as the average treatment effect on the treated and the method of ordinary least squares (OLS) will deliver an unbiased estimator of this effect.

2.2.3. Multiple periods–staggered adoption

The difference-in-differences estimator can be applied in a case with multiple periods and staggered adoption. Such a case exists here where water usage is observed monthly over time (multiple periods) and treatment does not occur all at once. Staggered adoption is a special case of treatment occurring over time where units are treated in different periods, but once treated they remain so. The key assumption underlying a difference-in-differences estimation, which is sometimes termed the parallel trends assumption, implies that, absent connection to recycled water, water usage would follow the same trend over time in all parks. This assumption remains crucial in a case with multiple periods and staggered adoption. Because it is not possible to run a controlled experiment, the treatment could be correlated with another exogenous effect that differs in magnitude across treatment and control sites. However, staggered adoption helps to mitigate this concern by reducing the possibility that another exogenous effect occurs simultaneously (since treatment occurs at different periods). Fig. 1 examines the robustness of the parallel trends in log total water usage during the pre-treatment period. The plotted trends are average total water usage across sites in the treatment group (solid line) and control group (dashed lines) during the subset of the study period where all 19 sites are reporting data. A sinusoidal pattern in water usage is observed that peaks in the summer season. The peaks in the control group are higher than that of the treatment group. A visual inspection of the trends of the control and treatment group prior to the adoption period provides suggestive evidence that the common trends assumption holds.

2.2.4. Two-way fixed effects

To examine the effect of recycled water conversions on total and potable water usage in the setting where there are multiple time periods and staggered adoption of treatment, the two-way fixed effects regression approach to DID estimation is used. A two-way fixed effects approach allows for there to be an individual intercept, or dummy variable coefficient, for each site. Two-way fixed effects estimation also allows for an individual intercept, or dummy variable coefficient, for each time period of data collection. This is a more flexible approach than the standard DID example given in Section 2.2.1, where there is a single intercept for treatment sites, a single intercept for control sites, and one indicator variable for the post-treatment period. In two-way fixed effects settings, one controls for time-invariant factors at individual sites, such as management structure and size, by estimating individual site intercepts. In addition, one controls for site-invariant factors that are distinct during each time period, such as the unit prices of potable and recycled water and weather, by estimating individual time period intercepts.

The effect of introducing recycled water on the log total water usage is estimated using (4), where γ is the fixed effect for the excluded site in the base year, α_i is the difference between the fixed effect for site i and the excluded site, β_t is the difference between the fixed effect for period t and the base year, D_{it} remains the indicator for a treated site in the post treatment period, and θ is the estimate of the DID treatment effect,

$$Y_{it} = \gamma + \alpha_i + \beta_t + \theta D_{it} + \varepsilon_{it} \quad (4)$$

When there are only two sites and two time periods, Eq. (4) collapses into the form of Eq. (1). Since there are only two groups and two time periods represented in Eq. (1), $\alpha_i = \delta\{TREAT_i = 1\}$, and $\beta_t = \rho\{t = 1\}$.

There is a notable complication that arises when using two-way fixed effects estimation in a setting with multiple time periods and staggered adoption of treatment. It is true, staggered adoption helps to mitigate the concern that an exogeneous event at the time of treatment affected control and treatment units differently, due to the non-simultaneous adoption of treatment. However, under two-way fixed effects estimation with staggered adoption, as consistent with Eq. 4 above, θ is equal to a weighted sum of the treatment effects in each treated unit (de Chaisemartin and D'Haultfuille, 2018):

$$\theta = E\left[\sum_{(i,t)\ :D_{i,t}=1} W_{i,t}\tau_{i,t}\right]$$

Due to the staggered adoption of treatment, $W_{i,t}$ is non-constant across units or time periods. Accordingly, only under the assumption of a constant treatment effect, $\tau_{i,t} = \tau \quad \forall\, i, t,$ does the two-way fixed effects estimator estimate an average treatment effect in this setting. Given this constraint, the assumption of a constant treatment effect is adopted moving forward. See Appendix A.3 for additional discussion of two-way fixed effects estimation and the estimation of the weights attached to the fixed effects estimator. The two-way fixed effects estimator is used to estimate the constant treatment effect, τ, the percentage change in total water usage that results from the connection of parks to recycled water infrastructure. Using the estimate of the effect of recycled water access on total water usage, one can again estimate the displacement ratio. However, before estimation of displacement is discussed, one must consider statistical inference.

2.2.5. Inference

So far, this research has shown how one obtains an unbiased point estimate for the effect of recycled water on total water usage given the study design and data structure. However, it is also critical to perform proper statistical inference, the calculation of appropriate standard errors for the estimates. Classical standard errors assume that there is no correlation between the error terms (the unobserved factors), ε_{it}, in the fixed-effects model. However, in the data it is likely that there is correlation, specifically among the multiple observations for each park. The park fixed effect accounts for all components that are site specific and do not vary over time, such as the soil condition and the size of the park. But there are other components that are also specific to the park but that do vary over time, such as the intensity of usage of athletic fields. These factors cause the unobserved components, captured in the error terms, to be correlated over time at the park level. As the specific form of these correlations is unknown, one can account for this by allowing for general correlation patterns across the errors for each park. Formally, the error terms are clustered by park and cluster-robust standard errors are reported.

The appropriate method of inference with cluster-robust standard errors depends on the number of clusters, not the number of observations, and on, in particular, the effective number of clusters. The effective number of clusters, defined by Carter, Schnepel, and Steigerwald (2016), accounts for variation across clusters in the observed and unobserved components (for example, if the general correlations in the unobserved components vary across clusters, as they likely do) and adjusts the number of clusters downward to account for this variation. The effective number of clusters can be estimated using the code developed by Lee and Steigerwald (2018) in the Stata package *clusteff*.

Because the effective number of clusters in our data is small, the recommendation of Lee and Steigerwald (2018) is followed, and the wild cluster bootstrap is used to compute the critical values for the *t*-statistic. The procedure outlined by Cameron and Miller (2015) is used to obtain the bootstrap critical values. In detail, the vector of estimated residuals for each cluster, $\{\widehat{\varepsilon}_{it}\}_{t=1}^{T}$ is multiplied by either 1 or -1 with equal probability. A bootstrap sample is created by combining the residual vectors with the regressors and estimating the coefficient of interest using OLS. The cluster-robust *t*-statistic is computed for the bootstrap sample. The procedure is repeated a maximum of 1,000 times (if the maximum number of combinations of clusters is less than 1,000, each combination is sampled once) and the distribution of the test statistics determines the upper and lower wild cluster bootstrap critical values.

2.2.6. Estimating the displacement ratio

The previous sections outline the difference-in-differences framework in the context of estimating and inferring the effect of access to recycled water on total water usage. One can use the estimated treatment effect to estimate the displacement ratio. First, the relationship between the treatment effect and the displacement ratio must be established. In the framework outlined above, $\theta$is the average treatment effect, the average *percentage* change in total water usage of treated parks caused by the connection to the recycled water infrastructure. But how does the change in total water usage relate to the displacement ratio? Clearly, θdoes not directly reveal the rate of displacement. In order to estimate the displacement ratio, d, one needs to calculate the total volume of recycled water and potable water used by treated units *after* treatment.

Let, $R = \sum_{i=1}^{n}\sum_{t=1}^{T} R_{it:D_{it}=1}$, where $R_{it:D_{it}=1}$is the volume in levels of recycled water used at site i at time t such that park i is treated in time t. Thus, R is simply a measure of all the recycled water used by all parks over the observed time frame, measured in volume. Let, $P = \sum_{i=1}^{n}\sum_{t=1}^{T} P_{it:D_{it}=1}$, where P is the potable equivalent of R. Thus, P is simply a measure of all the potable water used by treated parks after treatment. And let, $T = P + R$, defining T as the total water use by treated parks after treatment.

θ measures the average percentage change in total water usage after connection to recycled water over the study period. One observes T, the total post-treatment water use of treated sites. Thus, the total post-treatment water use in treated parks in the *absence* of treatment is $\frac{T}{1+\theta}$, since $\frac{T}{1+\theta} \cdot (1 + \theta) = T$. This means that connecting the parks to recycled water has changed total water use by $\frac{\theta}{1+\theta} \cdot T$. The total change in water usage is equal to the change in potable water usage plus the change in recycled water usage, $\frac{\theta}{1+\theta} \cdot T = \Delta P + \Delta R$, where $\Delta P$is the change in potable water usage relative to the counterfactual of no treatment and ΔR = R, since without treatment recycled water use would have been zero. Thus, one can define an equation for the volumetric change in potable water usage as a result of connecting parks to recycled water infrastructure:

$$\Delta P = \frac{\theta}{1+\theta} \cdot T - R \tag{5}$$

The displacement ratio, d, is simply a ratio defining the volume of potable water consumption avoided by each unit of recycled water consumption. That is:

$$d = \frac{-\Delta P}{\Delta R} \tag{6}$$

This indicates that a displacement rate of 1 is achieved when each unit of recycled water consumed decreases potable water consumption by one unit. By plugging in Eq. (5), the displacement ratio can be defined as follows:

$$d = \frac{-\Delta P}{\Delta R} = \frac{-\left(\frac{\theta}{1+\theta} \cdot T - R\right)}{R} = 1 - \frac{\theta\ T}{(1+\theta)R} \tag{7}$$

If the percentage change in total water usage is zero, i.e. θ= 0, then $d = 1$. This is representative of a scenario where each unit of recycled water used reduces potable water use by one unit. However if the total change in water usage, $\frac{\theta}{1+\theta} \cdot T$, is equal to the recycled water usage, R, then $d = 0$. This is representative of a scenario where the recycled water is used in addition to the potable water. Thus, each unit of recycled water displaces zero units of potable water. In order to estimate the displacement ratio and the change in potable water use, one can simply plug in an estimate of the average treatment effect, $\widehat{\theta}$, and the observed total water usage, T, and recycled water usage, R, by treated units post-treatment:

$$\widehat{d} = 1 - \frac{\widehat{\theta} T}{(1+\widehat{\theta})R} \tag{8}$$

For a known displacement ratio, one can utilize the displacement ratio to easily calculate potable water savings,ΔP, as $\Delta P = -\widehat{d}R$.

Importantly, the estimating equation for the displacement ratio depends on whether one considers the treatment effect, θ, in percentage terms or levels. Consistent with the assumptions of this work and the treatment effect estimation outlined above, the equations presented in this section are concerned with a treatment effect estimating the *percentage* change in total water usage. Appendix A.1 discusses the estimation of the displacement in level terms, while Appendix A.2 provides additional details and examples regarding the estimation of displacement.

3. Results

The following section presents the results of the two-way fixed effects regression to estimate the treatment effect for the previous described sample of 19 parks. Also presented, is the estimated treatment effect under various sample restrictions. In Section 3.2 the estimated treatment effects are used to estimate the corresponding displacement ratios using the results of Section 2.2.6.

3.1. Fixed-effects regression

Using the data described in Section 2.1 and the regression specification given by (4), the effect of water recycling conversions on total water usage was estimated (i.e. on potable + recycled water usage). These results pertain to the effect of water recycling conversions on potable water usage for the treated sites of interest – with discussion of the external validity of the results left to the discussion section. In column (1) of Table 3, the estimate $\widehat{\theta}$ uses the entire set of 2,836 observations. The point estimate indicates that the introduction of recycled water infrastructure increased total water usage by 9.65%. Due to the lack of precision, however, one is unable to conclude that the introduction of recycling has an effect on total water usage. The test for cluster heterogeneity was conducted using the program developed by Lee and Steigerwald (2018), called *clusteff*. This test is used to determine the appropriate method of calculating the 95% confidence interval of the estimates. The effective number of clusters is 16.9, which is considered small enough to advise the use of wild bootstrap critical values for inference, as described in Section 2.2.3. The use of wild cluster bootstrap, the method advised by Lee and Steigerwald(2018) for inference when the effective number of clusters is small, results in a 95% confidence interval of [-21.9,44.1] for the effect of recycled water conversions on the percentage change in total water usage across the sites. This implies an increase in total water use across sites, though not a statistically significant change.

To further examine the overall estimate, which implies no effect of recycling on total water use, several sample restrictions were applied. First, perhaps there is an initial reduction in water use, which diminishes over time. In Column (2) only the first year of water usage after connecting to recycled water was included. Again, one observes a small coefficient with a wide confidence interval regarding the effect of recycled water on total water usage. Second, it may be that water usage is most sensitive to recycling when water demands are highest, namely June through September. Attention was restricted to these four months in Column 5. Again, one is unable to conclude that access to recycled water changes total water usage. Columns (3) and (4) restrict the sample to one of the two regions within EBMUD. This restriction is imposed to explore if there is a fundamentally different response to recycled water conversions by region. Although the point estimates are quite different, the lack of precision again does not provide conclusive evidence that access to recycled water changes total water usage.

3.2. Displacement and total potable water savings

In Section 2.2.6 the calculation of displacement in treated sites was introduced as Eq. (8). Table 4 presents displacement findings for each of the sample restrictions. The 95% confidence interval for the displacement ratio is calculated using an analogous procedure, where one substitutes the upper and lower boundaries shown in Table 3 for $\widehat{\theta}$ in Eq. (8) to generate the upper and lower boundaries for the displacement ratio. For example, in the full sample (column 1), the point estimate of displacement is calculated as: $\widehat{d} = 1 - \frac{\widehat{\theta}T}{(1+\widehat{\theta})R} = 1 - \frac{0.0965*1565730}{(1+ 0.0965)\ *756217} =$ 81.7%. The bootstrap 95% CI immediately follows by substituting the upper and lower boundaries of the 95% CI from Table 3 for $\widehat{\theta}$.

Displacement, and in turn potable water savings, is present across all sample restrictions, except model specification 2, where a positive displacement rate cannot be confirmed. Columns (1), (2), and (5) of Table 4 show that the point estimate of monthly displacement hovers around 100% regardless of whether the post-treatment observations are restricted to just the first post-treatment year or only the summer months. Columns (3) and (4) suggest that displacement may be higher in region 1 in comparison to region 2.

Using the elements of Table 4, namely displacement and total recycled water usage, the total amount of potable water saved during the study period was estimated using Eq. (6) and compared with California household usage. In 2016, average residential water usage in California was 0.32 cubic meters (85 gallons) per person per day (Legislative Analyst's Office, 2017). This quantity varies by season, and in the peak months of June through September residential usage was 0.413 cubic meters (109 gallons) per person per day. In the sites in our sample that converted to recycled water, it is estimated that a total of 617829 cubic meters of potable water ($756217 cu\ m * 0.817$) were saved during the study period, or approximately 30.3 cubic meters per site, per day. Thus, the estimate of daily potable water savings over the ten treated sites is enough to cover the daily usage of 946 California residents.

4. Discussion

This research produced the first quasi-experimental estimate of the potable water savings that arise from recycled water conversions, and the first quasi-experimental displacement metric in the industrial ecology literature. In the East Bay Municipal Utility District, conversions from potable to recycled water achieve high levels of potable water savings and displacement at the sites of conversion. Because the data were collected from only one water district in a relatively small geographical area, future research can examine the relevance of our conclusions on a larger sample of water districts from diverse geographic areas, for example in other parts of California or across Australia, where infrastructure conversions to recycling have become common in recent decades. Moreover, since the study sample is of public parks, future research is needed to investigate wastewater displacement rates in industrial or residential settings. Such an undertaking would be aided by collection of observable characteristics that predict water usage such as rainfall, temperature, and local income levels. A more sophisticated approach, such as propensity score matching, may need to be applied in a more geographically diverse sample if the treatment is not assigned randomly conditional on these observables. In general, these concerns pertain to the external validity of our findings – the extent to which conclusions from this study can be generalized outside of the specific context of inquiry. As such, we hope future research investigates similar questions regarding material displacement in other contexts and for other materials.

4.1. Conclusions

From this work, one cannot conclude that total water usage is affected by connection to recycled water infrastructure. As a result, the best estimate of the displacement rate is 81.7%, though due to the large statistical uncertainty, it may be significantly higher or lower. We cannot conclude with confidence that displacement is incomplete. These findings are somewhat surprising to both the authors of this research and the community affairs representative from EBMUD who supplied these data. The unit cost of recycled wastewater is less than that of potable water, and recycled wastewater is sometimes perceived as an abundant resource relative to potable water, which can lessen the sensitivity of users to drought conditions. However, for EBMUD the recycled water program is part of a greater water conservation unit. Thus, it is possible that the treated units are exposed to additional information about conservation best practices, a possible mechanism that could contribute to the observed outcome. Still, the current estimate of the displacement ratio is 0.817, meaning each unit of recycled water used avoids the use of 0.817 units of potable water usage. This suggests that in EBMUD conversions to recycled water lead to high displacement resulting in significant potable water savings. The presented research provides statistical evidence to support this for the first time in the literature, and the finding should be encouraging to water districts and management entities that are considering the expansion of non-potable, discretized recycled wastewater infrastructure in an effort to save potable water. Furthermore, conversions to recycled wastewater as a water source for irrigation are expected to increase in the face of climate change. This research provides a general methodology that can be readily applied in water districts to rigorously monitor the effectiveness of their recycled water conversion programs. It can also be applied to other reuse and recycling case studies with natural quasi experiments that facilitate DID regression analysis. In general, quasi-experimental methodologies should be adopted when possible to ensure that policies that intend to produce conservation outcomes are meeting these objectives.

CRediT authorship contribution statement

Jason Maier: Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Visualization, Project administration. **Joseph Palazzo:** Conceptualization, Methodology, Formal analysis, Writing – original draft, Writing – review & editing, Visualization. **Roland Geyer:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Supervision. **Douglas G. Steigerwald:** Conceptualization, Methodology, Writing – original draft, Writing – review & editing, Supervision.

Declaration of Competing Interest

The authors declare no competing interests.

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Appendix A

A.1. Estimating the treatment effect in levels

As discussed in Section 3.2 of the main text, the parallel trends assumption is not invariant to scaling of the dependent variable. As a result, it is sensible to estimate the effect of recycled water on total water usage as well as a percentage change. Here, the two-way fixed effects regression given by (5) is estimated using the total water usage in level as the dependent variable. To be explicit, the model is:

$$Y_{it} = \gamma + \alpha_i + \beta_t + \pi D_{it} + \varepsilon_{it} \tag{A1}$$

In this case, the coefficient π has the interpretation of a change in volume. The sign of the coefficients and the width of the confidence intervals are consistent with those found in Table 3 of the main text, as expected.

Table A1

Table A1

Two-way fixed effects results with log total water usage as the dependent variable, using cluster-robust standard errors and wild bootstrap critical values. Actual clusters, effective clusters, number of observations, critical values, 95% confidence intervals, and sample restrictions are also shown.

	(1)	(2)	(3)	(4)	(5)
$\hat{\pi}$	2.08	-1.13	-1.03	6.25	-1.34
Total recycled water usage (cu m)	7557.7	1377.4	5069.1	2488.6	4709.3
Treated observations	681	120	326	355	232
Displacement	93.4%	104%	102%	68.5%	102%
Bootstrap 95% CI (%)	[70.2,115]	[59.5,142]	[75.9,135]	[-14.6,128]	[67.4,135]
Restrictions	None	1-year post	Region 1	Region 2	Peak only

The process of estimating displacement from a change in the level of total water use is computationally different than the process of estimating displacement from a percentage change in water use. Let, $R = \sum_{i=1}^{n}\sum_{t=1}^{T} R_{it}$ be total recycled water usage and let

$$n_{treat} = \sum_{i=1}^{n}\sum_{t=1}^{T} D_{it}$$

be the number of observations of treated sites. Because θ measures the average monthly change in total water usage after connection to recycled water, total water usage is changed by $\theta \cdot n_{treat}$ during the study period.

If total water usage is unchanged, then recycled water has replaced potable water 1 for 1 and the displacement ratio is 1. If, instead, total water usage increases, then 1 unit of recycled water replaces less than 1 unit of potable water and the displacement ratio is less than 1. Formally, the displacement ratio is (see appendix for additional details):

$$d = 1 - \frac{\theta \cdot n_{treat}}{R} \tag{2}$$

Total potable water savings immediately follow as:

$$\Delta P = R * d = R * \left[1 - \frac{\theta \cdot n_{treat}}{R}\right] = R - \theta \cdot n_{treat} \tag{3}$$

In this elementary example, we have only one post-treatment observation of water usage for each site. Thus, we can estimate displacement and total potable water savings in the treated site by applying (2) and (3):

$$\widehat{d} = 1 - \frac{\widehat{\theta} \cdot n_{treat}}{R_{22}} = 1 - \frac{\widehat{\theta}}{R_{22}}, \text{ and } \Delta P = R_{22} * d,$$

where R_{22} is the recycled water usage observed for the treated site (i=2) in the post-treatment period (t=2), and n_{treat} is equal to one. It is important to note that the numerator in the displacement quantity is an estimate of the average treatment effect for each period t multiplied by the appropriate number of time periods, while the denominator is a summation of the observed recycled water usage. This becomes a critical point, as the actual data set we collected contains multiple treated sites and multiple post-treatment periods. Handling this data set requires some adaptation of the simple DID regression method outlined above, as discussed in the following section.

A.2. Additional details on the displacement ratio

The displacement ratio is defined by Zink, et. al (2015) as $d = -\frac{\Delta Q_{prim}}{\Delta Q_{sec}}$, where ΔQ_{prim} is the change in the quantity of primary material in response to a change in the quantity of secondary material ΔQ_{sec}. The negative sign dictates that when ΔQ_{prim} is negative (i.e. the quantity of primary material decreases), displacement is positive. In this research, the secondary material is recycled wastewater and the primary material is potable water. Here, we add another layer of sophistication to the definition since we also estimate a counterfactual for potable water usage after the change in the quantity of recycled water.

Returning to the example of Section 2.2.1, consider the case where there are two time periods (t=1 is pre-treatment, t=2 is post-treatment) and two sites (i=1 is the control site, and i=2 is the treated site). Let $Y_{it} = P_{it} + R_{it}$, where Y_{it} is total water usage in site i in period t, and P_{it} and R_{it} are potable and recycled water usage. It is assumed that site 1 is a suitable control for site 2, i.e. the identification conditions for DID discussed in Section 2.2.1 are met. In addition, site 2 has no access to recycled water in the pre-treatment period, and converts a portion of its supplies to recycled water in the post treatment period, while site 1 uses potable water in both periods (i.e. $R_{11}, R_{12}, R_{21}, = 0$, and $R_{22} \neq 0$). The change in water usage in site 1 is used, the control site, as a counterfactual for what would have happened in site 2 in the absence of a conversion to recycled water. Now, one can define a quasi-experimental version of the displacement ratio that allows recycled water to also displace counterfactual potable water as: $d = -\frac{[P_{22}-P_{21}]-[P_{12}-P_{11}]}{R_{22}}$. The numerator is a difference-in-differences estimate of the change in potable water usage in the treated site. The denominator is the only non-zero quantity of recycled water usage in the system.

Using the identity $Y_{it} = P_{it} + R_{it}$, displacement can also be expressed as: $d = -\frac{[(Y_{22}-R_{22})-(Y_{21}-R_{21})]-[(Y_{12}-R_{12})-(Y_{11}-R_{11})]}{R_{22}} = -\frac{[Y_{22}-Y_{21}]-[Y_{12}-Y_{11}]-R_{22}}{R_{22}} = 1 - \frac{[Y_{22}-Y_{21}]-[Y_{12}-Y_{11}]}{R_{22}}$. Now, consider the estimation of the DID regression given by (1). The expression $[Y_{22} - Y_{21}] - [Y_{12} - Y_{11}]$ is represented by θ, and the displacement ratio is $d = 1 - \frac{\theta}{R_{22}}$.

In the two-way fixed effects setting, this generalizes to the case of multiple treated units, multiple time periods, and staggered treatment adoption. In Eq. (4), π replaces θ as a DID estimate of the treatment effect. Assuming that $\pi \cdot n_{treat}$ is a suitable proxy for the change in total water usage after accounting for counterfactual trends, the equivalent quasi-experimental displacement expression is $1 - \frac{\pi \cdot n_{treat}}{R}$ as discussed in Section 2.2.2.

In order to provide more clarity, several examples are provided of pre- and post-treatment water usage for treatment and control sites in the setting with two time periods and two sites, and show how these translate into displacement ratios. In each example, potable and recycled water usage pre- and post-treatment are given for the treated site, and potable water use in the pre- and post-treatment periods for the control site (in cu m). From this information we calculate θ, and in turn displacement, for each example. Then, we show that calculating displacement from the potable water usage gives the same result. We note that the pre-treatment column corresponds to t=1, and the post-treatment column to t=2, such that P_1 in the pre-treatment column is the potable water usage in site 1 during period 1, or P_{11}.

Example 1:

Table A2

In this first example, total water usage in the control site and the treated site are the same in both the pre- and post-treatment period. Thus, even though total water usage increased by 10cu m, $\theta = 0$ because the increase was the same in both sites. Displacement is 100%, because the 110 cu m of recycled water displaced both the 100 cu m from the pre-treatment period and the 10 cu m increase in potable water usage that we infer from the behavior of the counterfactual (control site). Thus, it is inferred that the introduction of recycled water had no effect on total water usage, and displaced potable water on a 1-to-1 basis.

Table A2

Pre and post-treatment water usage values for treatment (i=2) and control (i=1) and the displacement calculation for Example 1.

	Pre-treatment (t=1)	Post-treatment (t=2)	Displacement calculation
$P_{i=1}$	100	110	$\theta = 0$
$P_{i=2}$	100	0	$d = 1 - \frac{\theta}{R_{22}} = 1 - \frac{0}{110} = 100\%$
$R_{i=2}$	0	110	$d = -\frac{[P_{22} - P_{21}] - [P_{12} - P_{11}]}{R_{22}} = -\frac{-110}{110} = 100\%$

Example 2:
Table A3
In the second example, total water usage in the control site stays the same in both periods, while the treated site increases its total water usage by 50 cu m after introducing recycled water. In this case, $\theta = 50$. The 100 cu m of recycled water displaced 50 cu m of potable water usage, and no counterfactual potable water. The other 50 cu m of recycled water grew overall water usage at the site. Displacement is then 50%, and the calculation is equivalent when using difference-in-differences in total or potable water as shown above.

Table A3
Pre and post-treatment water usage values for treatment (i=2) and control (i=1) and the displacement calculation for Example 2.

	Pre-treatment (t=1)	Post-treatment (t=2)	Displacement calculation
$P_{i=1}$	100	100	$\theta = 50$
$P_{i=2}$	100	50	$d = 1 - \frac{\theta}{R_{22}} = 1 - \frac{50}{100} = 50.0\%$
$R_{i=2}$	0	100	$d = -\frac{[P_{22} - P_{21}] - [P_{12} - P_{11}]}{R_{22}} = -\frac{-50}{100} = 50.0\%$

Example 3:
Table A4
Example 3 shows how displacement is calculated when total water usage increases in both treatment and control groups, but the magnitude of the increase is different. The difference between the change in total water usage in the treated site and the change in total water usage in the control site is 50 cu m. Usage in the control site increases from 200 to 250, but in the treated site it increases from 200 to 300 cu m. In this case $\theta = 50$ once again. The treated site introduced 230 cu m of recycled water into its supply. This displaced the 130 cu m reduction in potable water usage from pre- to post-treatment, and another 50 cu m of counterfactual potable water usage inferred from the increase in potable water usage in the control site. The remaining 50 cu m of recycled water grew overall water usage. As a result, 78.3% of the recycled water displaced potable water as shown in the two displacement calculations.

Table A4
Pre and post-treatment water usage values for treatment (i=2) and control (i=1) and the displacement calculation for Example 3.

	Pre-treatment (t=1)	Post-treatment (t=2)	Displacement calculation
$P_{i=1}$	200	250	$\theta = 50$
$P_{i=2}$	200	70	$d = 1 - \frac{\theta}{R_{22}} = 1 - \frac{50}{230} = 78.3\%$
$R_{i=2}$	0	230	$d = -\frac{[P_{22} - P_{21}] - [P_{12} - P_{11}]}{R_{22}} = -\frac{-180}{230} = 78.3\%$

Example 4:
Table A5
The final example shows a case where total water usage decreases in the control site. In this example, the difference-in-differences value of θ is 110, as total water usage increases from 100 to 200 cu m in the treatment site and decreases from 100 to 90 cu m in the control site. To first order, 150 cu m of recycled water displaces 50 cu m of potable water. However, displacement is adjusted for the decrease in water usage in the control site, just as was done when the control sites increased water usage in previous examples. Since water usage decreased by 10 cu m in the control site, the 150 cu m of recycled water only displaced 40 cu m (50-10) of potable water after adjusting for the counterfactual. Then, for 150 cu m of recycled water, only 40 cu m displaced potable water and the displacement ratio is 26.7%.

Table A5
Pre and post-treatment water usage values for treatment (i=2) and control (i=1) and the displacement calculation for Example 4.

	Pre-treatment (t=1)	Post-treatment (t=2)	Displacement calculation
$P_{i=1}$	100	90	$\theta = 110$
$P_{i=2}$	100	50	$d = 1 - \frac{\theta}{R_{22}} = 1 - \frac{110}{150} = 26.7\%$
$R_{i=2}$	0	150	$d = -\frac{[P_{22} - P_{21}] - [P_{12} - P_{11}]}{R_{22}} = -\frac{-40}{150} = 26.7\%$

A.3. Testing for negative weights in two-way fixed effects estimation

The fixed-effects estimator estimates a weighted sum of ATEs across the treated cells. As this is a staggered adoption design, B_{fe} is more likely to assign a negative weight to treatments near the end of the end of the panel, and to groups that adopt the treatment early. The *twowayfeweights* package is used to uncover the weights used in regression 1. No negative weights are assigned in this case. Of the 681 observations, all have positive weights.

There are two important lessons to learn from this exercise. First, in the staggered adoption design, having a significant number of pre-treatment observations is critical to avoiding negative weights in the sum of ATEs as this results in a low average level of treatment for each group. Furthermore, negative weights are less likely with a large sample of units that never receive treatment. In this case for instance, data from control units were collected. Since these units were never treated, the average treatment in every time period is low, even towards the end of the panel. For further information, please see the literature cited in the main text.

A.4. Data collection and sample statistics

This section details additional information regarding the data collection and provides sample statstics. The data was collected in batches from a contact at East Bay Municipal Utility District. Table A6 outlines the dates of original data requests. The data is collected in real time by EBMUD, and the dates provided simply show when requests were made for the data at each site.

The following table presents site specific statistics (Table A7):

Table A6
presents information about data requests from EBMUD

Data request date	Sites data received	Notes
11/10/16	5	Initial data request,
2/12/18	1,2,3,4,6,7,8,9,10,11,16	First request for data sample
5/8/16	12,13,14,15,17,18,19	Request for additional control sites

Table A7
reports information about each site, including treated and untreated means, number of observations (n), the treatment timeline, and the first and last observation of each site.

Site	*n*	Sample mean (log cu m)	Treated observations / treatment date	Treated mean	Untreated Mean	First/Last observation
1	132	6.63 +/- 0.99	67 (06/09)	6.58 +/- 1.02	6.48+/- 0.96	01/04 – 12/14
2	132	6.51 +/- 1.56	64 (09/07)	6.45 +/- 1.61	6.58 +/- 1.53	01/02- 12/12
3						
	125	6.48 +/- 1.73	67 (03/06)	6.24 +/- 1.92	6.77 +/- 1.46	01/01 – 12/11
4	120	5.81 +/- 1.64	66 (03/06)	5.75 +/- 1.35	5.87 +/- 1.93	03/01 – 12/11
5	121	7.64 +/- 1.52	58 (03/07)	7.68 +/- 1.47	7.60 +/- 1.57	01/02-12/11
6	114	6.17 +/- 1.51	69(04/08)	6.57 +/- 1.45	5.64 +/- 1.44	01/03-12/14
7	132	5.65 +/- 1.26	57 (01/09)	5.66 +/- 1.25	5.64 +/- 1.28	01/03 – 12/14
8	126	5.56 +/- 1.13	69 (04/09)	5.81 +/- 1.12	5.28 +/- 1.08	01/03 - /12/14
9	130	6.37 +/- 2.09	69 (11/08)	6.23 +/- 2.10	6.54 +/- 2.10	01/01 – 12/14
10	168	4.79 +/- 1.54	62 (02/09)	4.75 +/- 1.45	4.82 +/- 1.63	01/01 – 12/14
11	168	8.05 +/- 1.37	0	-	8.05 +/- 1.37	01/01 – 12/14
12	168	7.44 +/- 1.09	0	-	7.44 +/- 1.09	01/01 – 12/14
13	168	8.43 +/- 1.20	0	-	8.43 +/- 1.20	01/01 – 12/14
14	165	6.44 +/- 1.65	0	-	6.44 +/- 1.65	01/01 – 12/14
15	157	5.37 +/- 1.38	0	-	5.37 +/- 1.38	01/01 – 12/14
16	168	6.47 +/- 1.48	0	-	6.47 +/- 1.48	01/01 – 12/14
17	135	5.31 +/- 1.55	0	-	5.31 +/- 1.55	03/01 – 12/14
18	162	5.98 +/- 2.14	0	-	5.98 +/- 2.14	01/01 – 12/14
19	161	5.23 +/- 1.74	0	-	5.23 +/- 1.74	01/01 – 12/14

References

Angelakis, A.N., Koutsoyiannis, D., Tchobanoglous, G., 2005. Urban wastewater and stormwater technologies in ancient Greece. Water Res. 39, 210–220. https://doi.org/10.1016/j.watres.2004.08.033.

Arbués, F., Garc, Á., Mart, R., 2003. Estimation of residential water demand : a state-of-the-art review. J. Socio. Econ. 32, 81–102. https://doi.org/10.1016/S1053-5357(03)00005-2.

Cameron, R.C., Miller, D.L., 2015. A Practitioner's Guide to Cluster-Robust Inference. J. Hum. Resour. 50, 317–372. https://doi.org/10.3368/jhr.50.2.317.

Carter, A.V, Schnepel, K.T., Steigerwald, D.G., 2016. Asymptotic Behavior of a t Test Robust to Cluster Heterogeneity. Rev. Econ. Stat. 1–27. https://doi.org/10.1162/rest_a_00639.

Catlin, J.R., Wang, Y., 2013. Recycling Gone Bad: When the Option to Recycling Increases Resource Consumption. J. Consum. Psychol. 23, 122–127. https://doi.org/10.5465/amr.2011.0193.

Dai, A., 2013. Increasing drought under global warming in observations and models. Nat. Clim. Chang. 3, 52–58. https://doi.org/10.1038/nclimate1633.

de Chaisemartin, C., D'Haultfuille, X., 2018. Double Fixed Effects Estimators With Heterogeneous Treatment Effects. SSRN Electron. J. 10.2139/ssrn.3148607.

DeOliver, M., 1999. Attitudes and Inaction: A Case Study of the Manifest Demographics of Urban Water Conservation. Environ. Behav. 31, 372–394.

Ekvall, T., 2000. A market-based approach to allocation at open-loop recycling. Resour. Conserv. Recycl. 29, 91–109.

Frischknecht, R., 2010. LCI modelling approaches applied on recycling of materials in view of environmental sustainability, risk perception and eco-efficiency. Int. J. Life Cycle Assess. 15, 666–671. https://doi.org/10.1007/s11367-010-0201-6.

Geyer, R., Kuczenski, B., Zink, T., Henderson, A., 2015. Common Misconceptions about Recycling. J. Ind. Ecol. 0, 1–8. https://doi.org/10.1111/jiec.12355.

Gilbertson, M., Hurlimann, A., Dolnicar, S., 2011. Does water context influence behaviour and attitudes to water conservation ? Australas. J. Environ. Manag. 18 https://doi.org/10.1080/14486563.2011.566160.

Goleta Water District, 2018. Recycled Water Program [WWW Document]. URL http://www.goletawater.com/conservation/recycled-water-program.

Guneralp, B., Guneralp, I., Liu, Y., 2015. Changing global patterns of urban exposure to flood and drought hazards. Glob. Environ. Chang. 31, 217–225. https://doi.org/10.1016/j.gloenvcha.2015.01.002.

Horticulture Australia Limited,, 2011. Recycled water treatment plant for Melbourne. ReWater 2–4.

Jimenez, B., Asano, T., 2008. Water Reclamation and Reuse around the World, in: Water Reuse: An International Survey of Current Practice, Issues, and Needs. IWA Publishing, pp. 3–27.

Jones, Edward R., et al., 2021. Country-level and gridded estimates of wastewater production, collection, treatment and reuse. Earth Syst. Sci. Data 13 (2), 237–254.

Koffler, C., Finkbeiner, M., 2018. Are we still keeping it "real"? Proposing a revised paradigm for recycling credits in attributional life cycle assessment. Int. J. Life Cycle Assess. 23, 181–190.

Lee, C.H., Steigerwald, D.G., 2018. Inference for Clustered Data. Stata J 18, 447–460.

Legislative Analyst's Office, 2017. Residential Water Use Trends and Implications for Conservation Policy [WWW Document]. URL https://lao.ca.gov/Publications/Report/3611 (accessed 10.12.18).

Martinez-Espineira, R., 2002. Residential Water Demand in the Northwest of Spain. Environ. Resour. Econ. 21, 161–187.

Palazzo, J., Geyer, R., Startz, R., Steigerwald, D.G., 2019. Causal Inference for Quantifying Displaced Primary Production from Recycling. J. Clean. Prod. 210, 1076–1084. https://doi.org/10.1016/j.jclepro.2018.11.006.

Palazzo, J., Liu, O.R., Stillinger, T., Song, R., Wang, Y., Hiroyasu, E.H.T., Zenteno, J., Anderson, S., Tague, C., 2017. Urban responses to restrictive conservation policy during drought. Water Resour. Res. 53, 1–17. https://doi.org/10.1002/2016WR020136.

Sun, M., Trudel, R., 2017. The effect of recycling versus trashing on consumption: theory and experimental evidence. J. Mark. Res. 54, 293–305. https://doi.org/10.1509/jmr.15.0574.

Yang, Y., 2016. Two sides of the same coin: consequential life cycle assessment based on the attributional framework. J. Clean. Prod. 127, 274–281. https://doi.org/10.1016/j.jclepro.2016.03.089.

Tang, C.Y., Yang, Z., Guo, H., Wen, J.J., Nghiem, L.D., Cornelissen, E., 2018. Potable water reuse through advanced membrane technology. Environ. Sci. Technol. 52, 10215–10223. https://doi.org/10.1021/acs.est.8b00562.

Zink, T., Geyer, R., 2018. Recycling and the myth of landfill diversion (forthcoming). J. Ind. Ecol.

Zink, T., Geyer, R., 2017. Circular economy rebound. J. Ind. Ecol. 21, 593–602. https://doi.org/10.1111/jiec.12545.

Zink, T., Geyer, R., Startz, R., 2017. Toward Estimating displaced primary production from recycling: a case study of U.S. aluminum. J. Ind. Ecol. 0, 1–13. https://doi.org/10.1111/jiec.12557.

Zink, T., Geyer, R., Startz, R., 2015. A Market-Based framework for quantifying displaced production from recycling or reuse. J. Ind. Ecol. 0, 1–11. https://doi.org/10.1111/jiec.12317.