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Essays Related to Water Transfer and Water Sharing: The Past and the Present

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ESSAYS IN WATER TRANSFER AND WATER SHARING: THE PAST AND THE PRESENT

by

Arpita Nehra

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ABSTRACT

Essays related to Water Transfer and Water Sharing: The Past and The Present

by

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This dissertation explores the impacts of resource procurement on regional economic growth and urbanization through a historical case study, moving on to discuss the welfare impacts of resource-sharing in two regions. The first essay focuses on the effects of the Owens Valley Water Transfer in the 1900s on the economic growth in Los Angeles. We apply the synthetic control and difference-in-differences methods to determine the treatment effect from the water transfer. The empirical results show that the Manufacturing Product Per Capita and Gross Domestic Product Per Capita was higher in the post-treatment period with a water transfer. Hence, we conclude that the water transfer accelerated the economic growth in Los Angeles county. The second essay extends the previous analyses to examine the impact on the urban sprawl. In this study, we rely on difference-in-differences for our main results owing to a much lesser degree of urban expansion in the control counties before the water was transferred. Our treatment effect from various difference-in-differences specifications is consistently positive and significant, and we obtain similar impacts from the various robustness checks. Thus, we conclude that the Owens Valley water transfer resulted in a higher degree of urban sprawl in Los Angeles post the Owens Valley water transfer. The third essay progresses to study the welfare impacts of water-sharing between Cache County and Wasatch Front. We apply the Nash Bargaining co-operative theory to a general equilibrium model to compute social welfare in each county. We use Compensating Variation (CV)/ Willingness-to-pay as measures of social welfare. We compare the willingness-to-pay with the costs proposed by the Bear River Development Project. The project will develop water resources in Cache County and Box Elder County and export water to the Wasatch Front in the south. The results showed that the costs were much higher as compared to the willingness to pay. We make two suggestions: i) the development of more water resources, or ii) dividing the total project costs equally among the regions sharing the water resources.

(136 pages)

PUBLIC ABSTRACT

Essays related to Water Transfer and Water Sharing: The Past and The Present

Arpita Nehra

This dissertation explores the impacts of resource procurement on economic growth and urbanization in a county through a historical case study, moving on to discuss the welfare impacts of resource-sharing in two regions. The first two essays explore the impact of the Owens Valley water transfer in the 1900s on the urban sprawl and the economic growth of Los Angeles. The main contribution that the first two essays make is to present an empirical analysis on the impact of procurement of resources on the economy. The third essay examines the welfare impacts of a proposed water sharing and development project. The findings suggest that the regions would be willing to pay for the water transfer only if the increase in new resources is large or the costs are shared equally among the involved regions, excluding environmental costs. This essay informs the policy of alternative methods ensuring overall net benefit to all the parties involved in the project. Studies like the one presented in this dissertation have become indispensable with the increase in competing uses of water.

This dissertation is dedicated to my parents, family, and friends with special gratitude for their love, support, and affection through one of the most important journeys in my life.

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Arpita Nehra

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CHAPTER 1

INTRODUCTION

Researchers have begun to observe water as "the new oil"; in the sense that wars used to be fought over oil in the past, and they are being fought over water in the present (Chellaney, 2013). Kofi Annan stated in 2001 that the reason for the third world war is going to be water (Singh and Kumar, 2021). Though plentiful, the global water demand has increased more than ten times because of population growth, affluence, and multiple uses of water (Mbote, 2007). A good example of a water conflict is in the Nile River Basin (Fadel et al., 2003). The woes of water sharing do not end here as there is a constant threat of drought, population explosion, and pollution resulting in water conflicts (Mbote, 2007). Moreover, the water conflict in some countries in this basin has given rise to the exacerbation of political, social, and economic instability in surrounding areas (Mbote, 2007). The situation of the Nile Water Conflict turning into a war is not unique to the region. There are various water conflicts in the world, that started historically and have continued causing problems till the present day. This dissertation studies one of these conflicts, i.e., the Owens Valley water conflict and, explores the impacts that the water transfer had on the urban expansion and growth of Los Angeles historically, and then examines an existing water-sharing project proposed in Utah.

With the increase in the amount of water transfers as a water management strategy, it has become of prime importance that the historical water transfers and water-sharing agreements are studied to make inferences regarding future decisions. The first essay takes a step in this direction and empirically investigates the impact of the Owens Valley water transfer on economic growth and the urban region. Back in the 1900s, the officials from Los Angeles sought water from the Owens Valley located in Eastern California by buying the agricultural lands (Libecap, 2004). We use Gross Domestic Product Per Capita (GDP Per Capita) as the indicator of economic growth. A synthetic control method is employed to show that the rise in the GDP Per Capita and Manufacturing Product Per Capita was higher with the water transfer and apply a difference-in-differences analysis to corroborate our results. The essay adds to the current literature by presenting empirical evidence on the acceleration of economic growth through resource procurement. Such evidence could be utilized while making water allocation decisions based on scientific analysis.

The second essay studies the impacts of the transfer on urban sprawl. We converted a geo-spatial data set using the historical land use-land cover maps and overlaying the same over the present Californian counties to compute the urban sprawl in our study period. We apply difference-in-differences and synthetic control methods for our analysis. However, given the sparse urban sprawl data in the pre-intervention period, we rely on difference-in-differences analysis for causal interpretation, unlike the first essay. We include a few robustness checks to validate our results. There have been a few studies relating water resources and urban sprawl in other fields. (Aakuraju and Amerasinghe, 2011; Hatab et al., 2019; Duias-Caraventas and Sanchez-Flores, 2011). This study extends the current literature by including a case study of the first-ever water transfer in the United States.

The third essay evaluates the welfare impacts of water-sharing and the Bear River Development Project. The Bear River Development Project is seeking to develop water resources in Cache County and Wasatch Front, and transfer water from Cache Valley to Wasatch Front. We apply the Nash Bargaining theory to a general equilibrium model ascertaining the social welfare from sharing water between Cache County and Wasatch Front. We use Compensating Variation or willingness-to-pay as measures for social welfare. The study makes a contribution to the literature by applying a game-theoretic approach to water allocation problems. We seek to develop a strategy that ensures that both the regions involved obtain a positive net benefit from the water transfer. With the threat of increasing water wars and conflicts, it is essential that such decisions are made on the basis of careful analysis ensuring fairness and efficiency for all the individuals involved.

The remainder of the dissertation is organized as follows. Chapters 2, 3, and 4 describe the three essays as explained in the introduction. Each essay includes a separate introduction and conclusions. In Chapter 5, we summarize the dissertation and discuss the possible policy implications.

CHAPTER 2

REGIONAL WATER TRANSFER AND ECONOMIC GROWTH: EVIDENCE FROM THE OWENS VALLEY WATER TRANSFER

2.1 Introduction

The literature has abundantly studied economic growth and natural resources under the purview of how economic growth has affected environmental sustainability (Dinda, 2004; Everett et al., 2010; Cherniwchan, 2012). However, studies have ignored that oft-times, government officials and bureaucrats have procured natural resources to develop a town into a metropolitan and even, a county. The Western US, particularly California is a classic example of such a development where water procurement from various sources facilitated economic growth.

Quinn (1968) points out two main assumptions that led to the emergence of water transfers and water markets: one was that large surpluses of unexploited wealth existed in the Western US, and two, public policy must encourage settlement and development in the West by making land, minerals, and water resources available. The West exhausted the unappropriated part of the naturally available water supplies at the turn of the century. The solution, found by one of the oldest metropolitan cities in the United States, Los Angeles, was the long-distance importation of water from the Owens Valley (Park, 2017).

This essay investigates the first region to import water from outside the city limits ever: Los Angeles. In the early 1900s, Los Angeles, a city in Southern California, sought water from an arid Owens Valley in Eastern California. A map showing the location of the two areas is given in Appendix 8.1. Los Angeles was a city developed despite the lack of all the basic facilities on the prospects of the future rather than on actual demand (Kahrl, 2000). The Owens Valley water supply was expected to be five times higher than the local supply when it first arrived in Los Angeles. The arrival of Owens Valley water resulted in the annexation of nearby areas by the city (Ostrom, 1950). Agriculture was given a higher priority as a means of economic livelihood before the railroad gained popularity by the end of the 19th century. Los Angeles always applied excess water to crop irrigation within the city limits (Ostrom, 1950). By 1935, Los Angeles had acquired 95 percent of the water from Owens Valley (Libecap, 2008).

The relevance of this historic occurrence resides in the fact that the Southern California water demands have created controversy throughout the West since the first water transfer. Moreover, the conflict has continued to the current period as the region is struggling to meet its ever-rising water demands (Howitt et al., 2002). The procurement of natural resources from outside where such resources are scarce is not just a historical phenomenon. Major water wars, like the Nile river basin conflict in the world, are being fought between different regions trying to fulfill their water demand from the same source (Mbote, 2007). Hence, policies formalizing water transfers have become essential at higher levels like state or country, alongside the county level. Furthermore, the focus in the literature related to water transfers has primarily been the parties' attitudes in the water market and welfare implications, or the impact of such transfers on water use (Howitt et al., 2002; Barbier and Chaudhary, 2013; Lund and Israel, 1995).

Although there is literature documenting the annexation of neighboring areas by Los

Angeles due to water procurement beyond its city's boundaries, the empirical studies to evidence the same are non-existent (Kahrl, 2000; Ostrom, 1950). Typically, population and development are considered as primary factors that lead to procurement of resources- however, the part played by officials and bureaucrats to obtain these resources to promote the economic growth of a region has not been tested empirically in the literature. Such an investigation has become necessary given the increasing water conflicts in various parts of the world.

This essay uses a comparative case study providing critical empirical evidence for the effect of the water transfer on Los Angeles' growth where the treatment and control groups are defined based on the year of water transfer, i.e., 1920. We use synthetic control and difference-in-differences methods to bring out the treatment effect of the Owens valley water transfer facilitating the economic growth in Los Angeles. We include a placebo test where the synthetic control method is applied to all the control units included in the study. No treatment effect in these units reveals that the treatment effect in Los Angeles is significant. The growth of Gross Domestic Product per Capita (GDP per capita) represents economic growth in the study. The synthetic control results show that the economic growth was higher in Los Angeles compared to other Californian counties with the water transfer and are supported by the difference-in-differences analysis. These results indicate that the procurement of natural resources facilitates economic growth in a region.

The essay is organized as follows. The second section briefly describes the background of the study. The third section presents the data and empirical strategy. The fourth section presents the results and a brief discussion. Finally, the last section concludes the empirical results.

2.2 Background

The nineteenth-century American West was made habitable as rural communities adjusted to the limitations of local water availability. Today, the search for water supply extends beyond the nearest river basin. The water transfer institutions highly impact the development of an economy (Quinn, 1968; Brewer, 1965). A dry American West started transforming from ranching, irrigated farming, and mining to urban growth, services, tourism, and manufacturing industry (Colby, 1990), involving some of the earliest urban centers in the United States. Kahrl (2000) mentions specifically for California: "More than gold and oil, railroad and freeway construction, the film and aerospace industries, water distribution has shaped the development of California's cities."

Californian growth was characterized by an aspect of uniqueness, with cities like Los Angeles being the pioneers of such development (Nash, 1972). Nash (1972) notes that California has been ahead of other areas by one generation. A large influx of population and industrial boom characterized the growth of California between 1900 and 1940. However, despite being a coastal city without a port and lacking sewers and schools, factors like advertisement and development based on future prospects rather than actual demand fed its continuous growth. The first step to procure resources for such a development was between 1905 and 1935- when the efforts of William Mulholland and Fred Eaton led to the biggest and the first-ever rural to urban water transfer in history: the *Owens Valley water transfer*.

The Owens Valley water transfer was highly controversial where Los Angeles was perceived as a thief stealing water and robbing the agricultural economy of Owens Valley (Libecap, 2004). The former secretary of the Interior, Ray Lyman Wilbur, once remarked, *"You didn't bring these people here with railroad trains. Water brought them. You can have all the salt oceans, the blue skies, and sunshine in this world, and you will all disappear* *unless you have water"* (Ostrom, 1950)[1]. The prime issue that generated the controversy was that the transfer had happened in a land market with high secrecy maintained around it to prevent a price increase. Kahrl (2000) mentions that when questioned for bringing in so much water, the officials exaggerated the demand of Los Angeles and even gave an account of dire consequences that the city would be in if there was no water transfer. He mentions that the water transfer derailed the agricultural potential that could surpass the other agricultural economies such as Imperial, Sacramento, and San Joaquin valleys. It is oft mentioned in the Owens valley literature that the agricultural lands were bought by the officials secretly so that people could not oppose the acquisition in addition to preventing price rise, which would finally lead to an end of irrigated agriculture in the valley (Kahrl, 2000; Libecap, 2004; Ostrom, 1950).

Libecap (2004) mentions that the negative publicity and citation of *Owens Valley syndrome* by various researchers, including the likes of Vincent Ostrom, provided a barrier to future agriculture to urban water transfers. He mentions that the water transfer to Los Angeles brought dramatic property gains from trade in Owens Valley. He states a counterfactual scenario, where, if the transfer did not happen, the economic gains for the Owens Valley would have been lesser than the gains from the transfer. He agrees that the disproportionate share of the total gains from the Owens Valley water transfer went to Los Angeles, given the nature of water demand and supply and a relatively inelastic demand of the urban users contrary to the farmers' elastic export supply in comparison (Libecap, 2008). The bitterness over being under-compensated lies in the fact that the value of water to Los Angeles was difficult to ascertain at the time (Libecap, 2004; 2008).

Hence, it would not be an understatement to posit that the Owens Valley water transfer calls for a crucial examination. Libecap (2004, 2008) has shown how an efficiency-enhancing trade was tied up in distributional conflicts. However, this study inspects a much

[1] Libecap (2004, 2008) notes that the intensity of the debate on the water transfer, perceived as interfering with natural resources, was to such an extent that a movie *'Chinatown'* was created around it.

simpler question: ***How does a water transfer intervention affect the future growth of a city?***

2.3 Empirical Analysis

2.3.1 Data

Our primary variable of interest is the Gross Domestic Product (GDP) per capita, following the literature on economic growth where GDP has been commonly used to indicate economic growth (Munir et al., 2020; Ruiz, 2017). We obtain the variables used in the study from NHGIS IPUMS, the University of Minnesota, from 1850-1950 (Manson et al., 2020). The main sectors contributing to the GDP during the study period were manufacturing and agriculture. Some data was also available in the other sectors apart from the two mentioned above, as shown in Appendix Table 2.4.

One of the major issues with the data was that the counties increase from 27 to 58 during the study period. However, for identification, we need an equal number of counties before and after the treatment period[2]. Some of the new counties, for instance, Orange was wholly a part of one original county, i.e., Los Angeles. Few counties split from more than one county; for instance, the Alpine county formed from parts of Amador, Calaveras, El Dorado, Mono, and Tuolumne counties. Nine counties were created by split-then-merge, which had to be dropped from the analysis.

[2]We include the original 27 counties for the current analysis.

Table 2.1

County details over the decades

Year	Total number of counties	Number of counties that split	Number of counties that split and merge
1850	27		
1860	43	14	2
1870	50	16	7
1880	52	18	8
1890	54	20	8
1900	57	22	9
1910	58	23	9

Table 2.1 gives a brief description of changes in the number of counties during the study period. There are no counties that merge per se unless they split from two or more counties, for example, the Alpine county, which formed from parts of five other counties. All the 27 counties were available to be included whether they split merge or not. There are 14 counties that neither split nor merged.

As mentioned earlier, the value of the agricultural product and the value of the manufacturing product are the main contributing sectors to calculate the GDP. Appendix Table 2.5 consists of disaggregated variables used to calculate the agricultural value of the product. However, the variable definition for the Value of Agricultural Product per Capita in 1930 was slightly different. We selected the variables in 1930, which was closest to the definitions for Agricultural Product per capita in the other years. Another pressing concern in the data was that the value of manufacturing product was missing in 1910 and 1950, which poses a serious challenge.

Data scientists typically deal with the missingness of data by removing all the missing data points and the associated observations- formally called a listwise deletion. Pepinsky (2018) mentions that this process is inefficient and could be biased when the probability that an observation is missing is related to its true value. Moreover, McNeish (2017) comments that although the method is more appealing due to the less intensive manner for handling missing values, there is a trade-off between convenience and less desirable performance with small samples. Since we also have a small sample in this study, a multiple imputation method is more reasonable than dropping the missing observations.

Multiple imputations have been widely used for dealing with missing data (Rubin, 1987; Rubin, 1996; Schafer, 1997; Barnard and Meng, 1999; Reiter and Raghunathan, 2007; Harel and Zhou, 2007, Akande et al., 2017). Most analysts adopt two methods: Joint Modeling (JM) and Fully Conditional Specification (FCS) (Buuren, 2007; Akande et al., 2017). The JM strategy is appealing since it accords with the theory in Rubin (1987)[3].

One of the most popular Joint Modeling approaches is expectation-maximization with bootstrapping algorithm. The expectation-maximization algorithm has been used in the literature for a long time (Bar-Hen, 2002). The literature involving the use of longitudinal and panel data has implemented the Amelia II package in R (Honaker et al., 2011), given its ease of use and generating results similar to Monte Carlo approaches (Honaker et al., 2011).

The enhancements to the newly developed algorithm work well with panel data in political science and macroeconomic fields (Honaker and King, 2010; Yang et al., 2015). Yang et al. (2015) used the package to impute 27 variables for their study. Moreover, our dataset requires an imputation method that can control for both cross-sectional and time components. Following the preceding imputation literature, we adopt the expectation-maximization with bootstrapping algorithm to impute missing data[4]. As a robustness check

[3]The most popular FCS approach is known as Multiple Imputation by Chained Equations (MICE) (Akande et al., 2017). This approach is still an open research area for multilevel or longitudinal data. Hence, it suffers from a significant drawback for implementation in our study.

[4]We rely on the literature since limited studies have used imputation for panel data; one of the examples of such studies is mentioned in the text.

measure, we also impute the data using other methods[5]. We also include diagnostics comparing the original and imputed dataset in Appendix Figure 2.9.

Table 2.2 shows descriptive statistics for all the variables.

Table 2.2

Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Gross Domestic Product per capita	270	417.215	529.873	18.674	161.548	502.873	5,418.325
Manufacturing Product per Capita	270	256.689	497.709	0.000	43.182	295.997	5,231.926
Agricultural Product per Capita	270	160.526	181.137	3.877	55.667	186.414	1,308.076
Percentage of Urban Population	243	29.333	28.440	0.000	0.000	49.113	98.391
Number of farms under 10 acres per capita	243	0.004	0.005	0.000	0.002	0.006	0.034
Number of farms from 10 to 49 acres per capita	243	0.013	0.011	0.0001	0.006	0.017	0.061
Number of farms from 50 to 99 acres per capita	243	0.007	0.005	0.0001	0.004	0.010	0.030
Number of farms under 100 acres per capita	243	0.025	0.017	0.001	0.013	0.034	0.087
Number of farms from 100 to 999 per capita	243	0.028	0.023	0.0001	0.010	0.042	0.121
Number of farms more than 1000 per capita	243	0.004	0.004	0.000	0.001	0.005	0.023
Number of farms per capita	243	0.058	0.031	0.001	0.033	0.080	0.155
Wages paid per person employed	186	2,965.844	8,270.749	150.664	505.847	1,370.432	88,250.000
Persons employed per capita	242	0.034	0.035	0.000	0.008	0.049	0.249
Value of farm property per capita	243	829.785	791.121	9.074	289.870	1,113.554	5,079.433
Value of land and buildings per capita	108	1,125.589	864.082	28.657	538.106	1,447.289	4,494.966

The main observations from the table are the differences between the largest values and 3rd quartiles of GDP per capita, Manufacturing Product per capita, Agricultural Product per capita, and Wages per person employed. The difference between these values is quite high, indicating the discrepancy in economic growth among various Californian counties. Moreover, the standard deviation and means are much higher in GDP per capita and Manufacturing Product per capita compared to Agricultural Product per capita. This observation

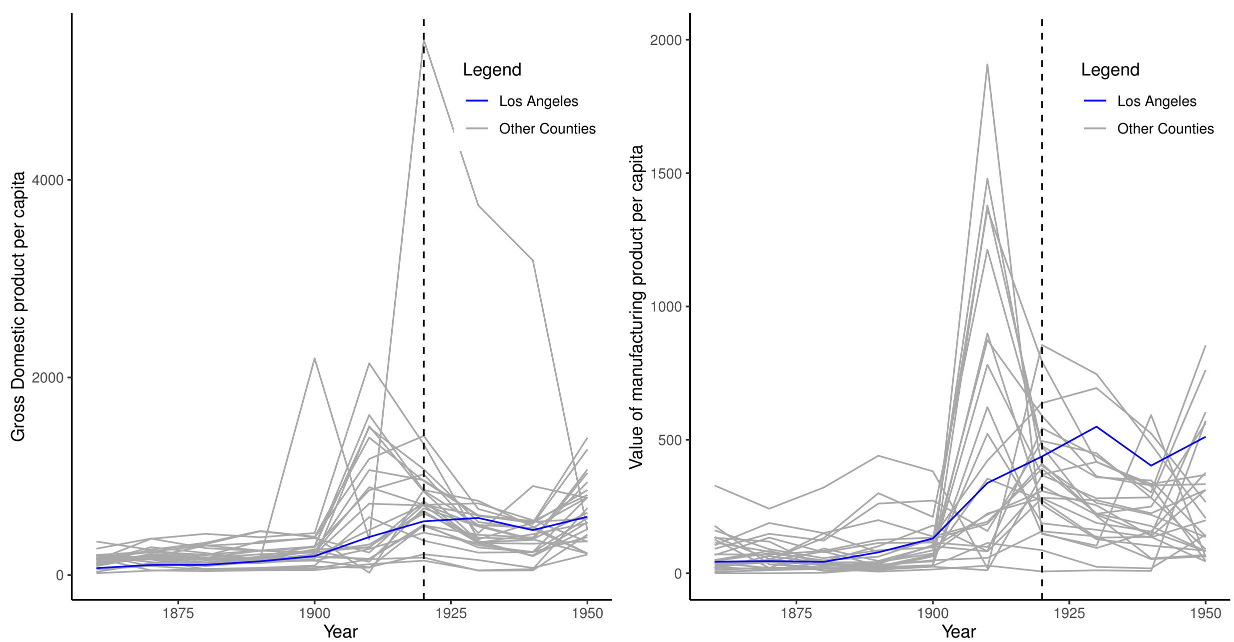
[5]Kalman Smoothing, Simple Weighted Moving Average, Exponential Moving Average, Linear Interpolation, Linear Weighted Moving Average, Random Sample, Spline Interpolation and Stine Interpolation in Appendix 2.7.3

is not surprising as urbanization was taking place (however, at different rates) in the state. The difference in the mean, 3rd quartile, and the maximum value in percentage of urban population is also very high, indicating urbanization in only a few counties in California.

The left panel of figure 2.1 shows the plot of GDP per capita for all the counties and the Value of Manufacturing Product Per Capita on the right panel. The blue line represents Los Angeles, and the gray lines represent the control counties. The dashed line in between marks the treatment year and divides the graph into pre and post-treatment periods. As we can observe, the two variables started increasing before the treatment year, and the GDP per capita slightly dropped after 1930. Moreover, we observe peaks in other counties. These observations could be a result of factors like capital, labor, etc. Hence, we use a non-parametric method, reducing the assumptions about the population distribution, i.e., synthetic control, to disentangle the impact of water transfer on economic growth and corroborate our results using the difference-in-differences analysis.

Figure 2.1

GDP per capita (Left Panel) and Manufacturing product per capita (Right Panel)



2.3.2 Empirical strategy

I. Synthetic Control Method

The econometric methodology adopted in this study draws on the precedent of analysis developed for studying the effect of an intervention on an outcome of interest. We use a synthetic control analysis developed by Abadie and Gardeazabal (2003) to estimate the effect of water transfer from Los Angeles to Owens valley in 1920 on economic growth. The basic intuition behind the method is to construct a 'synthetic control unit' based on a weighted combination of the available control units (in the pre-intervention period), which closely imitates the actual treatment unit. The change in the outcome of interest is then observed in the *counterfactual* treatment unit and compared with the actual treatment unit.

The synthetic control method is an extension of the difference-in-differences method. Many empirical researchers believe that the weighted control unit system which the method relies on is better than the traditional difference-in-differences method where the counties are given an equal weight assuming that they closely match the treatment unit in most of its attributes (Akhundjanov and Jakus, 2019; Abadie and Gardeazabal, 2003).

Akhundjanov and Jakus (2019) describe synthetic control as a two-step methodology; where the first step involves computing the unit weights, i.e., the weights assigned to the control units based on their closeness to the treatment unit in terms of measurable attributes and the co-variate weights, i.e., the weights assigned to the co-variates based on their power to the predict the outcome variable. Then, a synthetic control unit is constructed using the unit weights. An ideal synthetic control unit would imitate the treatment unit very closely in the pre-treatment period. The next step deals with the post-treatment time frame where the discrepancy between the post-intervention outcome of the synthetic control unit (which is assumed to represent what would have happened if there was no intervention) and the treatment unit reveals the treatment effect.

The theoretical properties of the synthetic control method are discussed by Abadie et al. (2010), Abadie and Gardeazabal (2003), and Akhundjanov and Jakus (2019). We explain these properties using an example of three counties and 5 time periods for simplicity. Assume i=1 is our treatment unit and i>1 for the other 2 counties observed for t=1,...,5. Hence, the other units serve as the potential control. Also, assume that water transfer happens at the time period 3.

Let Y_{it}^{NI} be the outcome variable, i.e., outcome variable for the three counties in periods 1, 2, and 3 when the intervention has not taken place and Y_{it}^{I} be the outcome variable for unit i=1 in period t if the unit i=1 in the post-intervention period, i.e. t>3. Hence, for the pre-intervention period, $Y_{it}^{I} = Y_{it}^{NI}$ would be satisfied for all i=1,2,3 and t=1,2,3. Assume $\Gamma_{it} = Y_{it}^{I} - Y_{it}^{NI}$ is the treatment effect from intervention. However, Y_{1t}^{NI} is not observable for $t > 3$, i.e. outcome for the unit i=1 when there is no intervention. Hence, the synthetic control unit aims at representing the actual treatment unit as closely as possible and replace Y_{1t}^{NI}.

The idea presented above can be validated as follows. Consider Z_i as a vector of observed explanatory variables of the GDP for the pre-intervention period. Also, assume $\overline{Y}_i^K = \sum_{t=1}^{2} k_t Y_{it}$ is a linear combination of pre-intervention outcomes for unit i where $K = (k_1, k_2, k_3)'$ is a set of weights for the explanatory variables in pre-treatment period. These linear combinations are used to control for the effect of unobservable common confounders that vary with time (Abadie et al., 2010; Akhundjanov and Jakus, 2019).

Let $W = (w_2, w_3)'$ be the vector of weights that is assigned to unexposed units in the pre-intervention period where $w_i \geq 0$ for $i = 2,3$ and $w_2 + w_3 = 1$. Different W-vector values would generate different synthetic control units. The optimal weights $W^* = (w_2^*, w_3^*)'$ must satisfy:

$$w_2^* \overline{Y}_2^{K_1} + w_3^* \overline{Y}_3^{K_1} = \overline{Y}_1^{K_1} \ ,$$

$$w_2^* \overline{Y}_2^{K_2} + w_3^* \overline{Y}_3^{K_2} = \overline{Y}_1^{K_2} \ ,$$

$$w_2^* \overline{Y}_2^{K_3} + w_3^* \overline{Y}_3^{K_3} = \overline{Y}_1^{K_3} \ \text{,and}$$

$$w_2^* Z_2 + w_3^* Z_3 = Z_1$$

Hence, W^* produces a weighted average of the control units in a way that closely imitates the actual treatment unit. Abadie et al. (2010) propose to select the $W^* = W(V)$ such that it minimizes the overall discrepancy between the characteristics of the synthetic control unit and the actual treatment unit in the pre-treatment period. The synthetic control unit can be obtained as:

$$\widehat{Y_{1t}^{NI}} = w_2^* Y_{2t}^{NI} + w_3^* Y_{3t}^{NI} \text{ for } t > T_0$$

And finally, the estimator of the treatment effect is:

$$\widehat{\alpha}_{1t} = Y_{1t}^{I} - \widehat{Y_{1t}^{NI}} \text{ for } t > 3$$

This method can be extended to any number of individual units and time periods. A generalized form of the synthetic control unit would then be:

$$\widehat{Y_{1t}^{NI}} = \sum_{i=2}^{N+1} w_i^* Y_{it}^{NI} \text{ for } t > t_0$$

such that t_0 is the time of intervention and 2,....N+1 are control units.

Inferences

The inferential techniques undertaken in the current study are akin to Abadie et al. (2010). They suggest, as in permutation tests, applying the synthetic control method to every possible control in the sample. This would allow researchers to assess whether the effect estimated for the region affected by the intervention is large relative to the effect estimated for a region chosen at random. This inferential exercise is said to be exact in the sense that, regardless of comparison regions, time periods, and data, it would always be possible to calculate the exact distribution of the estimated effect of the placebo interventions. The placebo interventions refer to an assumption that the water transfer happened in the control counties and the synthetic control analysis is performed on these counties. Since there was no such transfer, the expected result in this analysis is no treatment effect. The inferential method tries to assess whether the treatment effect is large in comparison to the distribution of the effects estimated for the regions not exposed to the intervention.

Abadie et al. (2010) mention that this approach to drawing an inference in comparative case studies is similar to recent developments in inferential methods for difference-in-differences models (Wooldridge, 2003; Athey and Imbens, 2006; Donald and Lang, 2007).

One of the main drawbacks of using a non-parametric method like Synthetic Control analysis is that there are no tests for statistical significance. Hence, we revert to a difference-in-differences analysis showing the significance and sensitivity of our results.

II. Difference-in-differences

A difference-in-differences method with two-way fixed effects and the individual effect is employed to provide statistical evidence on the direction and significance of the synthetic control results. We divide the duration of the study into two periods based on the year that the water transfer from Owens Valley to Los Angeles took place, i.e., 1920. Hence, 1850-1920 becomes the pre-intervention period and 1930-1950 is the post-intervention period. To study the effect of water transfer from Owens valley on the economic growth of Los Angeles, we estimate the equations as given below.

Two way fixed-effects:

$$Y_{it} = \alpha_{it} I(D_{it} T_{it}) + X'_{it}\beta + \lambda_t + \nu_i + \eta_{it}$$

Individual effects:

$$Y_{it} = \alpha_{it} I(D_{it} T_{it}) + X'_{it}\beta + \nu_i + \eta_{it}$$

Y_{it} is the observed outcome, i.e. the GDP per capita for county i and year t and X_{it} is the set of explanatory variables. D_{it} is the county dummy variable that equals 1, if i represents the treatment unit, i.e. Los Angeles and 0, for all other counties in California. T_{it} is a dummy variable for the pre and the post-treatment period, if t belongs to the pre-treatment period, i.e., $t \leq 1920$, $T_{it} = 0$ and if t belongs to the post-treatment period, i.e. $t > 1920$, $T_{it} = 1$, $I(.)$ represents the interaction between the time and county dummy, λ_t is the time effect, ν_i is the individual effect and η_{it} is the time-variant error term.

The parameter of interest is α_{it}, i.e., the coefficient of the interaction term between the pre and post-intervention dummy and the county dummy variables. It captures the water transfer through the impact of the characteristics of the treated county, LA, in the post-intervention period.

2.4 Results and Discussion

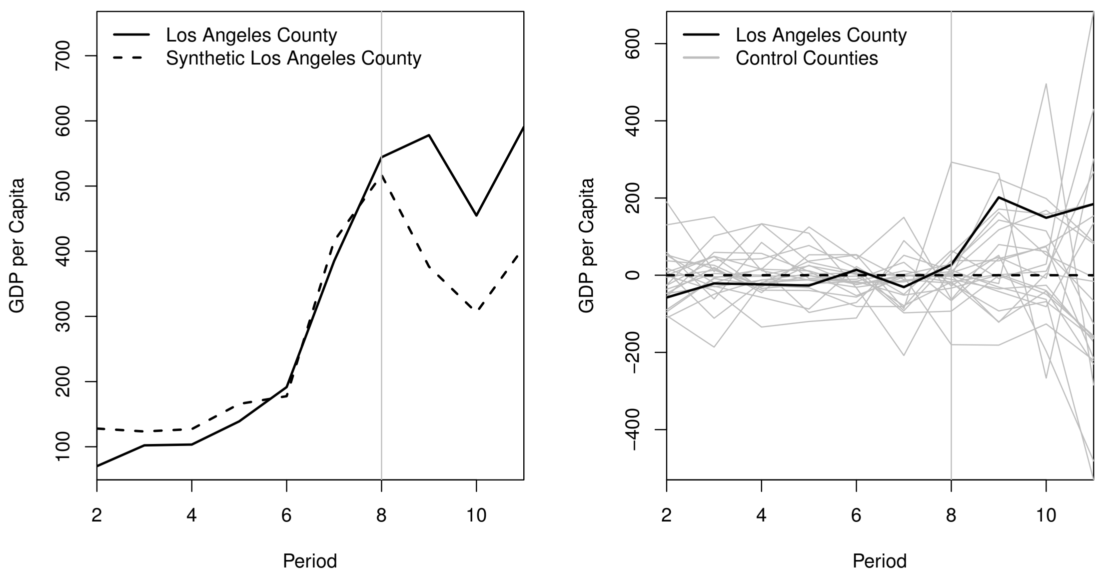
This section includes the results for the synthetic control method and the difference-in-differences analysis. 12 out of a total of 27 values in 1850 were zeroes for the primary dependent variable (GDP per capita). Hence, the year 1850 had to be dropped from the study.

I. Synthetic control Results

For the synthetic control analyses, *year* had to be converted to *Period* since we use decennial data. Hence period 2 represents the year 1860, period 3 represents the year 1870, and so on. Period 8 represents the treatment year, i.e., 1920. We excluded highly correlated predictors like Total Annual Agricultural Wages per Capita, Total capital invested per capita, etc. We summarize the county weights in Appendix Table 2.7.

Figure 2.2

Time plot (Left Panel) and falsification test (Right Panel) for GDP per capita



Appendix Table 2.8 describes the predictors used for this analysis. We show the time path of GDP per capita and a falsification test in Figure 2.2. The left panel of Figure 2.2 represents the time plot with a gray line anchored at period 8 (i.e. year 1920) to distinguish between the pre and post-treatment period. The synthetic Los Angeles follows the actual Los Angeles county very closely in the pre-treatment period; hence we may conclude that it's a good estimator of the actual Los Angeles. The time plot shows a significant increase after the year 1920 (time period 8), which confirms the hypothesis that the water transfer resulted in a higher GDP per capita than would have been without the water transfer. As observed from the earlier sections, there is evidence from the literature that the aim for the water transfer was to influence an even higher economic growth in the city, to the extent that it would annex all the nearby areas and develop into a county (Kahrl, 2000).

The right side of Figure 2.2 shows the falsification analysis. The black solid line represents the gap, i.e., the actual Los Angeles minus the synthetic Los Angeles county, and the gray lines show the gap for the placebo tests applied to the 26 remaining counties. It shows that the growth in GDP per capita seems to be significant. To investigate further, we break down the GDP per Capita into its main components, i.e., Manufacturing Product per Capita and Agricultural Product per Capita, and perform a synthetic control analysis on both the components separately.

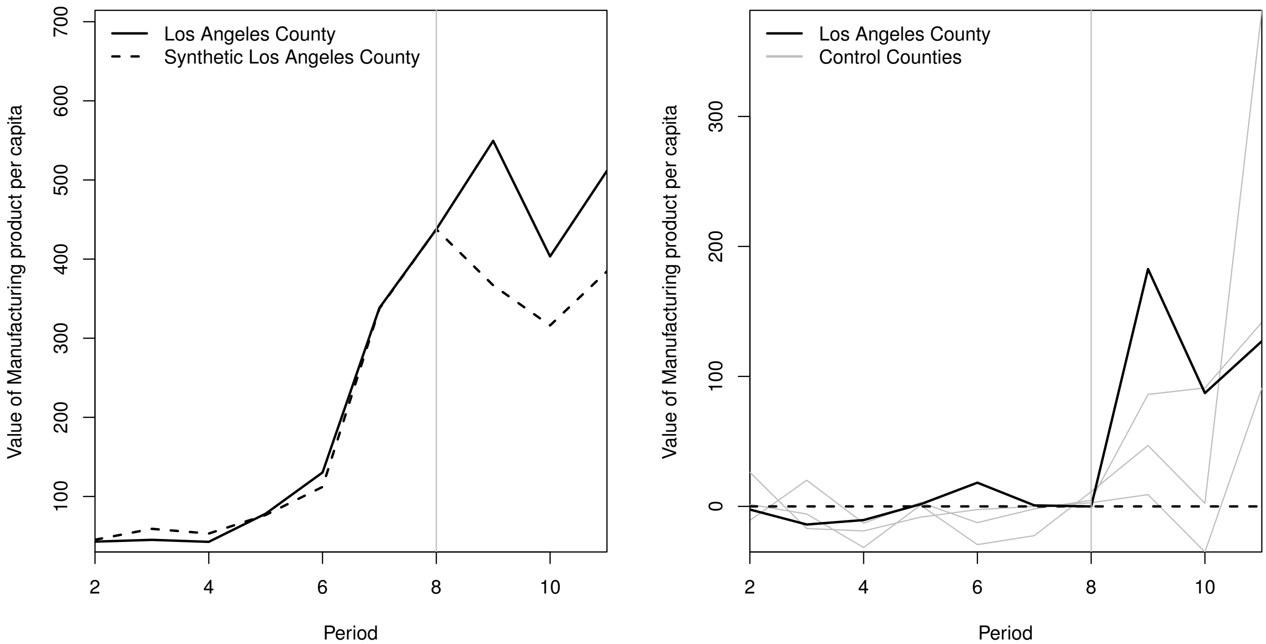
A. Value of Manufacturing output as the dependent variable

We perform a synthetic control analysis on the Manufacturing product per Capita. We provide a summary of the predictors used in this analysis in Appendix Table 2.9.

Figure 2.3 shows the time plot and a falsification test for the Value of Manufacturing Product per Capita. From the left panel, we observe that the synthetic unit follows the actual Los Angeles in the pre-treatment period closely showing that it is a good estimator of the latter. In the post-treatment period, the manufacturing product of actual Los Angeles seems to be significantly higher, similar to the analysis with the GDP per capita. Even the falsification test shows that the increase in Manufacturing Product per Capita is likely to be significant. Clearly, the Manufacturing Product per Capita was higher with the water transfer.

Figure 2.3

Time plot (Left Panel) and falsification test (Right Panel) for Manufacturing Product per Capita



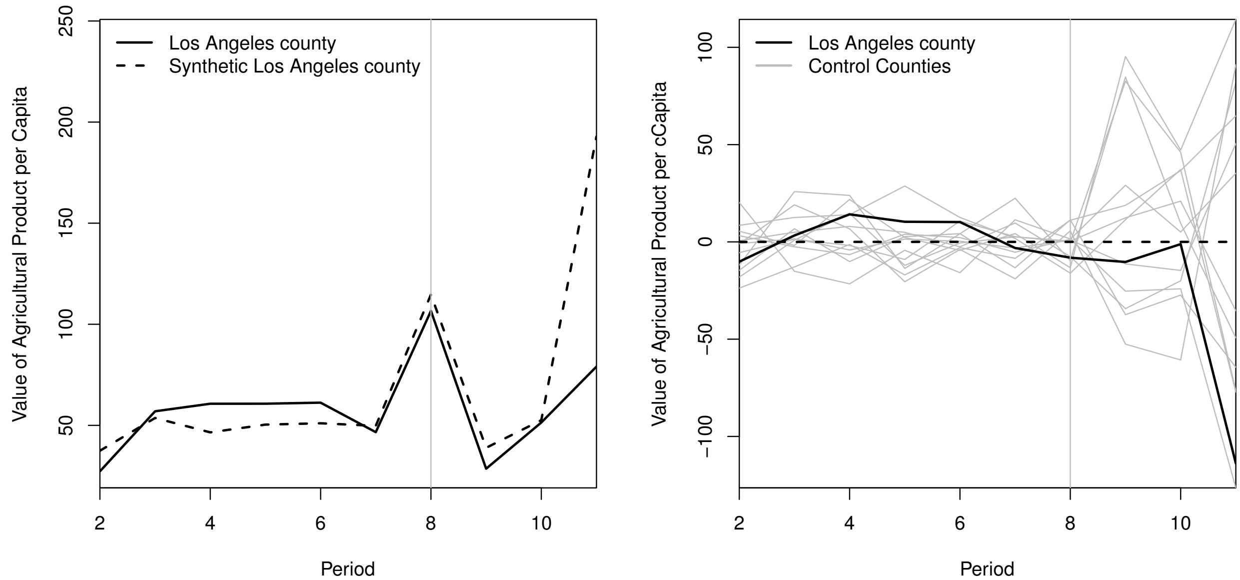
B. Value of Agricultural output as the dependent variable

Next, we perform the synthetic control analysis with Agricultural Product per Capita. Appendix Table 2.10 demonstrates the predictors used for the analysis. Figure 2.4 exhibits the time plot and a falsification analysis for the same.

The left side of figure 2.4 shows that the synthetic Los Angeles follows the actual Los Angeles county quite closely in the pre-treatment period, which shows that the synthetic Los Angeles county is a good predictor of the actual Los Angeles County. In the post-treatment period, the Agricultural product per Capita for Los Angeles County falls below its synthetic counterpart. Hence, it shows a negative treatment effect. The falsification analysis displayed on the right side of figure 2.4 substantiates this result.

Figure 2.4

Path plot (Left Panel) and falsification test (Right Panel) for Agricultural Product per Capita



The synthetic control analyses with the three dependent variables help us to make conclusions regarding the water transfer. The intervention being the water transfer from agriculture to urban led to a much higher increase in GDP per capita (primarily from the Manufacturing product per capita), as would have been without the water transfer and a decline in Agricultural Product per Capita. Table 2.3 shows the average discrepancy in the dependent variable trends between Los Angeles County and its synthetic counterpart. We observe large differences in GDP per capita and Manufacturing per capita, whereas there is a relatively small negative difference in Agricultural Product per capita.

Table 2.3

Summary of SC results

Variable	Gap (in $)	Percent
GDP per capita	178.2833	49.19766
Manufacturing Product per capita	132.3004	36.80267
Agricultural Product per capita	-113.83	-13.9228

Note. "Gap" is Per capita outcome variable in a treated unit - Per capita outcome variable in a synthetic control unit in dollars. We calculate "Percent" by dividing "Gap" by per capita outcome variable and then multiplying this value by 100. These values are averaged over the post-treatment period.

Figures 2.2 and 2.3 show a considerable difference in trajectories of the synthetic and actual Los Angeles counties. The synthetic unit experiences a decline in Manufacturing Product per capita (and hence, GDP per capita) immediately after the treatment year. On the other hand, both the variables increase in the actual Los Angeles county indicating that water transfer evaded the decline after 1920. However, the two figures show that the slopes of the trajectories are similar for the actual and synthetic Los Angeles units in the later periods, indicating a larger short-term effect of the transfer. As noted in previous sections, the water transfer is the main reason for the growth of Los Angeles County being cited as unique (Nash, 1972).

One of the drawbacks of the synthetic control analysis is that it does not give any parametric test for statistical significance. Hence, we include a difference-in-differences below for each of the dependent variables to compare our results from a non-parametric method to a parametric method.

II. Difference-in-Differences Results

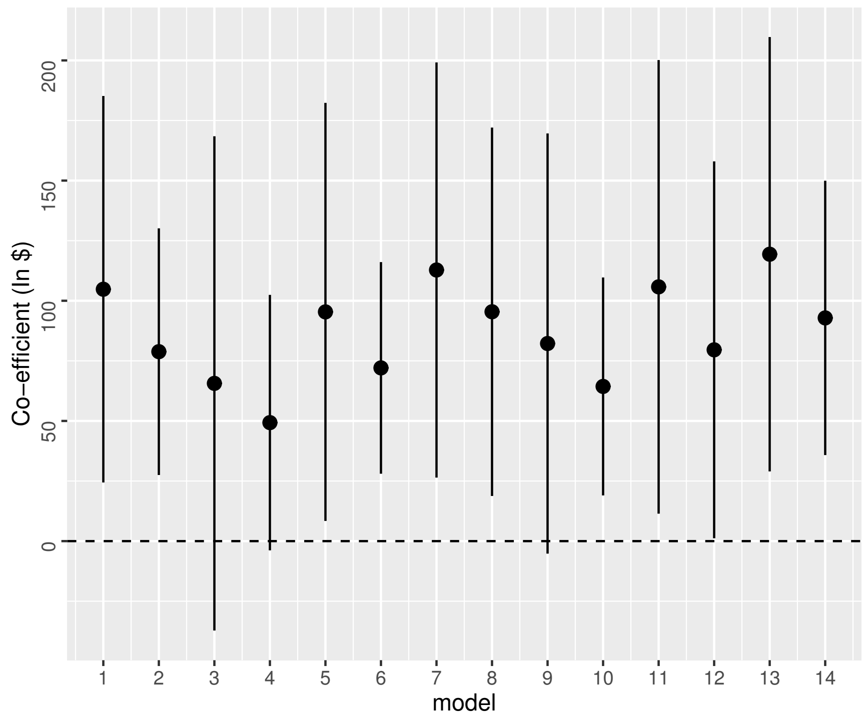
We employ the difference-in-differences technique using two fixed effects specifications to cross-validate our synthetic control analyses. However, given the lack of a common trend assumption, the estimates should be interpreted with caution.

Figure 2.5 describes the results with GDP per capita as the dependent variable. We use two specifications, including both time and county fixed effects in the left panel and time fixed effects in the right panel [6]. The key objective behind this analysis is to observe the changes in treatment effects with different groups of predictors. The black dots represent the GDP per capita and the lines represent confidence intervals. We can test the significance of the variables by observing the closeness of confidence intervals (black lines) to the *zero line*. We can observe that the treatment effect comes out to be positive and statistically significant in most of the specifications. Some of the specifications are significant at the 10 percent level. Different specifications are provided for each farm variable since they are highly correlated. The results show that Los Angeles County experienced substantial economic growth in the post-treatment period.

[6] Detailed tabular results specifying each model are included in Table 2.11, Appendix 2.7.5

Figure 2.5

Scatter plot of two-ways (Left Panel) and individual fixed effects (Right Panel) for Gross Domestic Product per capita with 95 percent confidence intervals. The tabular results are shown in Table 2.11, Appendix 2.7.5



Next, we describe the results when the dependent variable is Manufacturing Product per Capita in figure 2.6. For this analysis, we include the predictors that are only related to the manufacturing sector [7]. Similar to the case of GDP per capita, we observe a consistent positive treatment effect in most of the specifications. Thus, Los Angeles County experienced high growth in the Manufacturing sector post the water transfer. However, one of the shortcomings in this analysis is using few predictors related to the manufacturing sector.

[7]Detailed tabular results specifying each model are included in Table 2.11, Appendix 2.7.5

Figure 2.6

Plot of two-ways (Left Panel) and individual fixed effects (Right Panel) for Manufacturing Product per capita. The tabular results are shown in Table 2.12, Appendix 2.7.5

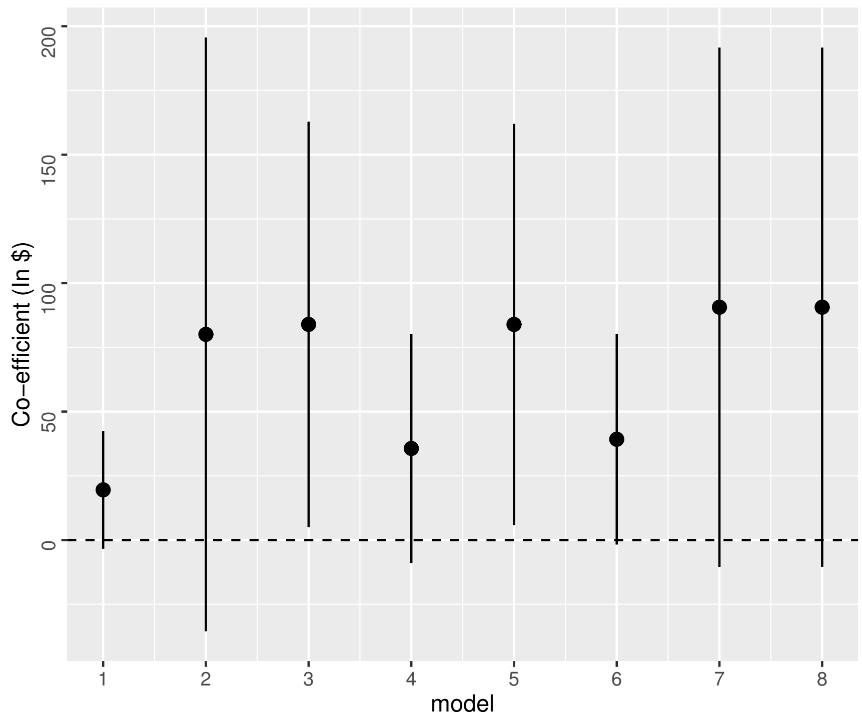
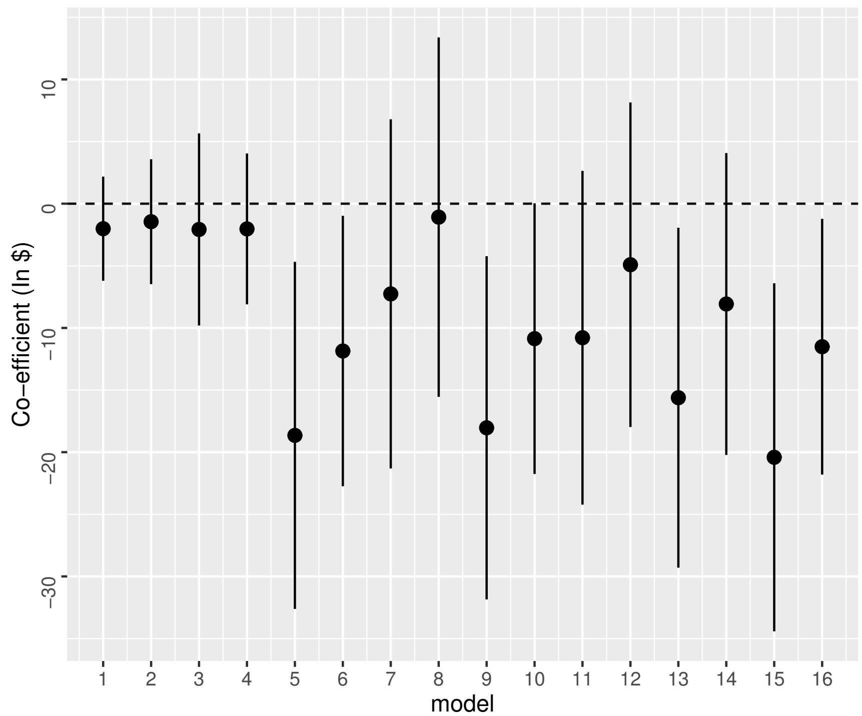


Figure 2.7 summarizes the difference-in-differences results with Agricultural Product per Capita as the dependent variable [8]. We observe a consistent negative sign for the treatment effect indicating a decline in Agricultural Product per Capita post the water transfer in Los Angeles County. The predictors with the number of farms (total and disaggregated by acreage) are each added separately in different specifications since they are correlated with each other.

[8]Detailed tabular results specifying each model are included in Table 2.12, Appendix 2.7.5

Figure 2.7

Plot of two-ways (Left Panel) and individual fixed effects (Right Panel) for Agricultural Product per capita. The tabular results are shown in Table 2.13, Appendix 2.7.5



We observe that the three difference-in-differences analyses conform to the synthetic control method results. However, we would have to revert to the synthetic control results given the lack of evidence for the common-trend assumption for causal inference, hence, the estimates should be interpreted with caution. Combining the DID estimates with SC results, we show the plausibility of a positive and statistically significant treatment effect on GDP per capita and Manufacturing Product per capita as well as a negative and statistically significant impact on agricultural product per capita. Thus, it would be safe to conclude that the Owens Valley water transfer led to a shift in Los Angeles from an agricultural economy to an urban economy, in addition to causing substantial growth in Los Angeles.

2.5 Conclusion

The Owens Valley water transfer was the first-ever and one of the most controversial attempts at effectuating the economic growth of a region. Prominent researchers from different backgrounds have painted a negative picture for the Owens Valley, including Kahrl (2000), an avid Owens Valley historian. The negativity was built around the premise that Los Angeles' officials procured water more than actual demand (Kahrl, 2000). This portrayal has shaped the current aversion towards agriculture to urban water transfer, as observed by Libecap (2004, 2008), in a detailed analysis of the Owens Valley water transfer.

This essay explores the impact of Owens Valley water transfer on GDP per capita broken into Manufacturing Product per Capita and Agricultural Product per Capita to make conclusions regarding economic growth post the transfer. We include a difference-in-differences method to support our synthetic control results and provide a parametric test of significance. We observe that the agricultural product per capita is lower when the water transfer takes place. The synthetic control results also show an increase in GDP per capita (from Manufacturing) in the presence of the water transfer. This result is substantiated using difference-in-differences. However, the increase in Manufacturing Product per capita was higher than the decline in Agricultural Product per Capita. The synthetic control method is more convincing over difference-in-differences since it allows weighing the counties based on the similarity between the control units and the actual treatment unit. Hence, we derive our causal inference from the synthetic control method and support them using difference-in-differences.

This essay is a novel attempt to study the effect of a water transfer on economic growth, disentangling the impacts on its two main contributing sectors, i.e. agricultural and manufacturing. The Owens Valley case was a pioneer for water transfers, not only in the Western

US but probably in the world, as per my knowledge. The manner in which it took place and the controversy it created established the opinion for future water transfers. Chong and Sunding (2006) mention four arguments [9] against water trading central to research and debate. Few of these perceptions formed post the Owens Valley water transfer (Chong and Sunding, 2006). Further, Libecap (2004) comments on the current conception of rural-to-urban water transfers being highly impacted by the Owens Valley experience. We contribute to the literature by providing empirical evidence regarding the impact of a water transfer on economic growth. Although it seems intuitive, the rising water conflicts necessitate empirical investigation for water allocation and its impacts on economic growth.

Moreover, the conflict between Owens Valley and Los Angeles never ended; it has continued until the present. The water choices made in the past have had significant consequences, which must be studied to inform policy for future decisions regarding the two areas. The history of Los Angeles has been repeated in many parts of the world[10], even with institutionalizations for water transfers existing in developed countries, like Australia and some parts of the United States. Future research could extend this study by comparing the impacts of a water transfer on the economic growth in both water-exporting and importing regions to ensure fair and efficient water allocation. In conclusion, the story of Owens Valley water transfer might have been based on lobbying by the then officials; however, the water transfer did have immediate positive impacts; a scientific basis for water allocation decisions is essential to avoid such conflicts in the future.

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[9] The four arguments they mention are: 1) Water transfer means reallocation from agriculture-to-urban uses. 2) Transfers result in large economic losses for the areas of origin 3) Interbasin trade should be prohibited because of large hydrologic effects 4) Water is a public good and should not be subject to market forces. The Owens Valley water transfer resulted in the first two perceptions. (Chong and Sunding, 2006)

[10] Some examples of such conflicts include the Cauvery water conflict, Israel-Palestine water conflict, Conflicts in the Middle East, and MENA region. (Ajami, 2014)

2.6 References

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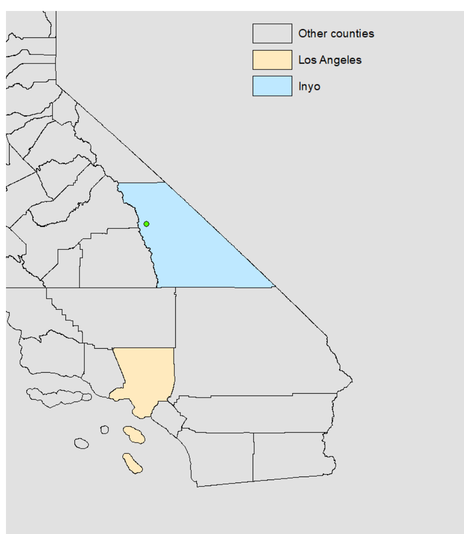
2.7 Appendix

2.7.1 California Map

Figure 2.8

Location map of California: The green dot shows the location of the Owens Valley, the blue area shows the Inyo county where the river is located and the yellow area shows the Los Angeles county which imported the water from the Owens valley.



2.7.2 Disaggregated Dependent variables

Table 2.4

Disaggregated Gross Domestic Product

1900	Value of animals sold live and slaughtered Value of dairy products Value of poultry Value of Bees Value of Miscellaneous products: Hemp, Castor Bean, Forest Products, Vegetables, Peppermint oil, willows Value of Fruit and nut production
1910	Dairy products Value of poultry and eggs produced Value of Honey and Wax produced Value of wool and mohair produced
1920	Value of poultry Value of beehives Receipts from sale of dairy products Reciepts from sale of eggs and chicken
1930	Sum of dairy products Total value of fleece Total value of poultry Total value of chicken and egg Total honey produced

Note. In other years, only the value of agricultural product and the value of manufacturing were available.

Table 2.5

Disaggregated components of the value of agricultural output

Year	Used Variables	Available variables	Comparison
1850	Estimated value of crop, orchard and market garden products	Value of Non- Field product groups	
	Estimated value of home manufactures and animals slaughtered	Value of each crop calculated as price*quantity	Similar
1860	Estimated value of crop, orchard and market garden products	Value of Non- Field product groups	
	Estimated value of home manufactures and animals slaughtered	Value of each crop calculated as price*quantity	similar
1870	Estimated Value of farm productions		
1880	Estimated value of all farm products		
1890	Estimated value of all farm products		
1900	Farm products not fed to livestock		
1910	Value of all crops	Value of crops: Cereals, other gains and seeds, hay and forage, vegetables, fruit and nut and all other crops	exactly same

1920	Value of crops: Cereals, other gains and seeds, hay and forage, vegetables, fruit and nut and all other crops (two from diff sets)	Value of all crops (two from diff sets)	exactly same
1930	Value of agricultural products: cereals, hay and forage, other grains and seeds, vegetables, fruits and nuts, all other field crops, garden vegetables and forest products	Total Value of crops: cereals, other grains and seeds, hay and forage, vegetables, fruits and nuts, other field crops All crops harvested Total farm products sold, traded or used by value Total value of field and orchard crops, vegetables and farm gardens by crop	

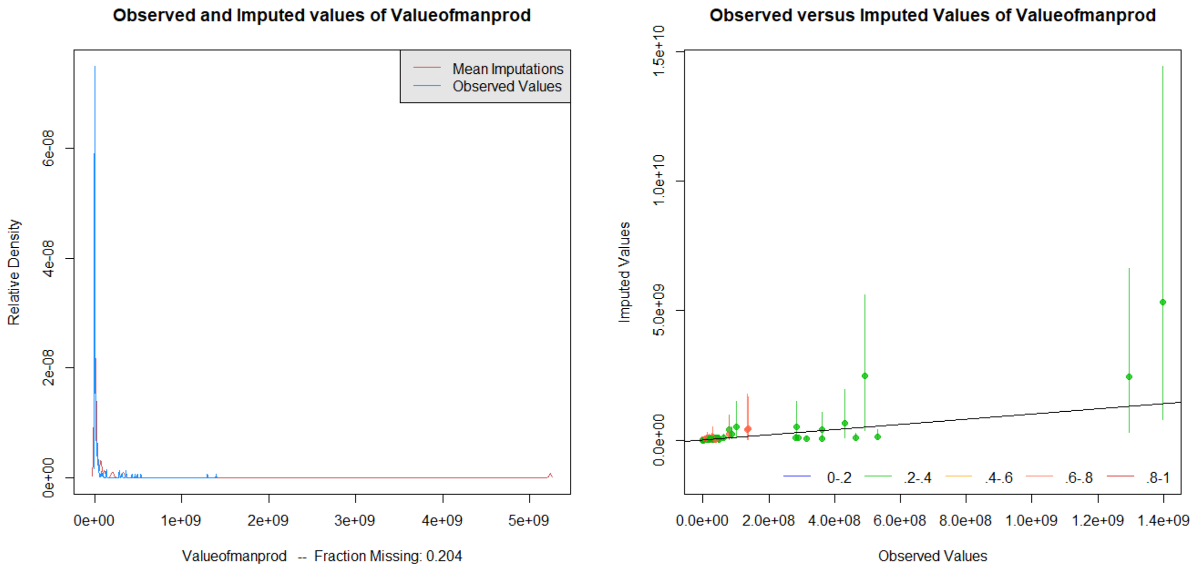
1940	Value of all crops	Value of crops : cereals, corn, wheat, hay and forage, other grains and seed, cotton and cottonseed, tobacco, irish and sweet potatoes, vegetables, fruit and nut, sales of horticulture specialties, other crop Total value of field and orchard crops, vegetables and farm garden crops	exactly same
1950	Value of farm products		

2.7.3 Diagnostics for imputation method

In this section, we show a few diagnostic checks for our imputation method. The left panel of figure 2.9 shows a comparison between the density of the observed and imputed values. The mean imputations do have some values which are higher than the observed values but that is because we are imputing the last year where increased value was observed for other variables in the last year as well. The right panel shows the over-imputation graph. The dots represent the mean imputations and the lines represent the confidence intervals. Since most of the confidence intervals contain the 45-degree line, it means that the true observed values fall within this range (Honaker et al., 2011).

Figure 2.9

Imputation Diagnostics: The left side of the figure shows a density plot of the observed values versus imputed values. The right side of the figure shows an overimputation graph which compares the observed and imputed values with a 45 degree line.



To compare expectation-maximization (Amelia) with other methods, we use time series imputation methods like Kalman smoothing, moving average, and interpolation to ensure that it generates model fit measures that are either similar or better than the time series methods. A good model fit would have a low value of the difference between the fit generated using the imputed dataset and that generated by the actual dataset. Table 2.6 provides these measures for five counties and shows that the expectation-maximization method generates reasonable model fit measures. We did not apply the time series methods further to other counties given that it is cumbersome and the expectation-maximization method gives reasonable results as per the literature.

Table 2.6

Model fit measures for various imputation methods

County	Measure	Amelia1-log	Amelia2-log	Amelia3-log	Amelia4-log	Amelia5-log	Exponential MA	Kalman Smoothing	Linear interpolation	Linear weighting MA	Random Sample	Simple weighting MA	Spline interpolation	Stine interpolation
Butte	Mean	1461642.159	894599.814	6242038.006	2208676.846	145664.6906	773379.6047	879600.45	819337.4	736255.978	482394.117	692000.674	541623.791	819337.4
Butte	Coefficient of Variation	0.100708081	0.06682126	0.801460709	0.140986992	0.04692537	0.17266709	0.159242051	0.1679152	0.17148787	0.17685885	0.16969496	0.10979214	0.1679152
Butte	Skewness	0.037900795	0.21564364	1.881100753	0.274607674	0.10907033	0.296893232	0.25519176	0.28430207	0.28869361	0.24324047	0.27743551	0.28430207	0.28430207
Butte	Kurtosis	0.630565299	0.75036674	6242038.006	0.084901786	0.106848825	0.129728626	0.081871979	0.11803643	0.1269723	0.02636914	0.12182524	0.11803643	0.11803643
Calaveras	Mean	107114.6077	667596.15	497905.0639	241532.8044	10682.61975	108859.2085	131226.5714	103681.775	98768.0683	179377.459	86235.5226	109904.22	103681.775
Calaveras	Coefficient of Variation	0.02562738	0.232529	0.037429568	0.024667861	0.045553941	0.000719201	0.053042864	0.00025968	0.01459848	0.19224778	0.03235448	0.00765445	0.00025968
Calaveras	Skewness	0.151169476	0.53682016	0.171528371	0.197576817	0.119741245	0.332955644	0.211834692	0.28227487	0.33305652	0.4570635	0.32680348	0.28227487	0.28227487
Calaveras	Kurtosis	0.717349146	1.9576607	497905.0639	0.669643983	0.070904208	1.075825749	0.840934487	0.97633479	1.0880983	0.74142954	1.09147797	0.97633479	0.97633479
Los Angeles	Mean	23020546.01	62962733.5	35644837.27	902614901.8	2168834.71	83042431.95	129284621.5	74933855.2	78001395.7	79456833.6	71567210.3	51337549.6	68071057.6
Los Angeles	Coefficient of Variation	0.119844387	0.27544439	0.02364039	0.797741487	0.147635357	0.284836983	0.228255377	0.22990255	0.29101412	0.32291126	0.29490374	0.13382131	0.20486854
Los Angeles	Skewness	0.174034239	0.26706955	0.241670604	1.563706143	0.070850566	0.318482129	0.182305492	0.25352624	0.31870235	0.36599399	0.30817293	0.25352624	0.23528407
Los Angeles	Kurtosis	0.271832316	0.29837739	35644837.27	5.512551904	0.377281343	0.432721836	0.187116065	0.42603509	0.39996189	0.36580768	0.34109019	0.42603509	0.42277881
Mariposa	Mean	2772037.606	65546492.6	4520808.284	32930543.75	21893889.03	6385021.07	7796023.734	7090636.23	6132225.06	914834.699	5853217.16	4424132.18	7090636.23
Mariposa	Coefficient of Variation	0.060719289	0.58914418	0.055071186	0.076970051	0.214785426	0.243873166	0.253746575	0.25706478	0.23559925	0.14994029	0.22519597	0.18973307	0.25706478
Mariposa	Skewness	0.111372718	1.82758655	0.309356678	0.338350934	1.161900881	0.332859502	0.377590083	0.38451972	0.30620749	0.03423635	0.27637245	0.38451972	0.38451972
Mariposa	Kurtosis	0.125641791	5.83215435	4520808.284	1.233434942	3.649210599	0.147912025	0.18072162	0.17946947	0.13732725	0.14071666	0.12811139	0.17946947	0.17946947
San Diego	Mean	1722494.182	44671542.6	15332884.53	85801.76435	7351116.559	3075863.754	3212095.9	3155840.25	2900593.4	604223.169	2685019.87	2111541.66	3092355.57
San Diego	Coefficient of Variation	0.026273397	0.63604455	0.044939062	0.08908133	0.305043803	0.254294477	0.207248925	0.23159279	0.25539854	0.15396715	0.25526179	0.13909122	0.22705363
San Diego	Skewness	0.268489494	1.72767045	0.663306021	0.057602315	0.504948394	0.295499814	0.190829967	0.24324349	0.29619308	0.07288553	0.29106355	0.24324349	0.23472975
San Diego	Kurtosis	0.541295468	5.63532622	15332884.53	0.00899451	0.439625015	0.229789776	0.156817901	0.20197062	0.22422804	0.03282502	0.20797347	0.20197062	0.19947382

2.7.4 County weights

Table 2.7

County Weights

County	Weights
GDP	
Marin	0.03
San Diego	0.37
San Franciso	0.16
Santa Barbara	0.14
Santa Clara	0.06
Yuba	0.24
Manufacturing product per capita	
San Diego	0.22
Santa Clara	0.33
Sonoma	0.45
Agricultural output per capita	
San Fransisco	0.63
Calaveras	0.42
Contracosta	0.03
Butte	0.04
Marin	0.02
Mariposa	0.01
San Diego	0.26
San Francisco	0.13
Santa Clara	0.08

Table 2.8

Predictors used for SC with GDP per capita

Predictors	Treated	Synthetic	Sample Mean
Percentage of Urban Population	46.33	39.66	21.05
Percentage of Rural Population	21.10	36.76	63.09
Value of land and buildings per capita	583.09	744.70	1259.56
Wages paid per person employed	3339.52	3274.05	3597.00
Persons employed per capita	0.03	0.03	0.03
Total capital invested per capita	15497.85	22702.17	23744.69
Capital invested in plant land per capita	8.43	20.25	20.47
Capital invested in buildings per capita	8.24	10.55	13.41
Capital invested in machinery per capita	22.49	30.97	30.61
Capital invested in live assets per capita	25.87	35.45	29.62
Capital invested in cash and sundries per capita	33.38	35.24	41.21
Value of farm property per capita	498.09	503.44	856.98
Number of farms under 10 acres per capita	0.00	0.00	0.00
Number of farms 10-49 acres per capita	0.02	0.01	0.01
Number of farms 50-99acres per capita	0.01	0.01	0.01
Number of farms 100-999acres per capita	0.01	0.02	0.04
Total Annual Agricultural Wages Paid Per Capita	12.59	12.88	27.24

Table 2.9

Predictors used for SC with Manufacturing Product per Capita

Predictors	Treated	Synthetic	Sample Mean
Percentage of Urban Population	46.33	32.90	21.05
Percentage of Rural Population	21.10	45.18	63.09
Wages paid per person employed	3339.52	2550.14	3597.00
Capital invested in plant land per capita	8.43	15.08	20.47
Capital invested in buildings per capita	8.24	10.57	13.41
Capital invested in machinery per capita	22.49	21.13	30.61
Capital invested in live assets per capita	25.87	27.18	29.62
Capital invested in cash and sundries per capita	33.38	44.37	41.21
Value of farm property per capita	498.09	715.33	856.98
Number of total farms per capita	0.04	0.06	0.06
Number of farms under 10 acres per capita	0.00	0.01	0.00
Number of farms 10-49 acres per capita	0.02	0.02	0.01
Number of farms 50-99 acres per capita	0.01	0.01	0.01
Number of farms 100-999 acres per capita	0.01	0.03	0.04
Number of farms more than 1000 acres per capita	0.00	0.00	0.00

Table 2.10

Predictors used for SC with Agricultural Product per Capita

Predictors	Treated	Synthetic	Sample Mean
Percentage of Urban Population	46.33	26.57	21.05
Percentage of Rural Population	21.10	59.29	63.09
Value of land and buildings per capita	583.09	604.56	1259.56
Wages paid per person employed	3339.52	3337.52	3597.00
Persons employed per capita	0.03	0.03	0.03
Total capital invested per capita	15497.85	15504.65	23744.69
Capital invested in plant land per capita	8.43	8.96	20.47
Capital invested in buildings per capita	8.24	8.42	13.41
Capital invested in machinery per capita	22.49	22.22	30.61
Capital invested in live assets per capita	25.87	26.25	29.62
Capital invested in cash and sundries per capita	33.38	33.25	41.21
Value of farm property per capita	498.09	421.89	856.98
Number of farms under 10 acres per capita	0.00	0.00	0.00
1 Number of farms 10-49 acres per capita	0.02	0.01	0.01
Number of farms 100-999 acres per capita	0.01	0.03	0.04
Total Annual Agricultural Wages Paid Per Capita	12.59	12.75	27.24

Table 2.11

Dependent variable as GDP per capita.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Los Angeles Dummy*Year Dummy	104.799**	78.825***	65.630	49.308*	95.367**	72.068***	112.801**	95.425**	82.213*	64.354***	105.789**	79.590**	119.364**	92.867***
	(40.029)	(25.522)	(51.164)	(26.417)	(43.276)	(21.885)	(42.978)	(38.097)	(43.499)	(22.537)	(46.957)	(38.975)	(44.965)	(28.367)
Percentage of urban population	−2.589	1.937	−3.049	1.557	−2.587	1.875	−4.864	−0.326	−3.291	1.233	−2.756	1.874	−4.175	0.407
	(8.598)	(6.762)	(8.403)	(6.890)	(8.857)	(6.972)	(9.029)	(7.405)	(8.783)	(7.062)	(8.808)	(7.145)	(8.177)	(6.713)
Value of land and buildings per capita	0.178***	0.306***	0.169***	0.311***	0.236**	0.351***	0.276***	0.351***	0.268***	0.363***	0.182***	0.306***	0.220***	0.328***
	(0.047)	(0.111)	(0.048)	(0.112)	(0.101)	(0.110)	(0.084)	(0.125)	(0.084)	(0.117)	(0.054)	(0.113)	(0.042)	(0.114)
Persons employed per capita	10,045.210**	10,829.900*	9,400.346**	10,782.080*	9,929.094**	10,674.200	10,576.930**	10,694.050*	9,816.473**	10,626.860	10,090.350**	10,816.840*	10,789.910**	11,289.070*
	(4,084.865)	(6,249.473)	(4,385.724)	(6,313.043)	(4,152.830)	(6,405.935)	(4,271.225)	(6,174.080)	(4,166.046)	(6,354.319)	(4,411.581)	(6,414.845)	(4,237.792)	(6,244.124)
Number of farms under 10 acres per capita			−25,787.360*	−15,848.660										
			(14,684.330)	(12,346.120)										
Number of farms 10-49 acres per capita					−7,336.348	−6,147.407								
					(11,069.810)	(9,652.236)								
Number of farms 50-99 acres per capita							−36,251.040	−27,918.170						
							(31,714.370)	(30,232.880)						
Number of farms under 100 acres per capita									−8,741.534	−6,113.624				
									(7,228.257)	(6,483.106)				
Number of farms 100-999 acres per capita											−428.352	−125.983		
											(4,565.244)	(4,428.178)		
Number of farms more than 1000 acres per capita													−51,549.500	−39,820.120
													(36,478.160)	(31,102.600)
Year FE	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No
County and Year FE	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes	No	Yes
Observations	81	81	81	81	81	81	81	81	81	81	81	81	81	81
R^2	0.592	0.382	0.609	0.392	0.597	0.388	0.610	0.400	0.607	0.396	0.592	0.382	0.615	0.407
Adjusted R^2	0.348	−0.030	0.362	−0.034	0.342	−0.042	0.363	−0.022	0.359	−0.029	0.334	−0.052	0.372	−0.009
F Statistic	18.157*** (df = 4; 50)	7.423*** (df = 4; 48)	15.272*** (df = 5; 49)	6.071*** (df = 5; 47)	14.499*** (df = 5; 49)	5.956*** (df = 5; 47)	15.322*** (df = 5; 49)	6.256*** (df = 5; 47)	15.168*** (df = 5; 49)	6.153*** (df = 5; 47)	14.239*** (df = 5; 49)	5.815*** (df = 5; 47)	15.672*** (df = 5; 49)	6.450*** (df = 5; 47)

Note: Robust Standard Errors in Parenthesis. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

2.7.5 Difference-in-Differences

Table 2.12

Dependent variable as Manufacturing Product per capita.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Los Angeles Dummy*Year Dummy	19.528*	80.052	83.936**	35.650	83.919**	39.219*	90.627*	90.627*
	(11.523)	(58.034)	(39.293)	(22.177)	(38.910)	(20.397)	(50.745)	(50.745)
Percentage of Urban Population			0.916	3.058			13.660	13.660
			(5.099)	(4.806)			(17.979)	(17.979)
Value of land and buildings per capita	−0.081	−0.394	0.006	0.143	0.004	0.124	−0.301*	−0.301*
	(0.073)	(0.259)	(0.051)	(0.105)	(0.047)	(0.097)	(0.162)	(0.162)
Persons employed per capita			9,484.456**	12,046.800**	9,467.018**	11,824.290**		
			(4,061.322)	(5,778.416)	(4,058.648)	(5,799.352)		
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
County and Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	108	108	81	81	81	81	108	108
R^2	0.006	0.065	0.607	0.553	0.606	0.547	0.090	0.090
Adjusted R^2	−0.347	−0.317	0.371	0.254	0.382	0.261	−0.299	−0.299
F Statistic	0.231 (df = 2; 79)	2.623* (df = 2; 76)	19.277*** (df = 4; 50)	14.821*** (df = 4; 48)	26.173*** (df = 3; 51)	19.762*** (df = 3; 49)	2.463* (df = 3; 75)	2.463* (df = 3; 75)

Note: Robust Standard Errors in Parenthesis. *p<0.1; **p<0.05; ***p<0.01

Table 2.13

Dependent variable as Agricultural Product per capita.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Los Angeles Dummy*Year Dummy	-2.012	-1.449	-2.074	-2.031	-18.648^{***}	-11.858^{**}	-7.259	-1.083
	(2.125)	(2.548)	(3.915)	(3.073)	(7.080)	(5.514)	(7.124)	(7.329)
Percentage of urban population			0.026	0.153	2.494^{***}	-1.380	2.345^{***}	-0.838
			(0.416)	(0.422)	(0.848)	(1.161)	(0.738)	(0.945)
Value of farm property per capita	0.111^{***}	0.136^{***}	0.110^{***}	0.136^{***}				
	(0.012)	(0.014)	(0.014)	(0.014)				
Number of farms per capita	-542.002^{*}	-473.393^{**}	-509.989	-430.075				
	(298.849)	(222.006)	(340.587)	(265.023)				
Number of farms under 10 acres per capita					$4{,}322.557^{**}$	1,620.462		
					(2,079.928)	(1,659.657)		
Number of farms 10-49 acres per capita							$4{,}544.700^{***}$	$4{,}394.926^{***}$
							(1,526.391)	(1,576.482)
Number of farms 50-99 acres per capita								
Number of farms under 100 acres per capita								
Number of farms 100-999 acres per capita								
Number of farms more than 1000 acres per capita								
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
County and Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	216	216	189	189	216	216	216	216
R^2	0.406	0.416	0.400	0.411	0.120	0.031	0.185	0.113
Adjusted R^2	0.314	0.298	0.286	0.271	-0.017	-0.164	0.058	-0.065
F Statistic	42.394^{***} (df = 3; 186)	42.446^{***} (df = 3; 179)	26.303^{***} (df = 4; 158)	26.511^{***} (df = 4; 152)	8.470^{***} (df = 3; 186)	1.898 (df = 3; 179)	14.070^{***} (df = 3; 186)	7.617^{***} (df = 3; 179)

	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Los Angeles Dummy*Year Dummy	-18.038^{**}	-10.863^{*}	-10.789	-4.913	-15.616^{**}	-8.073	-20.412^{***}	-11.511^{**}
	(7.001)	(5.520)	(6.808)	(6.619)	(6.934)	(6.157)	(7.099)	(5.216)
Percentage of urban population	3.181^{***}	-0.983	2.562^{***}	-0.811	1.915^{**}	-1.920	2.763^{***}	-1.840
	(0.838)	(1.159)	(0.761)	(0.985)	(0.880)	(1.340)	(0.829)	(1.368)
Value of farm property per capita								
Number of farms per capita								
Number of farms under 10 acres per capita								
Number of farms 10-49 acres per capita								
Number of farms 50-99 acres per capita	$5{,}833.762^{**}$	$4{,}307.363^{*}$						
	(2,519.618)	(2,369.915)						
Number of farms under 100 acres per capita			$2{,}604.483^{***}$	$2{,}310.981^{***}$				
			(874.564)	(865.132)				
Number of farms 100-999 acres per capita					$-1{,}467.969$	$-1{,}374.279$		
					(1,015.612)	(959.886)		
Number of farms more than 1000 acres per capita							1,281.711	$-5{,}828.969$
							(2,931.239)	(5,516.507)
Year FE	Yes	No	Yes	No	Yes	No	Yes	No
County and Year FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	216	216	216	216	216	216	216	216
R^2	0.126	0.043	0.168	0.084	0.135	0.063	0.108	0.037
Adjusted R^2	-0.010	-0.150	0.038	-0.100	0.0004	-0.125	-0.031	-0.156
F Statistic	8.945^{***} (df = 3; 186)	2.677^{**} (df = 3; 179)	12.476^{***} (df = 3; 186)	5.475^{***} (df = 3; 179)	9.698^{***} (df = 3; 186)	4.043^{***} (df = 3; 179)	7.537^{***} (df = 3; 186)	2.303^{*} (df = 3; 179)

Note: Robust Standard Errors in Parenthesis. $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

CHAPTER 3

URBAN SPRAWL IN LOS ANGELES AND THE ROLE OF OWENS VALLEY WATER TRANSFER

3.1 Introduction

The developed world experienced urbanization as early as the 20th and 21st centuries as a result of rapid industrialization taking place at the time (Zhang, 2016). Zhang (2016) mentions that the population in urban cities rose from a mere 5 percent in 1800 to 50 percent by the 1920s. Rapid urbanization has had immense impacts on environmental, social, and political factors. On the one hand, it leads to an improvement in economic growth and living standards; and on the other hand, it leads to increased pressure on natural resources and land space (Wilby and Perry, 2006; Karthiyayini et al., 2016). Moreover, the phenomenon of large urban areas taking up most of the land area available termed urban sprawl (Oueslati et al., 2015) started appearing in the early to the mid-nineteenth century in the developed world.

The term *Urban Sprawl* has been mentioned to take various forms- first, which involves low-density residential developments that give rise to business activities including manufacturing, and second, where even individual houses replace rural landscapes (Nechyba and

Walsh, 2004). Neychba and Walsh (2004) mention that 5% of the population lived in urban areas in 1790, a figure that tripled by 1850 and had surpassed 50% in 1920. We use the term urban sprawl following Neychba and Walsh (2004). Urban sprawl is considered to be a more serious issue as it involves increased travel time and costs, lack of availability of resources, and high population pressure (Aithal et al., 2017). The literature related to urban sprawl in terms of water resources has focused on the water stress faced by the rural and peri-urban areas for the water used in the agricultural sector due to the competition over freshwater resources from urban areas for domestic use (Aakuraju and Amerasinghe, 2011). Apart from this, the literature has also focused on water rights acquisitions by cities to expand their water supply (Dias-Caraventas and Sanchez-Flores, 2011; Hatab et al., 2019). Procurement of natural resources for the expansion of growing urban centers has become common in many parts of the world, and yet, there is little evidence of urbanization or urban sprawl as a result of obtaining additional resources.

This essay is an attempt to shed light on the causal relationship between water resources and urban sprawl; an increase in resources is often the reason for a town to transform into a metropolitan city. Back in the 1900s, the controversial Owens Valley transfer where all the sympathy went to the farmers from whom the lands and the water rights tied to them were secretively bought by the Los Angeles officials. This water transfer took place by exaggerating the city's requirements for water, where the ultimate objective was to annex the surrounding areas and build Los Angeles into a county (Kahrl, 2000). We show that water transfer played an important role in urban sprawl through a comparative case study using the synthetic control and difference-in-differences method.

The essay is organized as follows. The next section includes a brief literature review. The third section consists of the empirical analysis describing the data, the empirical strategy, and the results along with a few robustness checks. In the last section, we discuss and conclude the results from our analysis.

3.2 Background

I. Los Angeles Zoning policies

Zoning was flexible during the 1950s boom era where 60 percent of the land allowed all types of residential buildings (Vallianatos and Brozen, 2019). Whittemore (2012) describes the goal of Los Angeles' officials to zone the arterials for multi-family use, restrict the commercial uses located in clusters at the intersections, and reserve the interior streets for single-family residences and public facilities. This was visualized as an economically stable and attractive land-use division. However, this seemed to be a strenuous task as a lot of explanation regarding the scope and components of zoning was required for the discontented property owners. The popular demand led to communities becoming zoned for more intensive uses than what was originally envisioned during the post-war years. The long-term vision for Los Angeles planning included preserving agricultural land for profitable uses and containing urbanization in concentrated areas. However, a large number of property owners advocated for expanding the urban land. By the mid-1950s, rezoning to non-agricultural uses took place without referring to a proper plan (Whittemore, 2012).

II. Review of the urban sprawl literature

'Urban Sprawl' has been abundantly studied by researchers going far back as World War II where the major themes related to the issue were summarized in the 1940s (Nechyaba and Walsh, 2004). Income, population, and housing density are the most important explanatory variables for urban sprawl (Woo and Guldmann, 2010; Alig and Healy, 1987;

Paulsen, 2014). Alig and Healy (1987) have also used central city population, urbanized area population outside central cities, change in urban population, and rural population as explanatory variables for the study. More recent research has tested various urban containment policies and ownership of housing units for affecting the spatial structure of the US. (Woo and Guldmann, 2010; Paulsen, 2014). Woo and Guldmann (2010) have regressed socio-economic characteristics, housing characteristics, transport characteristics - the share of workers owning one or more cars, and government financial characteristics- by the state on population and employment density gradients. Paulsen (2014) uses four metrics to measure urban sprawl- change in urban housing unit density, marginal land consumed per net new urban household, the density of housing units in newly urbanized areas, and percent of net new urban housing in previously urbanized areas. The explanatory variables included were percent of undevelopable land, metropolitan land area, metropolitan percent minority, residents over 65, housing units built before 1950, general-purpose governments per 100 population, state planning role and Wharton Restrictions Index to measure the effect on urban sprawl.

There has been some literature related to water resources and urban sprawl. Hatab et al. (2019) mention that many researchers have argued that water acts as a resource bottleneck in socio-economic systems. This kind of research has been limited in the economic literature. This study tries to fill the gap by applying econometric methodologies to analyze the impacts of a water transfer on the urban sprawl in Los Angeles. Before moving on to discussing our empirical strategy and results, we briefly describe the data used for our analysis.

3.3 Empirical Analysis

3.3.1 Data

The data used in the study for the dependent variable is derived from the historical Land-cover change and land-use conversions global dataset acquired from NOAA's National Climatic Data Center (Meiyappan and Jain, 2012), and independent variables are obtained from NHGIS IPUMS for the decennial years 1850-1950.

The main dependent variable used for the analysis is the Urban Sprawl. The spatial data was converted into a usable format for the analysis using Zonal statistics from ArcGIS. The landcover map (specifically, urban landcover map) is provided in equal latitude and longitude earth grids with a spatial resolution of 0.5 by 0.5 in both latitude and longitude. Urban sprawl is measured in terms of *the percentage of the grid cell covered by the urban land*[1] in a given year. Hence, it can be interpreted as the percentage of land covered by urban areas. It has been suggested that the data be used on a global or a continental scale, but since we required data that goes back to 1850, it provides us with a good estimate of urban cover in that period. Therefore, urban sprawl is measured as the percentage of the total land cover in the analysis presented in this study.

Following the previous essay, the counties have to be merged for consistency through-

[1]The authors who created the urban landcover map used in this analysis retrieved the HYDE 3.1 spatially explicit urban land area dataset described in Klein Goldewijk et al. (2010). The authors use the term *Built-up Area* as "Built-up area is defined here as artificial areas contiguously occupied by humans (therefore not including vegetative land cover and water, nor roads)." They derived the urban/rural fractions for the USA from Dodd (1993) and have mentioned the sources for this fraction in the rest of the world as well in their paper. We mention only the United States in this study given that our study area comprises California.

out the study period. Hence, the data for the newer counties was aggregated to that of the counties where they emerged from; for instance, we aggregate the data from orange county to Los Angeles county. However, few counties were split from more than one county, for example, the mono county which was formed from Calaveras, Mariposa, and Fresno counties. Eight such counties were dropped from the analysis.

We summarize descriptive statistics for the variables included in the table given below.

Table 3.1

Descriptive Statistics

Statistic	N	Mean	St. Dev.	Min	Pctl(25)	Pctl(75)	Max
Urban Sprawl	189	0.393	1.777	0.000	0.000	0.000	16.378
Percentage of Urban Population	243	29.333	28.440	0.000	0.000	49.113	98.391
Value of land and buildings per capita	108	1,125.589	864.082	28.657	538.106	1,447.289	4,494.966
Persons employed per capita	242	0.034	0.035	0.000	0.008	0.049	0.249
Wages paid per person employed in manufacturing	186	2,965.844	8,270.749	150.664	505.847	1,370.432	88,250.000
Value of farm property per capita	243	829.785	791.121	9.074	289.870	1,113.554	5,079.433
Number of farms per capita	243	0.058	0.031	0.001	0.033	0.080	0.155
Number of farms under 10 acres per capita	243	0.004	0.005	0.000	0.002	0.006	0.034
Number of farms from 10 to 49 acres per capita	243	0.013	0.011	0.0001	0.006	0.017	0.061
Number of farms from 50 to 99 acres per capita	243	0.007	0.005	0.0001	0.004	0.010	0.030
Number of farms under 100 acres per capita	243	0.025	0.017	0.001	0.013	0.034	0.087
Number of farms from 100 to 999 per capita	243	0.028	0.023	0.0001	0.010	0.042	0.121
Number of farms more than 1000 per capita	243	0.004	0.004	0.000	0.001	0.005	0.023

The mean of our main dependent variable is 0.393, which means that the urban sprawl is 0.393% of the total landcover (as defined in the urban landcover map used). Another observation from the descriptive statistics table is the discrepancy between the mean and the maximum value of our main dependent variable, i.e., Urban Sprawl. This indicates that, although there was a lesser degree of urban sprawl in California on average (since the mean value of Urban sprawl is low), there was at least one county with a very high degree of urban sprawl (since the maximum value of Urban sprawl, i.e., 16.38 is much higher than the mean, i.e., 0.393) at some point in time. This hypothesis is verified by the difference in the mean of the urban population, i.e., 29.33%, and the maximum value, i.e., 98.39%. Hence, the average urban population in California throughout the period was around 30%, whereas there was at least one county, in which, the urban population was close to 100%. Further such high differences in the three quartiles, i.e., 150.66, 505.85, and 1370.43, and the maximum value, i.e., 88250, are observed in Wages per person employed in manufacturing, indicating the growth in the manufacturing sector and hence, urbanization.

Figure 3.1

Urban Sprawl: The blue line represents the treatment unit, i.e. LA and the gray lines show the plots for all the other counties. 1920 divides the graph into pre and post-treatment periods where, 1890-1920 is the pre-treatment period and 1930-1950 is the post-treatment period.

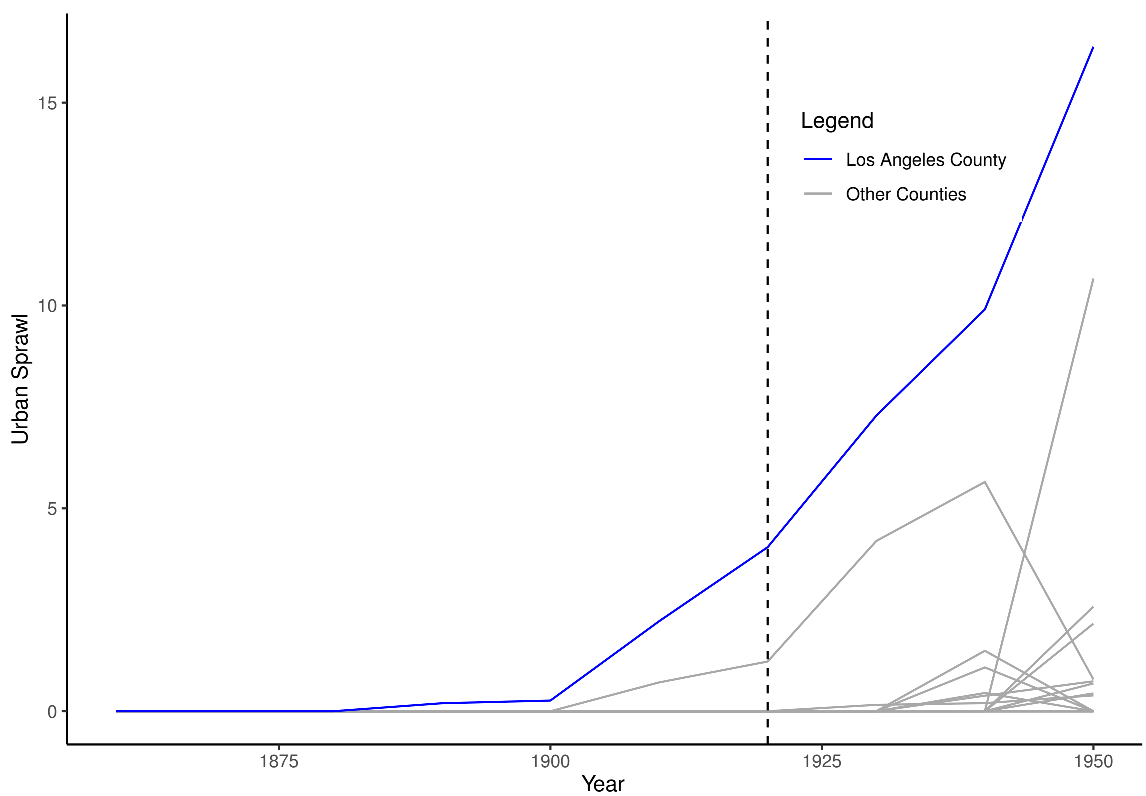


Figure 3.1 shows the plot of Urban Sprawl for all the counties. It seems that the urban

sprawl is much higher in the treatment unit, i.e., LA as compared to all the other counties. There were very few counties where urban areas were present during the study period as can be observed in the graph. We also observe that the increase started in the 1900s which is before our treatment period. Hence, we perform a difference-in-differences and synthetic control to investigate the reason for the same.

3.3.2 Empirical strategy

The econometric methodology follows from the previous essay. We use synthetic control and difference-in-differences analysis to test the impacts of the Owens Valley water transfer on the urban sprawl; back in the 1900s.

Synthetic Control Method

As explained in the previous essay, the synthetic control method tries to generate a 'synthetic unit' which minimizes the difference between the synthetic unit and the actual treatment unit, and then the difference between them in the post-treatment period gives us the treatment effect (Abadie et al., 2003; Abadie et al., 2010; Akhundjanov, 2019). A synthetic unit would be constructed using the predictors for the three units, such that it is the weighted average of the control units included in the study and follows the time plot of the treatment unit closely. The difference between the outcome variables of the synthetic unit and the actual treatment unit would give the desired treatment effect as shown below:

$\widehat{\alpha}_{1t} = \sum_{i=2}^{N+1} w_i^* Y_{it}^{NI}$ for $t > t_0$

such that $\widehat{\alpha}_{1t}$ is the treatment effect in the treatment unit represented by 1. w_i is the optimal weight in the city i and Y_{it} is the outcome variable in the city i at time t. The superscript NI indicates the control counties where the intervention does not take place.

Difference-in-Differences

Following the previous essay, we use two specifications for the difference-in-differences method. The first specification includes the time effects and the second specification includes both time and individual effects. The dependent variable is urban sprawl.

3.3.3 Empirical results

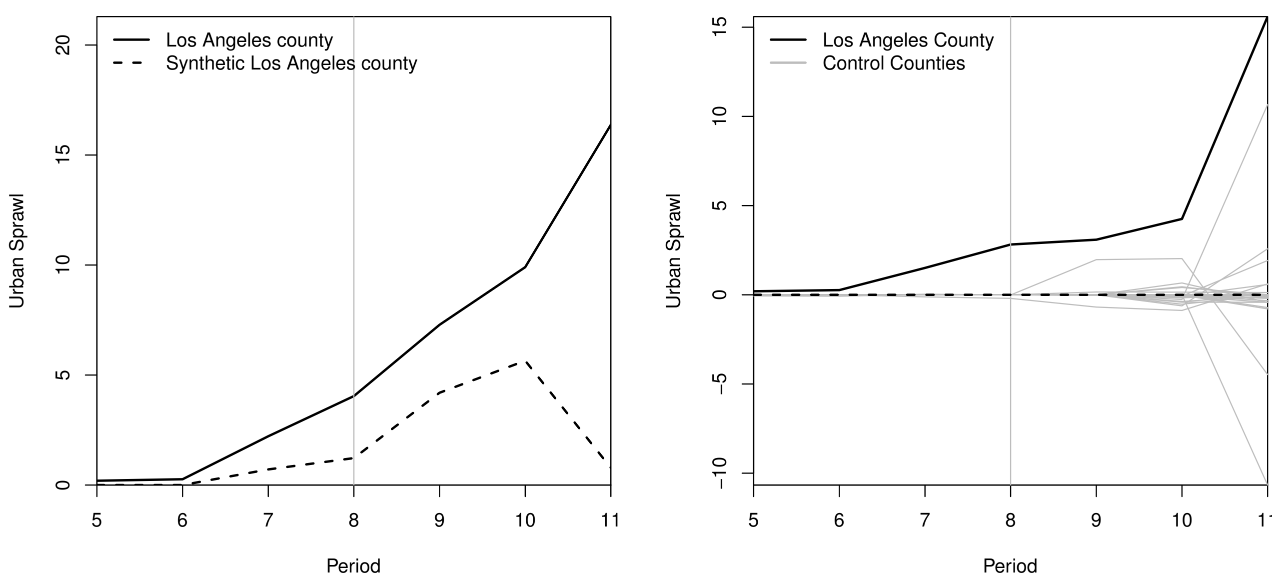
This section consists of the results from the synthetic control method and difference-in-differences analysis. The first year included in the analysis is 1890, since that is the first year when the Californian counties started attaining urban cover. The year 1920 was selected as the treatment year since it was in the early 1920s that the aqueduct was completed and water started flowing to Los Angeles (Libecap, 2004; 2008). For the synthetic control analyses, *year* had to be converted to *Period* since we use decennial data. Hence period 2 represents the year 1860, period 5 represents the year 1890, and so on. Period 8 represents the treatment year, i.e., 1920.

I. Synthetic control results

The left side of the figure given below shows the time plot of Urban Sprawl and, the right side shows a falsification test for the same. From the two figures, we observe that there seems to be a striking increase in urban sprawl; however, the increase seems to have started before the treatment period. One of the reasons for this could be that the county weights equal to 1 for only one county, i.e., Santa Clara.

Figure 3.2

Time plot (Panel A) and falsification test (Panel B) for Urban Sprawl. The Panel (a) consists of the time plot for the treatment unit (black) and the control units (gray) for Urban Sprawl. The vertical line divides the figure into pre and post-treatment period.



Although there seems to be a rise in urban sprawl in Los Angeles, it is difficult to construct a reliable synthetic unit since urban sprawl was observed in very few Californian counties during the study period[2]. There are very few counties with urban land cover in the pre-treatment period, because of which, we observe a significant difference in the 1900s. One of the critical features of Synthetic Control Analysis is that the fit in the pre-treatment period must be excellent (Ben-Michael et al., 2021), which becomes difficult to achieve

[2]We applied synthetic control analysis to various sets of predictors. In each specification, Santa Clara seemed to receive a unit weight.

for this analysis given the sparse observations in urban sprawl before the treatment year. Hence, we employ a difference-in-differences analysis as a more appropriate methodology to further study the rise in urban sprawl in Los Angeles.

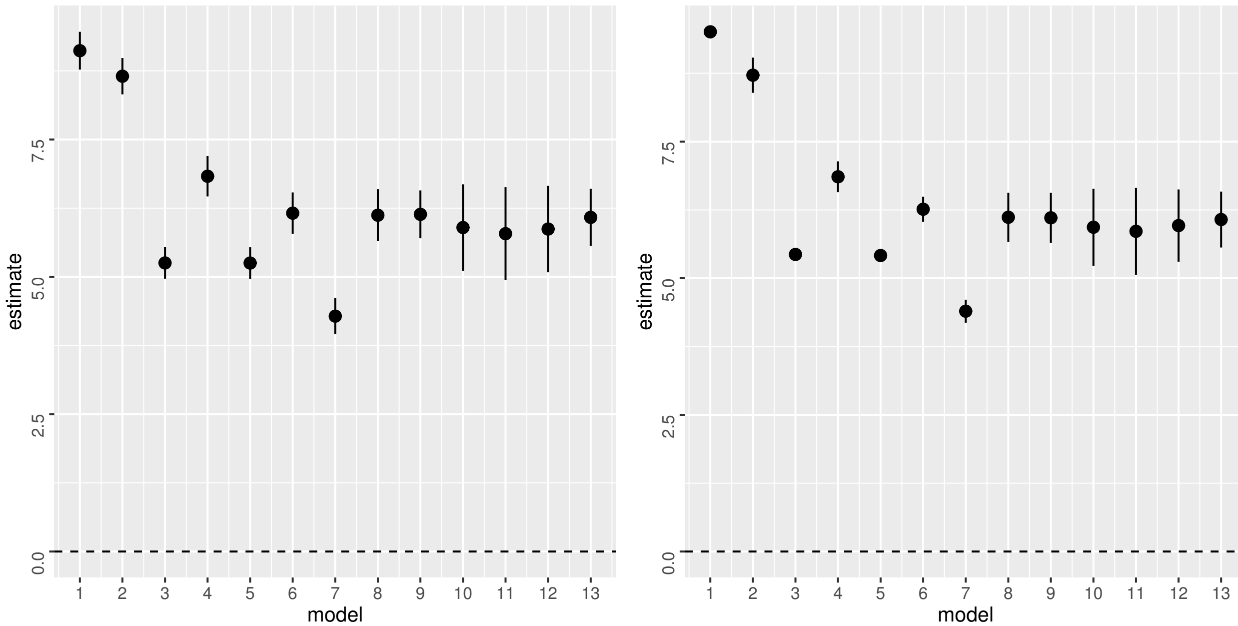
II. Difference-in-Differences

This section summarizes our main results from the difference-in-differences analysis. The main advantage of the difference-in-differences method for our analysis is that we can compute the treatment effect of the water transfer with the available urban sprawl data. We employ two specifications: twoways fixed effects and individual fixed effects. Figure 3.3 summarizes the results from our analyses. The black dots in the figure represent the coefficient of the treatment effect, i.e., the effect on urban sprawl if the county is Los Angeles in the post-treatment period and, the lines represent the confidence interval. The left panel consists of different specifications, including twoways fixed effects and, the right panel consists of the same specifications with the individual effects. The different specifications include different sets of control variables. We use different sets of control variables to ensure that the regressions exclude variables that are correlated with each other. The analysis includes manufacturing control variables, like persons employed per capita, wages paid per person employed, agricultural control variables like the value of farm property per capita, number of farms per capita categorized by the farm acreage, percentage of the urban population, and value of land and buildings per capita.

In each specification, we include each control variable by each category except the variables which are highly correlated with each other. Table 3.3 and Table 3.4 describe the results for twoways fixed effects and individual fixed effects, respectively, given in Appendix 3.6.1. From figure 3.3, we observe that the first two specifications have a higher positive effect on urban sprawl. However, these specifications do not include other control variables such as manufacturing, agriculture, etc.

Figure 3.3

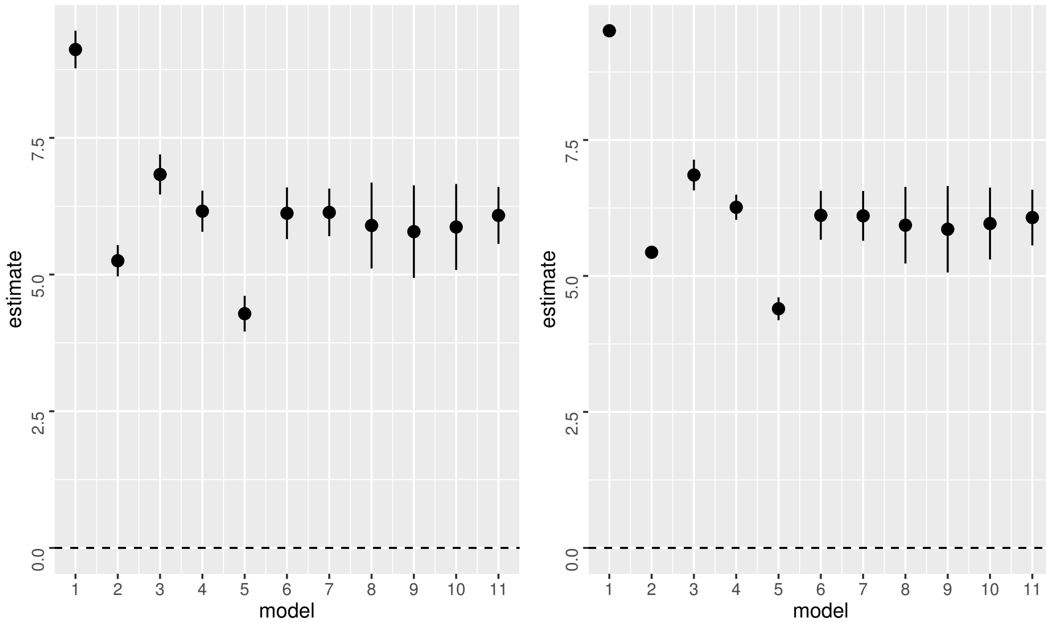
The left panel consists of the twoways fixed effects results and the right panel shows the results from the individual fixed effects models for the whole data set. Tables describing the results in detail are given in appendix 3.6.1.



The coefficient of the treatment effect in the next eleven specifications included in the two panels ranges from 4 to 7. This indicates that there was a 4-7 percentage points increase in urban sprawl in Los Angeles post the water transfer controlling for the manufacturing and agricultural control variables. The significance of the coefficient can be tested by observing the black lines in the figure, which show the confidence intervals. Since the intervals are not close to the *"the zero line"* (The horizontal black dotted line in Figure 3.3), we can conclude that our estimates are significant. This can be validated by tables 3.3 and 3.4 in appendix 3.6.1.

Figure 3.4

The left panel consists of the twoways fixed effects results and the right panel shows the results from the individual fixed effects models for the whole data set. Tables 3.5 and 3.6 describing the results in detail are given in appendix 3.6.1.



We perform another set of difference-in-differences regressions with twoways and individual fixed effects without the percentage of the urban population. We eliminate the variable from the analysis since it could be considered as an indicator of urbanization and hence, influence the results. Figure 3.4 displays the same specifications used in the main results after removing the percentage of the urban population variable. Tables 3.5 and 3.6 in Appendix 3.6.1 display the results in detail. We observe that most of the coefficients are similar to the analysis, including the percentage of the urban population. The coefficient of treatment effect is positive and significant in all the specifications. These results show that the percentage of the urban population does not bias the main results.

Our estimates are consistent throughout the specifications with different variables whether time trends are included or not. Hence, it seems that Los Angeles did experience a high degree of urban sprawl post the Owens Valley water transfer in 1920. In the next section, we perform a few robustness checks to corroborate our main results.

Robustness Checks

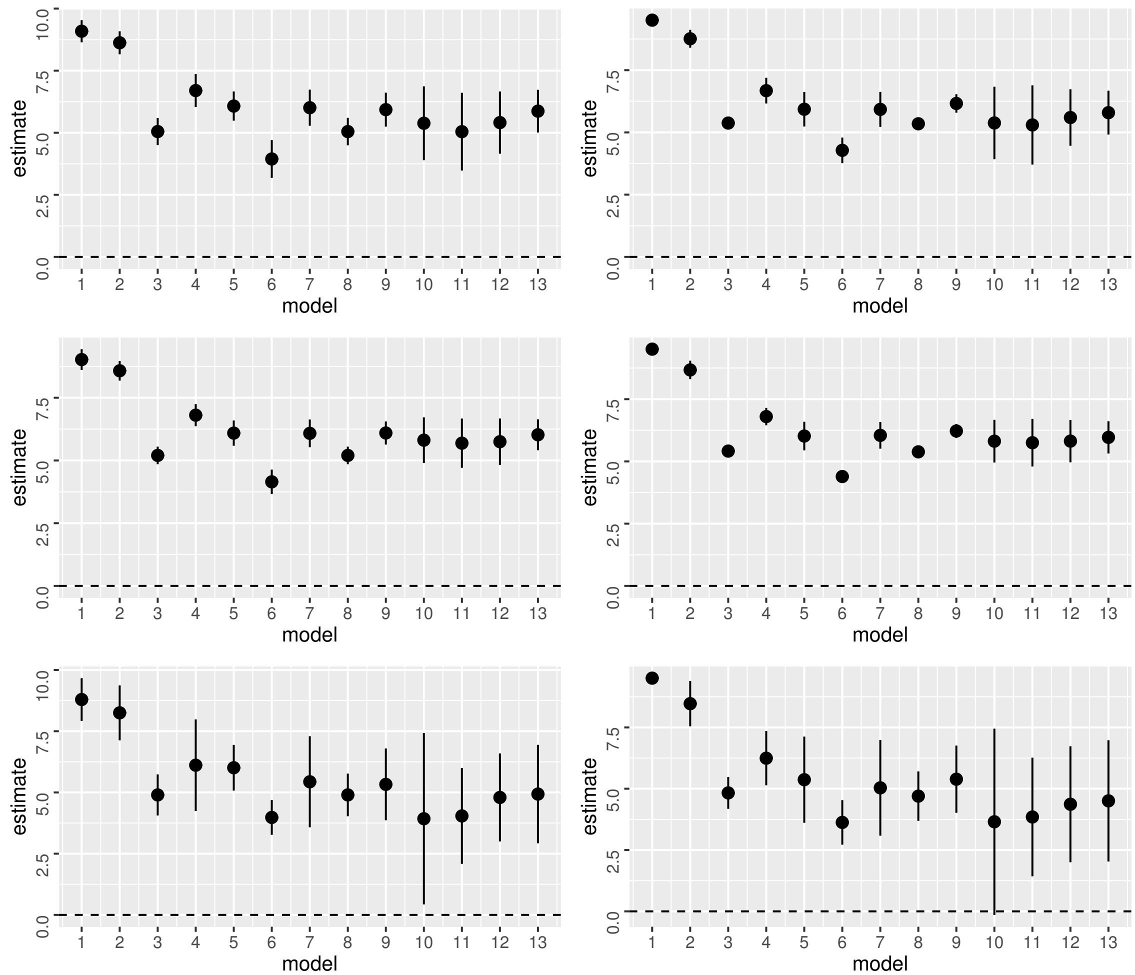
To demonstrate the sensitivity of our main findings from the previous section, we fit the twoways and individual fixed effects methods to different subsets of the data. We create two different subsets based on (i) similarity to Los Angeles in urban population (ii) by geography. Apart from this, we run the difference-in-differences regression on lagged independent variables.

A. Subsetting counties by the percentage of urban population

We start subsetting by the urban population, i.e., we observe the impact of water transfer on counties with a similar percentage of the urban population in the post-treatment period. We create three datasets where i) counties with higher than 50% of the urban population in the post-treatment period are included, ii) counties with higher than 30% of the urban population in the post-treatment period are included, and iii) counties with the urban population higher than 70% are included.

Figure 3.5

The left panel consists of the twoways fixed effects results and right panel shows the results from the individual fixed effects models for the whole data set. Tables 3.7-3.12 describe the results in detail in the appendix 3.6.1.



The first row in figure 3.5 consists of the coefficient of treatment effect for the dataset with the urban population higher than 50%, and the next two rows consist of treatment effect for the dataset with the urban population greater than 30% and 70% respectively with the left panel consisting of twoways fixed effects and right panel including only the individual effects. Tables 3.7-3.12 describe the results in detail in appendix 3.6.1.

The black dots in figure 3.5, consistent with previous figures, show the coefficient of treatment effect and, the lines represent the 95% confidence intervals. The significance of the treatment effect can be determined by observing the closeness of the confidence intervals to the dotted black line (the zero line). We observe that the confidence intervals are smallest when we include a higher number of counties (i.e. 30%) and largest when there are a fewer number of counties (i.e. 70%). However, in all specifications (apart from model 10 in the bottom-right), the treatment effect is significant and positive consistently. In the bottom-right figure, model 10, the treatment effect is significant at 10%, and hence, we observe the confidence intervals being very close to the dotted zero line. We also observe that the trend in the magnitude of treatment effect is consistent throughout all the subsets in various specifications.

A significant and positive treatment effect on data subset where counties similar to the treatment county (i.e. Los Angeles) are included might indicate that the water transfer increased Los Angeles' urban sprawl more than the increase that would have been observed in its absence. There were other Californian counties which experienced urban sprawl in the 1900s, but the sprawl in Los Angeles was higher since additional water quantity (from the Owens Valley) seems to have accelerated the urban sprawl.

B. Subsetting counties by geography (Removing the five northernmost counties)

In the next category of subsets, we include a geographical component. Since Los Angeles is located in Southern California, we eliminate the 5 northernmost counties. Hence, the next set of analyses includes 22 southernmost Californian counties.

Figure 3.6

The left panel consists of the twoways fixed effects results and the right panel shows the results from the individual fixed effects models for the whole data set. Tables 3.13 and 3.14 describe the results in detail given in appendix 3.6.1.

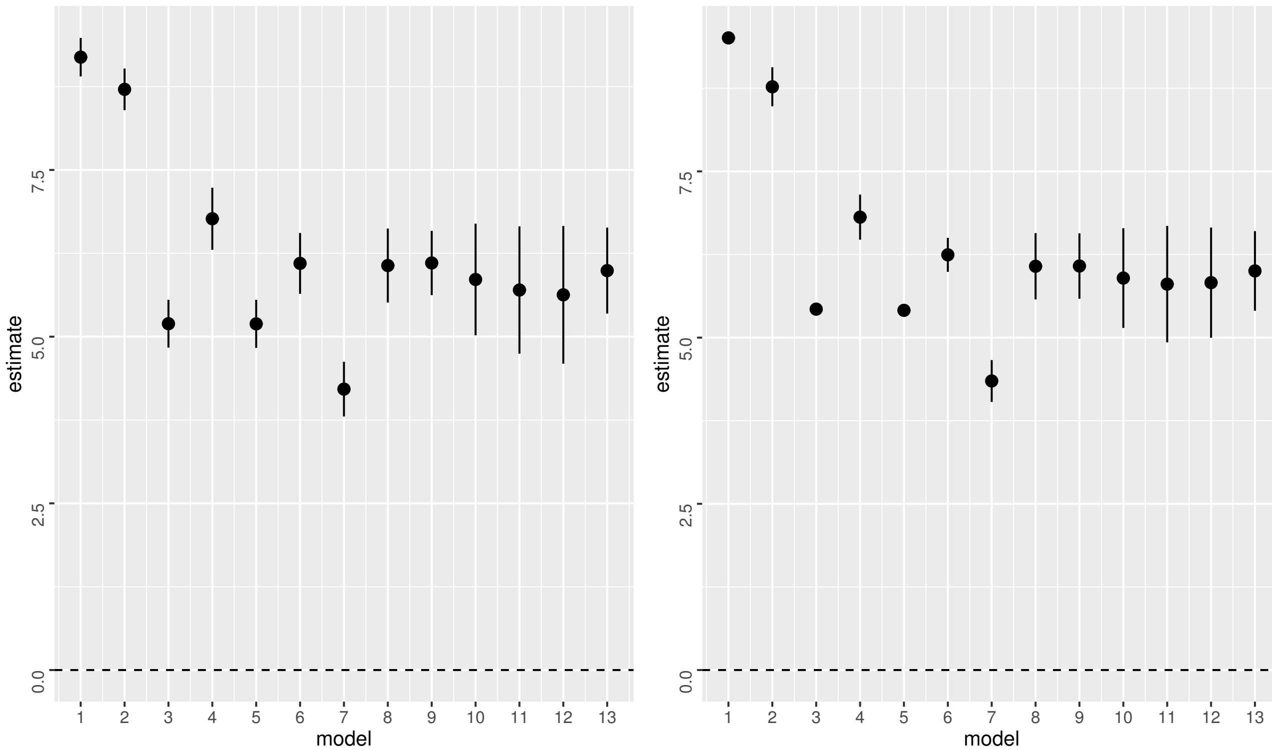


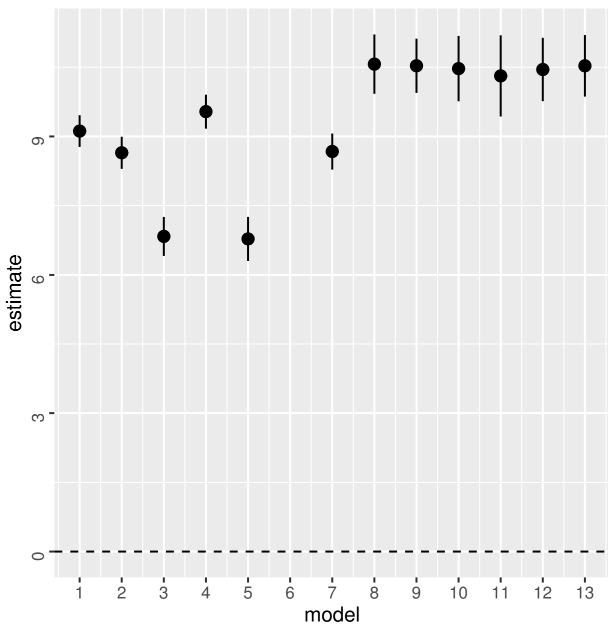
Figure 3.6 shows the trend of treatment effect coefficient throughout the 13 specifications with twoways fixed effects in the left panel and individual fixed effects in the right panel. Tables 3.13 and 3.14 describe the difference-in-differences results in detail, given in Appendix 3.6.1.

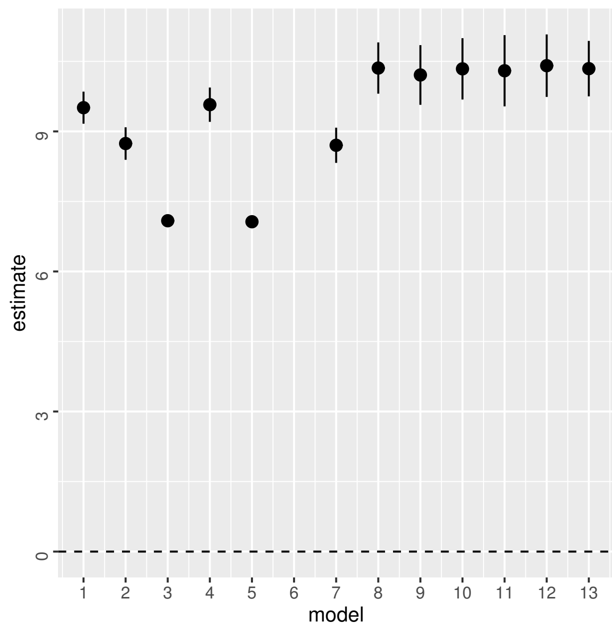
From the figure, we notice that the confidence intervals are a little larger when agricultural and manufacturing control variables are included compared with the ones observed in the main analysis. However, the trend of the treatment effect magnitude is similar to the ones observed in the previous figures. Moreover, the coefficient of treatment effect is significant in all specifications.

C. Using Lagged independent variables

Figure 3.7

The left panel consists of the twoways fixed effects results and, the right panel shows the results from the individual fixed effects models for the whole data set. Tables 3.15 and 3.16 describing the results in detail are given in appendix 3.6.1.





In the last set of robustness checks, we use a lag of all independent variables and run the twoways fixed effects (left panel) and individual fixed effects (right panel) with urban sprawl as the dependent variable. Figure 3.7 shows the plot of the treatment effect coefficient, which is positive and significant, consistent with the previous analyses, as shown in the study. Tables 3.15 and 3.16 in appendix 3.6.1 describe the results in detail.

In conclusion, the analyses included in robustness checks are consistent with the main results. Although the confidence intervals change in the various subsets of data, the treatment effect coefficient is significant throughout the analyses. Hence, it seems that the urban sprawl in Los Angeles increased considerably as a result of Owens Valley water transfer.

3.4 Discussions and Conclusions

The study presented seeks to empirically test the effects of the Owens Valley water transfer on Urban Sprawl in Los Angeles during the 1900s. We employ the synthetic control and difference-in-differences methods for our empirical analyses. Our synthetic control results show that there was an increase in the degree of the urban sprawl of Los Angeles, although the rise seemed to have begun earlier than the treatment year. Further, it is difficult to draw causal inference from this analysis since the pre-treatment fit is not excellent as required due to the lack of urban sprawl data in that period. Therefore, we apply a difference-in-differences analysis for drawing our inferences. We use specifications with individual and twoways fixed effects where different groups of variables are included. The coefficient of the treatment effect is significantly increasing throughout the different specifications suggesting that the water transfer might have led to an increase in the degree of the urban sprawl in Los Angeles.

The literature related to urban sprawl and water resources has focused on the impact of rising urban sprawl on natural resources and the lack of water resources in rural areas, owing to the increasing transfer of water rights in the urban sector. However, there is not much empirical evidence on the procurement of water resources for accelerating the process of urbanization. The research presented above intends to fill this gap in the literature. Further, we suggest that the decisions regarding water allocation should include a thorough study of the possible future impacts of such allocation on the parties involved.

In conclusion, the beginning of urban sprawl in Los Angeles in the 1900s may be attributable to the Owens Valley water transfer. Back in 1904, peak summer demand had reduced the local water reservoir flow from 35,782,000 gallons to 3,494,000 gallons (Ostrom, 1950). In 2016, reported the water demand was 110 gpcd in a city with a population of 10,039,107 as reported by Census (2019). Hence, to ensure proper management of resources with fairness, the distinction between the need and exaggerated demand promoting excess urbanization must be established. The robustness of our results could be improved if the study area is expanded through the West.

Due to the limitations of the urban sprawl data in the control counties, we faced issues in implementing the synthetic control method. In the future, these problems can be solved by collecting data for longer time periods and expanding the study area throughout the West.

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3.6 Appendix

3.6.1 Difference-in-Differences

In this section, we present 14 tables that correspond to difference-in-differences results from the main analysis and robustness checks. Tables 3.3 and 3.4 describe the main results with twoways and individual fixed effects; tables 3.5 and 3.6 repeat the same analysis without urban population as the main variable. Tables 3.7-3.12 include robustness checks when we include the counties similar to Los Angeles in terms of urban population (Tables 3.7 and 3.8 correspond to counties with higher than 50% population in the post-treatment period, tables 3.9 and 3.10 correspond to counties with higher than 50% population; and tables 3.11 and 3.12 correspond to counties with higher than 70% population.). The main reason to include the tables is to corroborate the results shown in the figures and to give a deeper understanding of the results.

From our control variables, we observe that persons employed per capita are significant in the main results (tables 3.3-3.5). However, the coefficient has a negative sign consistently, which means that unemployment increases urban sprawl. Although this might be surprising, it can be interpreted as a decrease in labor population per capita means that there is a higher concentration of labor population in the economy.

The main observation, however, from the table is that the treatment coefficient holds up as positive and significant, as shown in the figures throughout the main results and robustness checks. Hence, these results support our main hypothesis.

Table 3.2

The main results with twoways fixed effects.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Los Angeles∗Post-treatment)	9.116***	8.652***	5.253***	6.831***	4.284***	6.122***	5.251***	6.159***	6.137***	5.897***	5.785***	5.870***	6.082***
	(0.172)	(0.165)	(0.143)	(0.184)	(0.163)	(0.237)	(0.144)	(0.189)	(0.218)	(0.393)	(0.423)	(0.394)	(0.261)
Percentage of Urban population		−0.0003			0.003	0.014	−0.002	0.008	0.014	0.013	0.010	0.024	0.018
		(0.008)			(0.009)	(0.011)	(0.004)	(0.007)	(0.011)	(0.011)	(0.009)	(0.017)	(0.014)
Value of land and buildings per capita			0.0001		0.0004		0.0001						
			(0.0001)		(0.0002)		(0.0001)						
Wages paid per person employed				0.0001		−0.0001			0.00004	−0.0003	−0.0003	−0.0002	−0.0002
				(0.0002)		(0.0003)			(0.0003)	(0.0004)	(0.0005)	(0.0004)	(0.001)
Value of farm property per capita						0.0001		0.0001		0.0002	0.0003	0.0001	0.0001
						(0.0001)		(0.0001)		(0.0001)	(0.0002)	(0.0001)	(0.0001)
Number of farms per capita									1.076				
									(4.776)				
Number of farms under 10 acres per capita										−51.917			
										(49.093)			
Number of farms between 10-49 acres per capita											−23.381		
											(17.146)		
Number of farms between 100-999 acres per capita												19.076	
												(14.927)	
Number of farms more than 1000 acres per capita													53.747
													(44.491)
Persons employed per capita				−2.077***	−1.733	−3.317*			−3.904*	−3.257*	−2.497*	−2.375	−3.880*
				(0.772)	(4.789)	(1.923)			(2.130)	(1.851)	(1.462)	(1.542)	(2.298)
Observations	189	162	108	135	81	108	108	135	108	108	108	108	108
R^2	0.436	0.390	0.546	0.584	0.496	0.564	0.546	0.571	0.561	0.586	0.594	0.595	0.573
Adjusted R^2	0.316	0.233	0.361	0.448	0.160	0.362	0.352	0.431	0.356	0.384	0.396	0.398	0.365
F Statistic	120.047*** (df = 1; 155)	40.979*** (df = 2; 128)	45.671*** (df = 2; 76)	47.205*** (df = 3; 101)	11.802*** (df = 4; 48)	18.922*** (df = 5; 73)	30.082*** (df = 3; 75)	44.856*** (df = 3; 101)	18.636*** (df = 5; 73)	16.956*** (df = 6; 72)	17.531*** (df = 6; 72)	17.644*** (df = 6; 72)	16.099*** (df = 6; 72)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 3.3

The main results with individual fixed effects.

	Dependent variable:												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Los Angeles∗Post-treatment	9.508	8.714***	5.435***	6.856***	5.416***	6.263***	4.397***	6.115***	6.105***	5.933***	5.859***	5.964***	6.074***
		(0.161)	(0.015)	(0.141)	(0.030)	(0.115)	(0.105)	(0.225)	(0.229)	(0.352)	(0.397)	(0.330)	(0.256)
Percentage of Urban population		0.018*			0.004	0.011	−0.006	0.014	0.014	0.016	0.014	0.022	0.019
		(0.010)			(0.004)	(0.008)	(0.007)	(0.012)	(0.012)	(0.013)	(0.012)	(0.017)	(0.015)
Value of land and buildings per capita			−0.0001*		−0.0001*		−0.0001						
			(0.00005)		(0.00005)		(0.0001)						
Wages paid per persons employed				0.0003				0.0001	0.0001	0.0003	0.0003	0.0002	0.0001
				(0.0002)				(0.0001)	(0.0001)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
Number of farms per capita									−1.815				
									(2.037)				
Persons employed per capita				−2.856*			−8.605	−4.647*	−4.703*	−5.238*	−4.741*	−5.064*	−5.262*
				(1.520)			(6.226)	(2.665)	(2.746)	(2.931)	(2.577)	(2.939)	(3.100)
Value of farm property per capita						−0.00005		−0.00004		−0.0001	0.00003	−0.0001	−0.0001
						(0.00003)		(0.00003)		(0.00003)	(0.0001)	(0.0001)	(0.00004)
Number of farms under 10 acres per capita										−36.534			
										(32.734)			
Number of farms between 10-49 acres per capita											−15.711		
											(12.285)		
Number of farms between 100-999 acres per capita												11.895	
												(9.442)	
Number of farms more than 1000 acres per capita													41.274
													(34.067)
Observations	189	162	108	135	108	135	81	108	108	108	108	108	108
R^2	0.443	0.419	0.549	0.608	0.551	0.588	0.517	0.592	0.592	0.604	0.606	0.605	0.597
Adjusted R^2	0.349	0.296	0.389	0.500	0.384	0.475	0.227	0.426	0.425	0.435	0.439	0.437	0.425
F Statistic	127.959*** (df = 1; 161)	47.924*** (df = 2; 133)	48.132*** (df = 2; 79)	54.388*** (df = 3; 105)	31.868*** (df = 3; 78)	50.031*** (df = 3; 105)	13.365*** (df = 4; 50)	22.059*** (df = 5; 76)	22.028*** (df = 5; 76)	19.038*** (df = 6; 75)	19.261*** (df = 6; 75)	19.175*** (df = 6; 75)	18.502*** (df = 6; 75)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.4

Results without urban population and with twoways fixed effects.

	Dependent variable:										
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Los Angeles*Post-treatment	9.116***	5.253***	6.831***	4.290***	6.829***	6.672***	6.766***	6.539***	6.413***	6.739***	6.824***
	(0.172)	(0.143)	(0.184)	(0.156)	(0.182)	(0.168)	(0.205)	(0.370)	(0.427)	(0.247)	(0.185)
Value of land and buildings per capita		0.0001		0.0004							
		(0.0001)		(0.0002)							
Wages paid per person employed			0.0001		0.0001		0.0001	−0.00004	−0.0002	0.0001	0.0001
			(0.0002)		(0.0002)		(0.0002)	(0.0003)	(0.0004)	(0.0002)	(0.0003)
Value of farm property per capita					−0.00001	0.00003		0.00002	0.0002	−0.00001	−0.00001
					(0.0001)	(0.0001)		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Number of farms per capita							−3.464				
							(3.739)				
Number of farms under 10 acres per capita								−52.169			
								(41.071)			
Number of farms between 10-49 acres per capita									−23.713		
									(16.235)		
Number of farms between 100-999 acres per capita										10.142	
										(9.089)	
Number of farms more than 1000 acres per capita											23.838
											(23.308)
Persons employed per capita			−2.077***	−1.945	−2.129***		−2.585***	−2.313**	−1.580**	−1.003	−2.182**
			(0.772)	(4.785)	(0.775)		(0.905)	(0.918)	(0.750)	(1.223)	(0.900)
Observations	189	108	135	81	135	162	135	135	135	135	135
R^2	0.436	0.546	0.584	0.495	0.584	0.580	0.587	0.607	0.615	0.594	0.586
Adjusted R^2	0.316	0.361	0.448	0.176	0.442	0.472	0.446	0.468	0.478	0.451	0.440
F Statistic	120.047*** (df = 1; 155)	45.671*** (df = 2; 76)	47.205*** (df = 3; 101)	16.036*** (df = 3; 49)	35.056*** (df = 4; 100)	88.562*** (df = 2; 128)	35.484*** (df = 4; 100)	30.616*** (df = 5; 99)	31.569*** (df = 5; 99)	29.020*** (df = 5; 99)	28.076*** (df = 5; 99)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.5

Results without urban population and with individual fixed effects.

	Dependent variable:										
	UrbanSprawl										
	panel linear								*coefficient test*		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
Los Angeles*Post-treatment	9.508***	5.435***	6.856***	4.397***	6.780***	6.888***	6.718***	6.553***	6.484***	6.725***	6.772***
	(0.841)	(0.560)	(0.574)	(0.663)	(0.575)	(0.504)	(0.579)	(0.333)	(0.382)	(0.224)	(0.189)
Percentage of Urban Population				−0.006							
				(0.014)							
Value of land and buildings per capita		−0.0001		−0.0001							
		(0.0001)		(0.0001)							
Wages paid per person employed			0.0003**		0.0004**		0.0003*	0.001*	0.0005*	0.001	0.0004
			(0.0001)		(0.0001)		(0.0001)	(0.0003)	(0.0003)	(0.0003)	(0.0002)
Value of farm property per capita					−0.0001	−0.0001		−0.0001	−0.00003	−0.0001	−0.0001
					(0.0001)	(0.0001)		(0.0001)	(0.00004)	(0.0001)	(0.0001)
Number of farms per capita							−5.166				
							(3.494)				
Number of farms under 10 acres per capita								−38.423			
								(29.052)			
Number of farms between 10-49 acres per capita									−15.853		
									(11.454)		
Number of farms between 100-999 acres per capita										5.646	
										(4.916)	
Number of farms more than 1000 acres per capita											11.728
											(13.921)
Persons employed per capita			−2.856	−8.605**	−2.662		−2.994	−3.146**	−2.766**	−2.442*	−2.751*
			(2.311)	(3.857)	(2.309)		(2.300)	(1.480)	(1.307)	(1.260)	(1.388)
Observations	189	108	135	81	135	162	135	135	135	135	135
R^2	0.443	0.549	0.608	0.517	0.615	0.588	0.617	0.629	0.630	0.618	0.615
Adjusted R^2	0.349	0.389	0.500	0.227	0.503	0.501	0.506	0.517	0.519	0.504	0.499
F Statistic	127.959*** (df = 1; 161)	48.132*** (df = 2; 79)	54.388*** (df = 3; 105)	13.365*** (df = 4; 50)	41.458*** (df = 4; 104)	94.823*** (df = 2; 133)	41.798*** (df = 4; 104)	34.869*** (df = 5; 103)	35.109*** (df = 5; 103)	33.387*** (df = 5; 103)	32.942*** (df = 5; 103)
Note:											*p<0.1; **p<0.05; ***p<0.01

Table 3.6

Results when counties with greater than 50% population post-treatment are included and with twoways fixed effects.

	Dependent variable:												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Los Angeles∗Post-treatment	9.089***	8.623***	5.049***	6.700***	5.048***	5.931***	3.944***	6.009***	6.075***	5.383***	5.044***	5.409***	5.870***
	(0.223)	(0.232)	(0.274)	(0.333)	(0.276)	(0.342)	(0.381)	(0.364)	(0.294)	(0.744)	(0.783)	(0.627)	(0.430)
Percentage of Urban Population		0.002			0.007	0.008	0.030	0.019	0.028	0.026	−0.009	0.040	0.021
		(0.007)			(0.012)	(0.010)	(0.027)	(0.019)	(0.028)	(0.022)	(0.012)	(0.029)	(0.021)
Value of land and buildings per capita			0.001		0.001		0.001*						
			(0.0003)		(0.0004)		(0.001)						
Wages paid per person employed				−0.001				−0.001	−0.001	−0.002	−0.002	−0.003	−0.002
				(0.001)				(0.001)	(0.001)	(0.002)	(0.002)	(0.002)	(0.002)
Number of farms per capita									13.212				
									(22.904)				
Persons employed per capita				−0.704			1.591	−2.854	−2.791	−3.404	2.519	5.647	−1.593
				(1.627)			(11.148)	(2.516)	(3.252)	(2.880)	(2.607)	(4.107)	(2.444)
Value of farm property per capita						0.0003		0.0003		0.0004	0.001*	0.0002	0.0002
						(0.0002)		(0.0002)		(0.0002)	(0.0005)	(0.0002)	(0.0002)
Number of farms under 10 acres per capita										−182.332			
										(155.543)			
Number of farms between 10-49 acres per capita											−98.577		
											(60.522)		
Number of farms between 100-999 acres per capita												73.480	
												(44.287)	
Number of farms more than 1000 acres per capita													267.056
													(186.039)
Observations	98	84	56	70	56	70	42	56	56	56	56	56	56
R^2	0.610	0.569	0.553	0.580	0.555	0.570	0.542	0.569	0.569	0.629	0.650	0.671	0.606
Adjusted R^2	0.508	0.432	0.336	0.409	0.320	0.394	0.147	0.303	0.302	0.382	0.417	0.451	0.343
F Statistic	120.199*** (df = 1; 77)	41.602*** (df = 2; 63)	22.927*** (df = 2; 37)	22.561*** (df = 3; 49)	14.945*** (df = 3; 36)	21.649*** (df = 3; 49)	6.514*** (df = 4; 22)	8.983*** (df = 5; 34)	8.966*** (df = 5; 34)	9.323*** (df = 6; 33)	10.236*** (df = 6; 33)	11.212*** (df = 6; 33)	8.459*** (df = 6; 33)

Note: $^{*}p<0.1$; $^{**}p<0.05$; $^{***}p<0.01$

Table 3.7

Results when counties with greater than 50% population post-treatment are included and with individual fixed effects.

	Dependent variable:												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
I(Dummy_LA ∗Periods)	9.508	8.761***	5.375***	6.677***	5.347***	6.162***	4.280***	5.924***	5.931***	5.380***	5.300***	5.598***	5.794***
		(0.180)	(0.054)	(0.258)	(0.070)	(0.186)	(0.257)	(0.351)	(0.347)	(0.728)	(0.796)	(0.568)	(0.440)
Percentage of Urban Population		0.015			0.007	0.015	0.006	0.028	0.025	0.039	0.020	0.046	0.034
		(0.011)			(0.008)	(0.012)	(0.026)	(0.024)	(0.023)	(0.029)	(0.016)	(0.035)	(0.028)
Value of land and buildings per capita			−0.0003		−0.0003		−0.0001						
			(0.0002)		(0.0002)		(0.0002)						
Wages paid per person employed				0.001				−0.0001	−0.0001	0.0001	0.0002	0.0002	0.0001
				(0.0004)				(0.0004)	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0004)
Number of farms per capita									−4.193				
									(7.257)				
Persons employed per capita				−3.208**			−12.566	−7.710	−8.038	−9.857	−7.211	−7.277	−8.603
				(1.485)			(13.067)	(5.085)	(5.427)	(6.397)	(4.763)	(5.305)	(5.834)
Value of farm property per capita						−0.0001		−0.0001		−0.0001	0.0001	−0.0003	−0.0002
						(0.0001)		(0.0001)		(0.0001)	(0.0002)	(0.0002)	(0.0002)
Number of farms under 10 acres per capita										−140.313			
										(113.864)			
Number of farms between 10-49 acres per capita											−53.489		
											(46.751)		
Number of farms between 100-999 acres per capita												33.317	
												(25.014)	
Number of farms more than 1000 acres per capita													158.967
													(132.661)
Observations	98	84	56	70	56	70	42	56	56	56	56	56	56
R^2	0.625	0.603	0.554	0.624	0.557	0.598	0.542	0.615	0.612	0.647	0.641	0.641	0.628
Adjusted R^2	0.562	0.516	0.387	0.510	0.375	0.477	0.217	0.428	0.423	0.461	0.451	0.452	0.432
F Statistic	138.366*** (df = 1; 83)	51.685*** (df = 2; 68)	24.890*** (df = 2; 40)	29.300*** (df = 3; 53)	16.315*** (df = 3; 39)	26.310*** (df = 3; 53)	7.094*** (df = 4; 24)	11.816*** (df = 5; 37)	11.669*** (df = 5; 37)	10.998*** (df = 6; 36)	10.710*** (df = 6; 36)	10.727*** (df = 6; 36)	10.143*** (df = 6; 36)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.8

Results when counties with greater than 30% population post-treatment are included and with twoways fixed effects.

	Dependent variable:												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Los Angeles∗Post-treatment	9.022***	8.576***	5.201***	6.807***	5.201***	6.096***	4.148***	6.082***	6.091***	5.810***	5.689***	5.748***	6.025***
	(0.207)	(0.196)	(0.175)	(0.220)	(0.175)	(0.231)	(0.244)	(0.276)	(0.252)	(0.455)	(0.491)	(0.463)	(0.308)
Percentage of Urban population		−0.004			−0.0001	0.008	0.013	0.018	0.017	0.015	0.009	0.028	0.020
		(0.011)			(0.007)	(0.008)	(0.016)	(0.015)	(0.015)	(0.013)	(0.011)	(0.020)	(0.017)
Value of land and buildings per capita			0.0003		0.0003		0.001						
			(0.0002)		(0.0002)		(0.0005)						
Wages paid per person employed				−0.0001				−0.0004	−0.0002	−0.001	−0.001	−0.001	−0.001
				(0.001)				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Number of farms per capita									0.734				
									(7.784)				
Persons employed per capita				−1.875**			1.903	−3.521	−4.453	−3.037	−0.905	0.348	−2.806
				(0.766)			(5.204)	(2.401)	(2.683)	(2.006)	(1.333)	(2.108)	(2.025)
Value of farm property per capita						0.0002		0.0002		0.0003	0.0004	0.0002	0.0002
						(0.0001)		(0.0002)		(0.0002)	(0.0003)	(0.0002)	(0.0001)
Number of farms under 10 acres per capita										−61.623			
										(57.248)			
Number of farms between 10-49 acres per capita											−33.326		
											(26.470)		
Number of farms between 100-999 acres per capita												38.462	
												(26.596)	
Number of farms more than 1000 acres per capita													116.684
													(87.620)
Observations	154	132	88	110	88	110	66	88	88	88	88	88	88
R^2	0.435	0.389	0.548	0.582	0.548	0.572	0.512	0.567	0.561	0.596	0.605	0.620	0.585
Adjusted R^2	0.308	0.223	0.355	0.437	0.344	0.424	0.165	0.351	0.342	0.383	0.397	0.420	0.367
F Statistic	96.258*** (df = 1; 125)	32.788*** (df = 2; 103)	36.926*** (df = 2; 61)	37.585*** (df = 3; 81)	24.214*** (df = 3; 60)	36.052*** (df = 3; 81)	9.968*** (df = 4; 38)	15.212*** (df = 5; 58)	14.851*** (df = 5; 58)	14.017*** (df = 6; 57)	14.537*** (df = 6; 57)	15.506*** (df = 6; 57)	13.401*** (df = 6; 57)
Note:													*p<0.1; **p<0.05; ***p<0.01

Table 3.9

Results when counties with greater than 30% population post-treatment are included and with individual fixed effects.

	Dependent variable:												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Los Angeles∗Post-treatment	9.508	8.674***	5.415***	6.801***	5.384***	6.221***	4.392***	6.046***	6.019***	5.813***	5.752***	5.815***	5.966***
		(0.185)	(0.023)	(0.174)	(0.043)	(0.139)	(0.119)	(0.268)	(0.287)	(0.428)	(0.478)	(0.425)	(0.324)
Percentage of urban population		0.020*			0.006	0.012	−0.005	0.020	0.018	0.021	0.019	0.029	0.024
		(0.011)			(0.006)	(0.009)	(0.012)	(0.017)	(0.016)	(0.017)	(0.015)	(0.022)	(0.019)
Value of land and buildings per capita			−0.0002**		−0.0002**		−0.00004						
			(0.0001)		(0.0001)		(0.0001)						
Wages paid per person employed				0.0004				0.00000	−0.00002	0.0003	0.0002	0.0003	0.0001
				(0.0003)				(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0003)	(0.0002)
Number of farms per capita									−3.719				
									(4.064)				
Persons employed per capita				−3.164*			−9.075	−5.754	−5.912*	−6.458*	−5.389*	−5.481	−6.063
				(1.647)			(7.058)	(3.457)	(3.510)	(3.695)	(3.055)	(3.311)	(3.639)
Value of farm property per capita						−0.0001*		−0.0001		−0.0001	0.00001	−0.0002	−0.0001
						(0.0001)		(0.00004)		(0.0001)	(0.0001)	(0.0001)	(0.0001)
Number of farms under 10 acres per capita										−43.982			
										(41.399)			
Number of farms between 10-49 acres per capita											−19.554		
											(17.426)		
Number of farms between 100-999 acres per capita												20.154	
												(15.197)	
Number of farms more than 1000 acres per capita													72.068
													(59.481)
Observations	154	132	88	110	88	110	66	88	88	88	88	88	88
R^2	0.443	0.421	0.551	0.613	0.554	0.593	0.519	0.601	0.601	0.616	0.616	0.619	0.608
Adjusted R^2	0.349	0.298	0.390	0.504	0.383	0.478	0.218	0.430	0.430	0.443	0.442	0.448	0.432
F Statistic	104.116*** (df = 1; 131)	39.344*** (df = 2; 108)	39.302*** (df = 2; 64)	44.965*** (df = 3; 85)	26.038*** (df = 3; 63)	41.213*** (df = 3; 85)	10.777*** (df = 4; 40)	18.342*** (df = 5; 61)	18.350*** (df = 5; 61)	16.021*** (df = 6; 60)	16.009*** (df = 6; 60)	16.250*** (df = 6; 60)	15.526*** (df = 6; 60)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.10

Results when counties with greater than 70% population post-treatment are included and with twoways fixed effects.

	Dependent variable:												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Los Angeles∗Post-treatment	8.793***	8.251***	4.898***	6.112***	4.899***	5.330***	3.980***	5.436***	6.008***	3.928**	4.041***	4.796***	4.933***
	(0.436)	(0.561)	(0.420)	(0.935)	(0.435)	(0.733)	(0.356)	(0.930)	(0.467)	(1.749)	(0.978)	(0.899)	(1.005)
Percentage of urban population		0.016			−0.002	0.047	0.059	0.078	0.155*	0.039	0.007	0.101**	0.079
		(0.024)			(0.028)	(0.035)	(0.036)	(0.045)	(0.075)	(0.034)	(0.027)	(0.045)	(0.046)
Value of land and buildings per capita			0.002		0.002		0.001						
			(0.002)		(0.002)		(0.002)						
Wages paid per person employed				−0.002				−0.004	−0.006**	−0.004*	−0.003	−0.006**	−0.004
				(0.002)				(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.003)
Number of farms per capita									85.863				
									(63.092)				
Persons employed per capita				13.950			−49.126	−6.041	−11.046	5.620	3.871	5.643	1.029
				(13.709)			(32.878)	(14.234)	(12.272)	(13.673)	(11.160)	(5.456)	(9.581)
Value of farm property per capita						0.002*		0.001		0.001	0.002*	0.001	0.001
						(0.001)		(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
Number of farms under 10 acres per capita										−527.478			
										(349.277)			
Number of farms between 10-49 acres per capita											−164.029**		
											(58.054)		
Number of farms between 100-999 acres per capita												137.115**	
												(47.422)	
Number of farms more than 1000 acres per capita													601.573
													(379.199)
Observations	49	42	28	35	28	35	21	28	28	28	28	28	28
R^2	0.603	0.565	0.554	0.600	0.554	0.612	0.612	0.661	0.710	0.756	0.714	0.812	0.740
Adjusted R^2	0.456	0.363	0.248	0.353	0.198	0.372	0.031	0.295	0.398	0.450	0.356	0.576	0.414
F Statistic	53.161*** (df = 1; 35)	18.205*** (df = 2; 28)	9.943*** (df = 2; 16)	10.504*** (df = 3; 21)	6.215*** (df = 3; 15)	11.033*** (df = 3; 21)	3.161* (df = 4; 8)	5.061*** (df = 5; 13)	6.377*** (df = 5; 13)	6.181*** (df = 6; 12)	4.992*** (df = 6; 12)	8.621*** (df = 6; 12)	5.684*** (df = 6; 12)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.11

Results when counties with greater than 70% population post-treatment are included and with individual fixed effects.

	Dependent variable:												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Los Angeles∗Post-treatment	9.508	8.468***	4.830***	6.245***	4.698***	5.388***	3.626***	5.036***	5.368***	3.652*	3.848***	4.367***	4.505***
		(0.461)	(0.325)	(0.553)	(0.505)	(0.685)	(0.454)	(0.976)	(0.879)	(1.899)	(1.209)	(1.182)	(1.237)
Percentage of urban population		0.032			0.023	0.045	0.051	0.137*	0.163	0.116*	0.084	0.174*	0.146*
		(0.028)			(0.030)	(0.029)	(0.043)	(0.073)	(0.109)	(0.058)	(0.067)	(0.084)	(0.079)
Value of land and buildings per capita			−0.002*		−0.002*		0.00004						
			(0.001)		(0.001)		(0.002)						
Wages paid per person employed				0.001				−0.003**	−0.003*	−0.001	−0.002	−0.002	−0.002
				(0.001)				(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
Number of farms per capita									18.144				
									(55.978)				
Persons employed per capita				−0.373			−45.662	−33.934***	−39.811**	−28.362***	−29.221***	−35.426***	−30.954**
				(5.029)			(26.901)	(9.703)	(15.135)	(6.780)	(8.667)	(11.007)	(10.641)
Value of farm property per capita						−0.001		−0.001		−0.001	−0.0001	−0.001	−0.001
						(0.001)		(0.001)		(0.001)	(0.001)	(0.001)	(0.001)
Number of farms under 10 acres per capita										−438.020			
										(377.207)			
Number of farms between 10-49 acres per capita											−136.091		
											(91.432)		
Number of farms between 100-999 acres per capita												90.948	
												(57.227)	
Number of farms more than 1000 acres per capita													526.921
													(389.522)
Observations	49	42	28	35	28	35	21	28	28	28	28	28	28
R^2	0.641	0.631	0.590	0.658	0.598	0.666	0.733	0.738	0.734	0.785	0.762	0.791	0.780
Adjusted R^2	0.579	0.542	0.417	0.534	0.397	0.545	0.465	0.558	0.551	0.613	0.572	0.623	0.604
F Statistic	73.103*** (df = 1; 41)	28.258*** (df = 2; 33)	13.659*** (df = 2; 19)	15.999*** (df = 3; 25)	8.929*** (df = 3; 18)	16.593*** (df = 3; 25)	6.852*** (df = 4; 10)	9.024*** (df = 5; 16)	8.824*** (df = 5; 16)	9.123*** (df = 6; 15)	8.025*** (df = 6; 15)	9.434*** (df = 6; 15)	8.856*** (df = 6; 15)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.12

Results when 5 northernmost counties are excluded and with twoways fixed effects.

	Dependent variable:												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Los Angeles*Post-treatment	9.192***	8.709***	5.194***	6.768***	5.192***	6.099***	4.213***	6.066***	6.105***	5.857***	5.699***	5.627***	5.991***
	(0.144)	(0.156)	(0.180)	(0.233)	(0.180)	(0.228)	(0.205)	(0.277)	(0.241)	(0.419)	(0.477)	(0.516)	(0.322)
Percentage of urban population		0.004			−0.002	0.008	0.006	0.015	0.018	0.014	0.012	0.032	0.021
		(0.006)			(0.006)	(0.008)	(0.013)	(0.013)	(0.015)	(0.012)	(0.011)	(0.022)	(0.017)
Value of land and buildings per capita			0.0002		0.0002		0.0005						
			(0.0001)		(0.0002)		(0.0003)						
Wages paid per person employed				0.0002				−0.0001	0.00004	−0.0003	−0.0003	−0.0005	−0.0002
				(0.0003)				(0.0004)	(0.0003)	(0.001)	(0.001)	(0.001)	(0.001)
Number of farms per capita									5.012				
									(8.659)				
Persons employed per capita				−1.980***			−3.465	−3.719	−4.253	−3.476	−2.661	−1.894	−4.520
				(0.715)			(8.636)	(2.297)	(2.559)	(2.123)	(1.786)	(2.095)	(2.800)
Value of farm property per capita						0.0002		0.0002		0.0002	0.0004	0.0002	0.0002
						(0.0001)		(0.0001)		(0.0001)	(0.0002)	(0.0001)	(0.0001)
Number of farms under 10 acres per capita										−50.954			
										(49.609)			
Number of farms between 10-49 acres per capita											−26.646		
											(20.344)		
Number of farms between 100-999 acres per capita												34.727	
												(22.367)	
Number of farms more than 1000 acres per capita													71.562
													(60.510)
Observations	154	132	88	110	88	110	66	88	88	88	88	88	88
R^2	0.607	0.567	0.548	0.582	0.548	0.571	0.508	0.564	0.561	0.584	0.596	0.625	0.576
Adjusted R^2	0.519	0.449	0.355	0.438	0.345	0.423	0.159	0.346	0.342	0.365	0.383	0.427	0.353
F Statistic	193.123*** (df = 1; 125)	67.477*** (df = 2; 103)	36.984*** (df = 2; 61)	37.636*** (df = 3; 81)	24.277*** (df = 3; 60)	35.929*** (df = 3; 81)	9.812*** (df = 4; 38)	15.013*** (df = 5; 58)	14.835*** (df = 5; 58)	13.320*** (df = 6; 57)	14.002*** (df = 6; 57)	15.814*** (df = 6; 57)	12.902*** (df = 6; 57)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.13

Results when 5 northernmost counties are excluded and with individual fixed effects.

	Dependent variable:												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Los Angeles*Post-treatment	9.508	8.773***	5.428***	6.812***	5.410***	6.245***	4.348***	6.073***	6.077***	5.896***	5.805***	5.827***	6.003***
		(0.147)	(0.019)	(0.170)	(0.034)	(0.128)	(0.157)	(0.249)	(0.246)	(0.375)	(0.438)	(0.414)	(0.299)
Percentage of urban population		0.015*			0.004	0.012	−0.003	0.016	0.016	0.017	0.016	0.028	0.022
		(0.009)			(0.005)	(0.009)	(0.009)	(0.014)	(0.014)	(0.014)	(0.014)	(0.021)	(0.018)
Value of land and buildings per capita			−0.0001*		−0.0001*		−0.00004						
			(0.0001)		(0.0001)		(0.0001)						
Wages paid per person employed				0.0004				0.0001	0.0001	0.0003	0.0002	0.0004	0.0001
				(0.0002)				(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
Number of farms per capita									−1.202				
									(3.199)				
Persons employed per capita				−2.944*			−11.220	−5.304*	−5.482	−5.799*	−5.396*	−5.930	−6.276
				(1.566)			(9.288)	(3.132)	(3.369)	(3.341)	(3.025)	(3.556)	(3.780)
Value of farm property per capita						−0.0001		−0.00005		−0.0001	0.00004	−0.0001	−0.0001
						(0.00004)		(0.00004)		(0.00004)	(0.0001)	(0.0001)	(0.0001)
Number of farms under 10 acres per capita										−36.874			
										(34.644)			
Number of farms between 10-49 acres per capita											−17.551		
											(14.764)		
Number of farms between 100-999 acres per capita												18.387	
												(13.419)	
Number of farms more than 1000 acres per capita													61.491
													(49.149)
Observations	154	132	88	110	88	110	66	88	88	88	88	88	88
R^2	0.614	0.593	0.550	0.612	0.551	0.590	0.532	0.597	0.596	0.608	0.611	0.618	0.605
Adjusted R^2	0.549	0.506	0.388	0.503	0.380	0.474	0.240	0.425	0.424	0.431	0.436	0.447	0.427
F Statistic	208.221*** (df = 1; 131)	78.676*** (df = 2; 108)	39.093*** (df = 2; 64)	44.750*** (df = 3; 85)	25.792*** (df = 3; 63)	40.807*** (df = 3; 85)	11.369*** (df = 4; 40)	18.064*** (df = 5; 61)	17.995*** (df = 5; 61)	15.505*** (df = 6; 60)	15.732*** (df = 6; 60)	16.211*** (df = 6; 60)	15.304*** (df = 6; 60)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.14

Results with lagged variables and twoways fixed effects.

	Dependent variable:												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Los Angeles∗Post-treatment	9.116***	8.646***	6.833***	9.538***	6.779***	8.673***		10.567***	10.531***	10.470***	10.312***	10.450***	8.584***
	(0.172)	(0.174)	(0.211)	(0.184)	(0.240)	(0.196)		(0.322)	(0.294)	(0.354)	(0.440)	(0.344)	(0.268)
Lagged percentage of urban Population		0.0003			−0.013	0.002	−0.019	0.0003	−0.0005	−0.0001	−0.001	0.004	0.002
		(0.010)			(0.012)	(0.012)	(0.022)	(0.007)	(0.009)	(0.007)	(0.007)	(0.011)	
Lagged Value of land and buildings per capita			0.0001		0.00004		−0.0001						
			(0.0004)		(0.0005)		(0.001)						
Lagged Wages paid per person employed)				0.0002				0.0002	0.0003	0.0001	0.0001	0.0002	0.0003
				(0.001)				(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lagged Persons employed per capita				−0.232			−13.985	−1.273	−1.808	−1.275	−0.989	−0.934	0.259
				(1.480)			(23.152)	(2.654)	(2.571)	(2.682)	(2.802)	(2.929)	(3.513)
Lagged Value of farm property per capita						0.0001		0.0001		0.0001	0.0002	0.0001	0.0001
						(0.0004)		(0.0004)		(0.0004)	(0.0004)	(0.0004)	(0.0004)
Lagged Number of farms per capita									0.282				
									(6.816)				
Lagged Number of farms under 10 acres per capita										−19.224			
										(39.638)			
Lagged Number of farms between 10-49 acres per capita											−10.366		
											(10.593)		
Lagged Number of farms between 100-999 acres per capita												7.455	
												(10.290)	
Lagged Number of farms more than 1000 acres per capita													19.584
													(27.260)
Observations	189	135	108	135	108	135	81	108	108	108	108	108	108
R^2	0.436	0.346	0.187	0.399	0.190	0.347	0.019	0.350	0.349	0.351	0.352	0.352	0.271
Adjusted R^2	0.316	0.141	−0.144	0.202	−0.156	0.134	−0.602	0.048	0.046	0.036	0.037	0.037	−0.084
F Statistic	120.047*** (df = 1; 155)	27.036*** (df = 2; 102)	8.759*** (df = 2; 76)	22.322*** (df = 3; 101)	5.866*** (df = 3; 75)	17.926*** (df = 3; 101)	0.316 (df = 3; 49)	7.873*** (df = 5; 73)	7.843*** (df = 5; 73)	6.496*** (df = 6; 72)	6.517*** (df = 6; 72)	6.511*** (df = 6; 72)	4.458*** (df = 6; 72)

Note: *p<0.1; **p<0.05; ***p<0.01

Table 3.15

Results with lagged variables and individual fixed effects.

	Dependent variable:												
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)
Los Angeles∗Post-treatment	9.508***	8.740***	7.086***	9.572***	7.065***	8.703***		10.357***	10.208***	10.340***	10.299***	10.408***	8.404***
	(0.172)	(0.174)	(0.033)	(0.184)	(0.045)	(0.188)		(0.275)	(0.320)	(0.328)	(0.381)	(0.335)	(0.259)
Lagged percentage of urban population		0.016			0.003	0.014	−0.026	0.002	−0.002	0.002	0.002	0.0002	0.003
		(0.010)			(0.005)	(0.009)	(0.024)	(0.008)	(0.009)	(0.008)	(0.008)	(0.012)	
Lagged value of land and buildings per capita			−0.0004*		−0.0004		−0.0004**						
			(0.0002)		(0.0002)		(0.0002)						
Lagged Wages paid per person employed				0.001				0.001*	0.001*	0.001*	0.001*	0.001*	0.001*
				(0.001)				(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)	(0.0003)
Lagged Persons employed per capita				−4.077***			−19.365	−5.547	−6.155	−5.596	−5.562	−5.453	−6.288
				(1.480)			(18.712)	(4.014)	(4.208)	(3.947)	(4.001)	(3.868)	(5.378)
Lagged value of farm property per capita						−0.0002		−0.0003*		−0.0003*	−0.0003	−0.0003*	−0.0002*
						(0.0001)		(0.0002)		(0.0002)	(0.0002)	(0.0001)	(0.0001)
Lagged number of farms per capita									−11.489*				
									(6.077)				
Lagged number of farms under 10 acres per capita										−3.106			
										(34.641)			
Lagged number of farms 10-49 acres per capita											−2.278		
											(8.707)		
Lagged number of farms 100-999 acres per capita												−2.641	
												(8.294)	
Lagged number of farms more than 1000 acres per capita													12.720
													(23.262)
Observations	189	135	108	135	108	135	81	108	108	108	108	108	108
R^2	0.443	0.364	0.209	0.423	0.209	0.377	0.085	0.393	0.385	0.393	0.393	0.393	0.316
Adjusted R^2	0.349	0.196	−0.072	0.263	−0.085	0.204	−0.436	0.145	0.134	0.134	0.134	0.134	0.024
F Statistic	127.959*** (df = 1; 161)	30.373*** (df = 2; 106)	10.425*** (df = 2; 79)	25.610*** (df = 3; 105)	6.873*** (df = 3; 78)	21.138*** (df = 3; 105)	1.570 (df = 3; 51)	9.827*** (df = 5; 76)	9.497*** (df = 5; 76)	8.082*** (df = 6; 75)	8.084*** (df = 6; 75)	8.088*** (df = 6; 75)	5.779*** (df = 6; 75)

Note: *p<0.1; **p<0.05; ***p<0.01

CHAPTER 4

NASH BARGAINING MODEL FOR FAIR WATER ALLOCATION: ENSURING OVERALL GAINS

4.1 Introduction

Early evidence of a water transfer from one region to another was found when Los Angeles transferred water through pipelines from the Owens Valley in California. Los Angeles sought after water from Owens lake, amongst other sources owing to its population growth in the 1920s. Such a transfer was possible only through buying the land since the water rights were tied to land ownership. When the farmers became aware of their intentions, they alleged that Los Angeles officials had *stolen* their water. Further, the farmers' appeal to the press about the inequities left lasting perceptions of injustice in the water transfer (Libecap, 2008).

Water markets and water trade emerged as informal contracting where the owner with some form of water right could authorize the other party to access the same. In the past 20 years, water markets have developed in countries like Chile, Mexico, the US, and Australia (Libecap, 2008). Grafton et al. (2011) make a comparison of water markets in the US West and Australia. They suggested that policy attention must focus on promoting water trade while simultaneously mitigating the legitimate third-party concerns about how and where water is used, especially the conflicts between consumptive and in-situ uses of water. In Australia, surface statutory water rights in the Murray-Darling basin are defined in terms of divisions per irrigation season which are separate from the land rights. The water markets provided the highest benefit to the irrigators in this area when trade allowed high-value irrigation users to continue irrigating because of the transfers from broad-acre agriculture (Grafton et al., 2011).

There are a few researchers who are not in favor of water markets (Chong and Sunding, 2006). Chong and Sunding (2006) mention four debates central to water transfer and water trading. The first, water transfer means reallocation from agriculture-to-urban uses; the second, transfers result in large economic losses for the areas of origin, the third, inter-basin trade should be prohibited because of large hydrologic effects, and the last, water is a public good and should not be subject to market forces. However, Barbier and Chaudhary (2013) model water and growth in the agricultural economy showing that a decline in water availability would not affect agricultural output or welfare unless they belong to water constrained" or are pushed to a "water-constrained " economy; water-constrained economy being the one where water in the economy is limited to fulfilling the needs. Hence, water allocation calls for a thorough scientific investigation ensuring that regions or the economies involved receive a net benefit.

This essay seeks to compute the welfare impacts of water sharing between two regions. Using game theory and general equilibrium analysis, we derive the welfare impacts of water sharing between the Cache county and Wasatch Front in the north-central part of Utah. The Bear River Development Project proposed by the Utah Division of Water Resources has been entrusted with the development of the surface waters of Bear River and its tributaries. Under the BRDP, the Divison of Water Resources is expected to develop water resources to distribute them to the Wasatch Front and Cache county. Our results show that Wasatch

Front and Cache Valley would be willing to pay for the water-sharing agreement if the costs are shared equally amongst the counties involved.

The main contribution of the study is a straightforward application of the Nash Bargaining Solution to the general equilibrium and a comparison of the welfare measures to the costs provided by the Bear River Development Project. From the policy perspective, the essay seeks to propose a strategy to ensure that both the counties involved in sharing the Bear river water derive the same or greater welfare as it was before such an arrangement. Using a benefit-cost analysis, the question we seek to answer is: whether the involved regions' willingness to pay for the water-sharing agreement covers the costs of the Bear River Development Project.

The remainder of the essay is outlined as follows. In the next section, we briefly describe the Nash Bargaining model and its application in water economics. The third section outlines our conceptual model. We then describe our data and calibration methodology, followed by simulation results. The final section discusses our main findings, the implication for policy, and further research.

4.2 Background

Various models have been applied for water resources allocation like simulation methods, optimization methods, game theory, etc. However, game theory has been dominantly used for studying water resource allocation. This is because the allocation of resources has more than two concerned agents, who either simultaneously or sequentially make the decisions regarding the quantity of water they want to use and the purposes of water use.

Hence, game theory serves as an important tool to study water allocation. Different researchers have classified these studies in different ways. Madani (2010) divided game theory into five parts, i.e., water or benefit allocation among water users, groundwater management, transboundary water allocation, water quality management, and other types of resource management. Dinar et al. (2015) divided the application of game theory in the conflict of water resources allocation into three aspects: (1) the application of non-cooperative negotiation theory in water resources allocation (2) the application of graph model in water resources allocation conflict (3) application of Nash-Harsanyi bargaining theory to water resources allocation problem. Leader-follower models, Bankruptcy models, and the Nash–Harsanyi model, which is an extension of the Nash Bargaining model, are few other modeling techniques used by researchers to study water allocation.

Han et al. (2018) use a multi-agent model with hydrological constraints to resolve a water conflict in the HanJiang river basin. They developed a bilevel optimization model of common interest and a multi-agent cooperative GT-based optimization model. The paper suggested that the policymakers realize the needs and acceptable values of agents and adjust the same according to their feedback.

The branch of game theory that deals with situations related to negotiations for sharing goods is called bargaining theory. The main issue that the players face is setting up an agreement that dictates the terms of cooperation. The main focus of bargaining theories is on the efficiency and distribution of bargaining properties (Muthoo, 2001). The literature has typically relied on two main bargaining theories: Nash's axiomatic bargaining solution and Rubinstein's solution to the infinite-horizon bargaining with the alternating offers (Yildiz, 2011). In the given study, we use the Nash bargaining model to find a cooperative solution to water sharing between two regions.

The Nash bargaining model

Nash (1953) presented a bargaining theory with a strong foundation in economics. It is an n-player game used to model bargaining interactions. He assumed that there are n decision-makers. Osborne and Rubinstein (1990) and Nash (1953) have discussed the properties of the Nash Bargaining model as explained below. Let X be the decision space and f_i: $X \to R$ be the objective function of decision-maker i.

The model also assumes that when decision-makers cannot reach an agreement, they will get low objective values. Nash denotes this value with d_i for each decision-maker i and assumes $d = (d_1, d_2 \ldots d_n)$ (Osborne and Rubinstein, 1990; Nash 1953).

Osborne and Rubinstein(1990) mention that the Nash bargaining solution f* can be obtained as a unique solution to the problem :

$$\max_{f_1,\ldots,f_n} (f_1 - d_1)(f_2 - d_2)\ldots.(f_n - d_n)$$

$$\text{s.t.} \quad x$$

$$f_i \geq d_i, i = 1, 2, \ldots., n$$

Hence, the stakeholders make their decisions collectively by solving the maximization problem stated above (Nash 1953; Osborne and Rubinstein, 1990). In addition to this, the Nash bargaining model satisfies some desirable axioms like efficiency, symmetry, scale covariance, and independence of irrelevant alternatives (Clippel, 2007).

The Nash bargaining solution gives us a unique way to allocate water more efficiently and equitably. When there are two regions under purview, both would have a comparative advantage over one another in a particular sector where one might need more water than the other. In turn, it can benefit the other region by providing the resources that it might require. As a result, both end up benefiting from the trade and reaching a Pareto optimal solution. A constraint of the Nash Bargaining solution ensures that the benefit derived from bargaining is never less than that under non-cooperation. Harsanyi (1958) presents an extension to the Nash Bargaining model where the author extended the two-person Nash bargaining solution to the n-person Nash Harsanyi model. There are studies where a model for trading between more than one region or agent is possible. This model is useful when water is shared and allocated for more than one agent.

4.3 Model Specification: The algebra of water sharing

This section consists of the Nash Bargaining model that we seek to build in the study along with an autarky model.

The current study includes two regions: Cache Valley and Wasatch Front (denoted as CA and WF). We assume that the economy consumes two goods: the agricultural good and the composite good, i.e., A_i^D and C_i^D respectively, where i= CA, WF. Let x_{ji} and k_{ji} be the two inputs for production, i.e., water and composite input [1] where, j is the sector for which the input is used and, i is the region in which it is used. All the models are expressed as constrained maximization problems. Both the economies aim at maximizing their utility while minimizing the costs of production simultaneously. It is assumed that there is a unit price in the composite sector and, the relative price in the agriculture sector is denoted by P_{Ai}. Factor mobility is assumed in all the models.

I. The Autarkic model

[1] In theory, composite input includes land, capital and labor. However, in the numerical simulation, we include only labor and capital due to data constraints.

We start building what we call an "Autarky Model" where no water sharing is assumed. These regions have a limited supply of water. We consider a small, closed economy with a Cobb-Douglas utility function since it is the most common function used in the general equilibrium studies (Gilbert and Tower, 2012) subject to a budget constraint[2]:

$$\max_{A_i^D, C_i^D} V_i(A_i^D, C_i^D) = \delta_i A_i^{D^{(\alpha_i)}} C_i^{D^{(1-\alpha_i)}} \tag{4.1}$$

$$\text{s.t.} \quad W_i = C_i^D + P_{Ai} A_i^D, i = 1,2 \tag{4.2}$$

where $V_i(A_i^D, C_i^D)$ represents the utility obtained by region i after consuming the two goods, W_i is the income (Regional Gross Domestic Product) of the region, α_i is the cobb-douglas parameter and δ_i which is the parameter for residual change in the demand not affected by the preference of goods.

We can derive optimal demands for agricultural and composite goods as follows:

$$(A_i^D)^* = \alpha_i W_i / P_{Ai} \tag{4.3}$$

$$(C_i^D)^* = (1 - \alpha_i) W_i \tag{4.4}$$

The firms in region i= CA, WF choose to minimize the costs of inputs, $r_x x_{Ai} + r_k k_{Ai}$ subject to a cobb-douglas production function, $A_i^S = \gamma_i x_{Ai}^{\beta_{Ai}} k_{Ai}^{(1-\beta_{Ai})}$ for the agriculture sector and $C_i^S = \theta_i x_{Ci}^{\beta_{Ci}} k_{Ci}^{(1-\beta_{Ci})}$. r_x and r_k are respectively input prices for water and composite input. θ_i is and γ_i are the parameters for technical change; and β_{ji} is the cobb-douglas parameter. The reason for choosing a cobb-douglas function remains the same- being one of the most widely used production functions in economics given the fact that it adheres to

[2]The First-Order Conditions are shown in Appendix 4.8.1

most of the assumption made in the producer theory of economics.

Hence, we can obtain the factor demands for water and capital as follows:

$$x_{Ai}^{*} = A_i^S/\gamma_i[(r_k/r_x)(\beta_{Ai}/(1-\beta_{Ai}))]^{(1-\beta_{Ai})} \tag{4.5}$$

for water and,

$$k_{Ai}^{*} = A_i^S/\gamma_i[(r_x/r_k)((1-\beta_{Ai})/\beta_{Ai}]^{\beta_{Ai}} \tag{4.6}$$

for composite input.

Positive production is assumed in both regions. Accordingly, there are three sets of equilibrium conditions: the zero profit condition, the market-clearing conditions, and the constraints on the two inputs, i.e., composite input and water. K_i is the composite input available in a region for both agricultural and composite purposes. W_i is the water available in a region for both agricultural and composite sectors. The market-clearing conditions portray that the aggregate demand is equal to aggregate supply in the economy. The equations are shown as below:

The zero-profit condition

$$P_{Ai} = (r_x x_{Ai}^{*} + r_l l_{Ai}^{*})/A_i^S \tag{4.7}$$

The constraint on composite input and water

$$K_i = k_{Ai}^{*} + k_{Ci}^{*} \tag{4.8}$$

$$X_i = x^*_{Ai} + x^*_{Ci} \tag{4.9}$$

Market Clearing Condition

$$A_i^D = A_i^S \tag{4.10}$$

$$C_i^D = C_i^S \tag{4.11}$$

Solving these equations would give the optimal values of the demands in the agricultural and composite sector, the optimal values of inputs used in the agricultural and composite sectors, the optimal values of the prices of the water and composite input values used, and the optimal value of the price of agriculture in each region. However, these are the values for each region when there is no co-operation. The data that we use to arrive at these values and the simulation procedure would be explained in the next section.

II. The Proposed Nash Bargaining model

Essentially, the purpose of the autarky model is to derive the values of $\bar{V}_i$ which gives the utility when there is no agreement for water sharing. Such a value is required to compute a disagreement point, i.e., the utility value which is lower than the one achieved in the non-cooperation scenario. Hence, the intuition for the Nash Bargaining model is fairly simple, water sharing would be possible if and only if the utility derived by both the regions, i.e., V_i is greater than $\bar{V}_i$. Hence, the Nash Bargaining solution which would be the objective function for this model comes out to be as follows:

$$\max_{A_1^D, A_2^D, C_1^D, C_2^D} = (\delta_1 A_1^{D^{(\alpha_1)}} C_1^{D^{(1-\alpha_1)}} - \bar{V}_1)(\delta_2 A_2^{D^{(\alpha_2)}} C_2^{D^{(1-\alpha_2)}} - \bar{V}_2) \tag{4.12}$$

$$\text{s.t.} \quad W_1 = C_1^D + P_{A1}A_1^D \tag{4.13}$$

$$W_2 = C_2^D + P_{A2}A_2^D \tag{4.14}$$

The production sector and the equilibrium conditions remain the same apart from the constraint for water. To allow water sharing between the two regions, we combine the water constraint from both the regions in the following way,

$$R_1X_1 + R_2X_2 = x_{a1} + x_{a2} + x_{c1} + x_{c2} \tag{4.15}$$

where R_i is the rate of increase in the quantity of water in region i.

We compute the value of water transfer using the equation below.

$$wvalue_i = (1+t_i)(r_{Xi}(R_iX_i - (x_{Ai} + x_{Ci}))) \tag{4.16}$$

where $wvalue_i$ is the value of the water transfer in region i and t_i is the tax on the water-sharing agreement. The term $R_iX_i - (x_{Ai} + x_{Ci})$ represents the amount of water that is transferred from/to each region and the equation shows the value of water transferred. Hence, the value of water transfer is simply the value of water post the water-sharing agreement that is available after use for each region including any tax/subsidy that is imposed on the agreement.

We incorporate *the value of water transfer* in the income equation. The "income" of the *water-exporting region* is reduced since it gives up the value of water that is transferred to the other region. Hence, the income equation is given below:

$$W_i = C_i^D + P_AA_i^D - (1+t_i)(r_{Xi}(r_iX_i - (x_{Ai} + x_{Ci}))) \tag{4.17}$$

Additionally, we now allow trade in the agricultural sector between the two regions to capture *embodied water*. Embodied water is another way to trade water between the two regions. Hence, the market-clearing condition which equated region 1's agricultural demand to region 1's agricultural supply (refer to equation 4.10) changes to equating aggregate agricultural demand to aggregate agricultural supply in both regions as shown below:

$$A_1^D + A_2^D = A_1^S + A_2^S \tag{4.18}$$

with the same price P_A in both the economies.

Finally, we compute the Compensating Variation using the equation $CV = W' - W$ where W' is the wealth under Nash Bargaining solution and W is income in autarky. We replace W using the utility equation and the optimal levels of A_i^D and C_i^D, which is $V_i^o = W_i((\alpha_i/P_A)^{\alpha_i})(1-\alpha_i)^{1-\alpha_i}$

$$CV_i = W_i - (((P_A^{\alpha_1})v_o{}^i)/(\delta_i(\alpha_i^{\alpha_i})(1-\alpha_i)^{(1-\alpha_i)})) \tag{4.19}$$

where CV_i is the Compensating Variation for region i.

4.4 Calibration and Simulation results

Data for Calibration

The main variables used for simulating the Nash Bargaining model from the previous section are as follows: Agricultural production, Composite sector production, Gross Domestic Product values, Population, and capital used in agricultural and composite sector, respectively. Table 4.1 describes the sources for the data. We obtained these variables from the IMPLAN dataset. In this study, we aggregated the 500 sectors in the IMPLAN dataset into agricultural and composite sectors.

Table 4.1

Data Sources

Variable Name	Source
Production	IMPLAN
Water	
Consumption	United States Geological Survey (USGS)
Prices	Edwards et al. (2017)
Capital	IMPLAN
GDP	IMPLAN

We obtained the data for water use from a United States Geological Survey report (USGS, 2017) in a million gallons per day and the data for water prices from Edwards et al. (2017). We converted the data to acre-foot per day from million gallons per day. We further computed the dollar value of water to maintain consistency with our other variables.

Calibrating the model

The autarky model constructed in the specification section performs an additional role. It helps us to retrieve the values of the unobserved parameters in the real-time data for calibration. Kynland and Prescott (1982) were the pioneers for calibrating theoretical models in economics. They first applied this methodology to the real business cycles (Kynland and Prescott, 1982).

Hence, we start with compiling the data to create what is called a *Social Accounting*

Matrix (SAM), which is conceptually an extension of the input-output table. Input-output tables describe the flows of the value of goods and services between all the individual sectors of the national economy over a certain time period (Martana et al., 2012). These tables are extended to a SAM by including the relationships between production factors and final demands, showing the amount of income distributed to households and government as well as transferred abroad and invested (Martana et al., 2012). Therefore, a social accounting matrix is a system of representing the transactions involving the movement of goods and factors of production; and the corresponding flows of payments. Since every payment by an agent in the economic system represents a receipt to some other agent in the system, the rows and columns of a social accounting matrix must be balanced.

Below is the Social accounting matrix derived by the data that was collected from various sources as mentioned above:

Table 4.2

Unbalanced Social Accounting Matrix for cache Valley

CACHE COUNTY

	AGRICULTURAL GOOD	COMPOSITE GOOD	WATER	COMPOSITE INPUT	HOUSEHOLD	TOTAL
AGRICULTURAL GOOD					47475653.57	47475653.57
COMPOSITE GOOD					4871939330	4871939330
WATER	11012.746	3384.757				14361.503
COMPOSITE INPUT	191692.5511	3128751				3320443.551
HOUSEHOLD			14631.5	3320443.9		3335075.4
TOTAL	202705.2971	3132099.757	14631.5	3320443.9	4919414984	

Table 4.3

Unbalanced Social Accounting Matrix for Wasatch Front

WASATCH FRONT

	AGRICULTURAL GOOD	COMPOSITE GOOD	WATER	COMPOSITE INPUT	HOUSEHOLD	TOTAL
AGRICULTURAL GOOD					38184801.25	38184801.25
COMPOSITE GOOD					28173176520	28173176520
WATER	12561.26	12161.19				24722.45
COMPOSITE INPUT	124980.7	18604452				18729432.7
HOUSEHOLD			24722.45	18729432		18754154.45
TOTAL	137541.96	18616613	24722.45	18729432	28211361321	28248869631

From the two tables, we observe that the Social Accounting Matrix is not balanced, which is common in literature since the data is obtained from different sources or statistical discrepancies. It could also be because variations in the data availability make it necessary to combine the data from different periods (Goulder and Hafstead, 2013; Gilbert and Tower, 2012). We incorporate water use data from 2015 and the rest of the data from 2017 in our dataset.

RAS procedure for balancing the Social Accounting Matrix

We employ the RAS procedure for balancing the social accounting matrices of the regions involved. In this method, we scale the row and column entries to reach the target row and column sums using the GAMS software[3] (Gilbert and Tower, 2012). Following social accounting matrices are obtained once we use the RAS procedure:

Table 4.4

Balanced Social Accounting Matrix for Cache County

CACHE COUNTY

	AGRICULTURAL GOOD	COMPOSITE GOOD	WATER	COMPOSITE INPUT	HOUSEHOLD	TOTAL
AGRICULTURAL GOOD					47475650	47475650
COMPOSITE GOOD					4871939000	4871939000
WATER	6592720	14592980				21185700
COMPOSITE INPUT	40882930	4857346000				4898228930
HLD			21185700	4898228950		4919414650
TOTAL	47475650	4871938980	21185700	4898228950	4919414650	

Table 4.5

Balanced Social Accounting Matrix for Wasatch Front

WASATCH FRONT

	AGRICULTURAL GOOD	COMPOSITE GOOD	WATER	COMPOSITE INPUT	HOUSEHOLD	TOTAL
AGRICULTURAL GOOD					38184798.97	38184798.97
COMPOSITE GOOD					28173172820	28173172820
WATER	5617878.968	31572820				37190698.97
COMPOSITE INPUT	32566920	28141600000				28174166920
HOUSEHOLD			37190698.97	28174166920		28211357619
TOTAL	38184798.97	28173172820	37190698.97	28174166920	28211357619	

[3]We use a for-loop command in GAMS-IDE version 24.7.4 for balancing the social accounting matrix

We can observe from the tables that our Social Accounting Matrices balance.

The given study consists of five parameters for the Nash bargaining model, i.e., β_{ji}: the parameter on cobb-douglas production functions, α_i: the parameter on cobb-douglas utility function, θ_i: the parameter for technical change in the composite production function, γ_i: the parameter for technical change in the agricultural production function and δ_i which is the parameter for residual change in demand not affected by the preference of goods.

We can use the consumption, production, input use, and endowment values to compute the parameter values from the autarky model using equations 4.1-4.11. Finally, we can input the calculated parameter values in the equations for the Nash Bargaining model to observe the changes in the economy when there is a water agreement. Hence, the objective of the calibration exercise is achieved by balancing the Social accounting matrices for both the regions and computing the parameter values.

Simulation Results

We enter the calibrated values of the parameters in the Nash Bargaining model to derive the simulated variables. We start discussing the results with the Nash Bargaining model with a 10% increase in the water quantity in Cache Valley and a 1% increase in the Wasatch Front. The quantities are increased following the Bear River Development Project, which aims at developing the surface water resources of the Bear River and its tributaries. Since the values for water use, aggregate supply, aggregate demand, etc., are in dollars, we normalize all the prices to be 1.

Table 4.6

Nash bargaining results when water quantity increase by 10% in Cache Valley and 1% in Wasatch Front

Wasatch Front results	Autarky (in $)	Nash Bargaining (in $)	Percentage change
Agricultural demand	38235.39	38580.84	3.45
Composite Demand	28173149.41	28173192.07	0.43
Water use in agriculture	5624.35	6072.86	4.49
Water use in composite sector	31566.35	32853.71	12.87
Utility for Wasatch Front	2792216.46	2792254.72	0.38
Income	28211386.97	28212735.35	13.48
Value of water transfer		-1306.66	
Compensating Variation per capita		3.534	
Cache Valley results	Autarky (in $)	Nash Bargaining (in $)	Percentage change
Agricultural demand	47919.33	48385.89	4.67
Composite Demand	4871496	4873091.48	15.95
Water use in agriculture	6608.36	6732.19	1.24
Water use in composite sector	14630.21	15266.28	6.36
Utility for Cache Valley	2328484	2329459	9.75
Income	4919434	4919739	3.05
Value of water transfer		1306.66	
Compensating Variation per capita		6.075	

The table shows the results for the Wasatch Front and Cache Valley from the Autarky and Nash Bargaining Models. We consider the case when the increase in surface water resources in Cache Valley is 10% and in Wasatch Front is 1%. The main observation from the table is an increase in all the variables in both economies. This seems to be obvious, given the increase in water resources in both the economies under the Bear River Development Project. Hence, we include a percentage change in all variables from Autarky to Nash Bargaining in the last column to observe the impacts of the project and the Nash bargaining agreement on the two regions.

Although water-use increases in both the economies, the increase in composite sector water-use of Wasatch Front is higher as compared to the region's agricultural sector as well as water use in Cache Valley. This result seems reasonable because the additional water from new local water resources and water transferred from Cache Valley might be diverted to urban development in Wasatch Front. Hence, additional resources would be utilized towards the sectors apart from agriculture. High percentage changes in water use are not observed in Cache Valley; however, there is a high percentage change in demand for composite goods. This indicates that the benefit received by the Cache Valley from the water sharing agreement is translated into the growth of the composite sector in the county.

Further, we observe a positive value of water transfer in Cache Valley, which indicates that it is the water exporting region and a negative value of water transfer in Wasatch Front showing that it is the water importing region. High growth in income (Gross Domestic Product) is noticed in the Wasatch Front region. The main reason for such high growth is the additional value added by the water import from Cache Valley. The percentage increase in the utility of Cache Valley is observed to be relatively higher, perhaps, from the growth in the composite sector.

Finally, we observe a positive compensating variation per capita in both the regions with higher compensating variation per capita in Wasatch Front. This result indicates that the water-importing region has a higher willingness to pay for the water-sharing agreement. In conclusion, both the economies, i.e., Cache County and Wasatch Front, obviously seem to be doing better with a water-sharing agreement and additional water resources built under the Bear River Development Project.

4.5 Sensitivity Analysis

Table 4.7 shows the percentage changes in variables with an increase in the percentage of water quantity. In this section, we will present a brief cost-benefit analysis to ascertain the feasibility of the Bear River Development Project.

Table 4.7

Results from Nash Bargaining Model

Cache Valley	r1=0.2 (in %)	r1=0.3 (in %)	r1=0.4(in %)	r1=0.5 (in %)	r=0.6 (in %)	r=0.7 (in %)	r=0.8
Agricultural demand	9.02	13.17	17.10	20.86	24.46	27.90	31.20
Composite demand	31.04	45.04	59.04	71.22	83.04	94.60	105.51
Water use in agriculture	2.30	3.36	4.42	5.47	6.52	7.57	8.61
Water use in composite sector	12.46	18.56	24.66	30.77	36.86	42.97	49.07
Utility for Cache Valley	19.16	27.16	36.16	43.40	51.16	57.67	64.29
Wealth	5.66	8.66	11.66	14.76	17.66	20.87	23.92
Value of water transfer	25.4507	36.8558	47.3954	57.166	66.25	74.7186	82.633
Compensating Variation per capita	11.67119	17.1479	22.50223	27.73349	32.84254	37.83129	42.70223
Wasatch Front	r1=0.2 (in %)	r1=0.3 (in %)	r1=0.4(in %)	r1=0.5 (in %)	r=0.6 (in %)	r=0.7 (in %)	r=0.8 (in %)
Agricultural demand	6.81	10.00	13.03	15.92	18.69	21.34	23.88
Composite Demand	2.7	4	5.6	7.5	10	12.05	14.62
Water use in agriculture	9.09	13.69	18.29	22.89	27.49	32.08	36.67
Water use in composite sector	26.06	39.25	52.45	65.66	78.87	92.09	105.31
Utility for Wasatch Front	0.83	0.83	1.83	2.14	2.83	3.10	3.59
Wealth	26.1303	36.1303	56.1303	63.1714	76.1303	85.2785	95.7685
Value of water transfer	-25.4508	-36.8558	-47.3954	-57.166	-66.25	-74.7186	-82.633
Compensating Variation per capita	6.98313	10.27459	13.42336	16.44217	19.3421	22.13275	24.82258

From the table, we observe that the trends with an increase in water quantity are consistent. In Cache Valley, the highest percentage changes are observed in demand for composite goods and utility (probably, driven by the composite sector growth). Apart from that, we observe that there is a considerable increase in composite sector water use at higher levels of percentage increase in water quantity.

In Wasatch Front, we observe that the highest changes are observed in composite sector water use and income. As mentioned in the previous section, the increase in income seems to be driven by the additional water received by the region. Also, the growth of the composite sector is not surprising since Wasatch Front is primarily an urban economy.

The main conclusion from the table is that new generating facilities and a water-sharing agreement would improve the economies for both regions; however, the social welfare estimates must be compared with the cost estimates to examine the feasibility of the project and the net social welfare.

The Project has proposed the following costs for each county. The costs are shown in the per-capita form.

Table 4.8

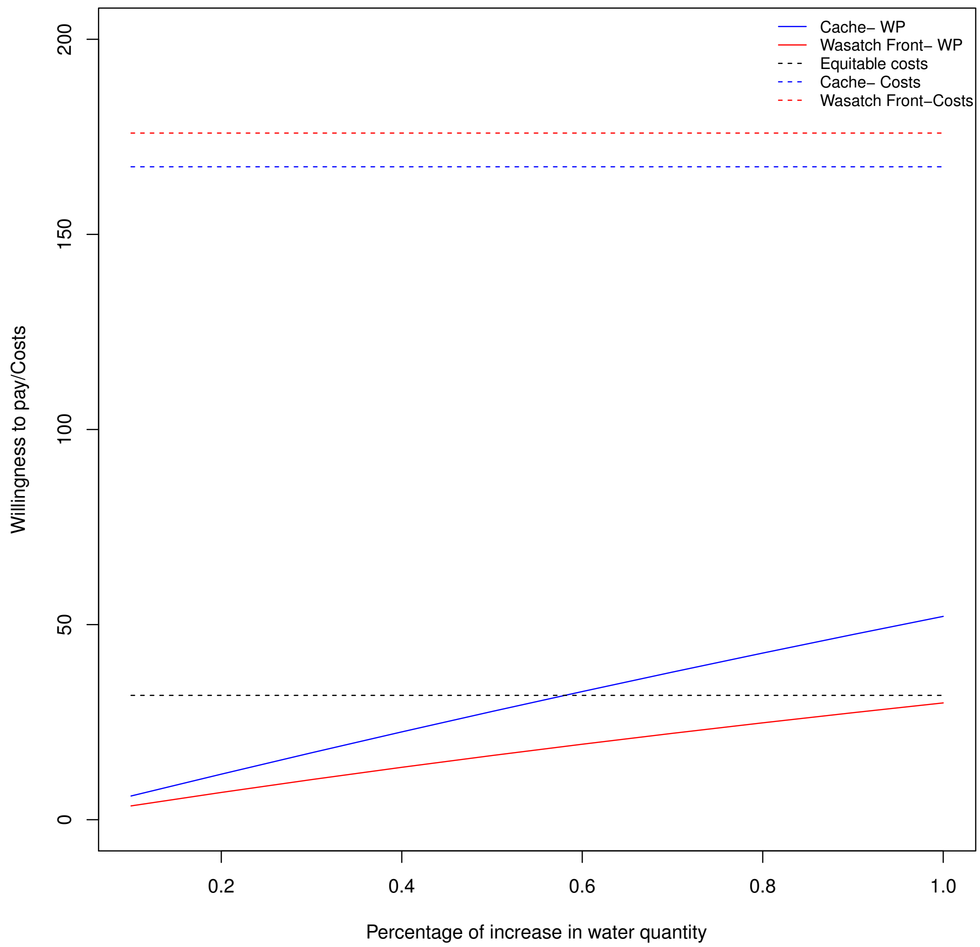
Costs proposed by the BRDP and suggested equal costs

Region	Per-capita costs
Cache county	167.3313
Wasatch Front	175.9689
Equally shared costs	31.861

A comparison between the per-capita willingness-to-pay and the costs proposed show that the influx of water has to be much higher even to reach a break-even point as shown in figure 4.1. However, we propose another way of sharing costs to ensure positive net benefits for each county. Instead of sharing different costs for different counties, the costs of the whole project could be shared by the counties involved equally.

Figure 4.1

Willingness to pay for the water sharing agreement. Costs retrieved from Utah Division of Water Resources (2019).



The bold lines in Figure 4.1 show the willingness-to-pay-per-capita and, the dotted lines show the costs per capita. We observe a high discrepancy between the blue and red bold and dotted lines. This discrepancy suggests that the costs proposed by the Bear River Development Project are much higher as compared to the willingness to pay for the development of the resources in the two regions. From the figure, we also observe that the willingness-to-pay for the water-sharing agreement is less flatter in Cache valley. This indicates that the willingness-to-pay is more sensitive in Cache Valley as compared with

Wasatch Front to an increase in the quantity of water. This might be because a higher increase in water quantity would indicate that there is excess water supply remaining after local water use in Cache Valley. Hence, the higher the increase in the water quantity, the higher is the willingness to pay for the water-sharing agreement. On the other hand, the willingness to pay for Wasatch Front is flatter. Since Wasatch Front is relatively water-scarce compared to Cache County, it is willing to pay for the water-sharing agreement even at lower levels of water quantity increase in the Cache County (even if it means a lesser amount of water transferred).

Hence, we propose an alternate cost-sharing scenario. Instead of attributing separate costs to each county, the total costs of the project could be shared equally among all the counties benefiting from the development of water resources. The black dotted line shows the costs per capita when they are shared equally among the counties involved. The relatively steeper willingness-to-pay of Cache county breaks even with the costs at around 60 percent increase in the water quantity. However, we observe that even with costs shared equally, a considerable amount of water increase in Cache county is required by Wasatch Front to arrive at a break-even point with the costs.

Another suggestion would be to use side payments to transfer the positive net benefits from one region to another where such benefits exist. Side payments in the model developed in this study would be in form of inducing taxes or other costs on the region where a positive net benefit is observed or offering a subsidy (reducing the costs) for the region with no net benefits. Side payments have been increasingly used in game theory for inducing the parties to take part in the agreement (Kimbrough and Sheremeta, 2012). They can play a major role in the Bear River Development Program, ensuring that both the regions, i.e., Cache County and Wasatch Front benefit from the development of new surface water resources as proposed by the project.

4.6 Discussions and Conclusions

We apply the Nash Bargaining Solution to a General Equilibrium model developed in the essay and compare the derived social welfare to the costs proposed by the Bear River Development Project. The Bear River Development Project seeks to develop water resources in Cache and Box Elder counties and pump some of the water from these resources to the counties in Wasatch Front. We use compensation variation/ willingness-to-pay as the measure for computing the social welfare of the involved counties. Our results show that there is an increase in welfare with a water-sharing agreement between the two counties. However, it is essential that the costs of the Bear River Development Project be shared equally or the region without any net benefit be supported by side payments so that the project leads to positive net social welfare for both regions. We compute the social welfare when water-sharing takes place, and compare it to the costs proposed in the project. We intend to ascertain the compensation ensuring that the benefits derived by the parties involves are higher than the costs incurred by them for the project.

This analysis attempts to inform the policy of alternative methods either in the cost-sharing, side payments, the development of resources, or a combination of the three strategies to ensure that all the parties involved benefit from the Bear River Development Project. Typically, implementation of such projects where water is pumped to another county leads to dissatisfaction among the residents of the water-supplying county since they believe that they do not benefit from sharing their resources. Hence, a scientific method could ensure efficiency and equity when such projects are executed. The study presented in this essay is an attempt to apply a popular bargaining approach to compute social welfare from a water-sharing agreement between two regions. We employ a general equilibrium setup and use numerical simulation, given the advantages of using limited data and being flexible to combine data from different years.

With water sharing and water trade becoming common trends in the present-day world, a thorough analysis of the welfare impacts of such projects is indispensable. In most parts of the world, such agreements take place based on negotiations by the concerned parties resulting in conflict at various levels (Rani and Rani, 2002; Fadel et al., 2003). Researchers from various backgrounds like hydrology, engineering, etc. have attempted to use decision and game theory to provide a scientific basis for agreements including water-sharing and water trade (Madani, 2010; Han et al., 2018). However, further developments and a wider application of these studies are required in economics (Madani, 2010).

The study applied one of the most popular approaches of game theory to a water allocation problem. However, it must be noted that our results apply in the absence of environmental costs. Utah might have observed an increase in winter precipitation; however, it does not lead to a long-term increase in the state's snowpack (Wang et al., 2012). With the current drought faced by the Western US, climate change becomes an important factor that needs to be considered for such water allocation. A national climate assessment report (Garfin et al., 2013) states that *"We can no longer rely on the past for making the future decisions*. It further claims that the long period of warm summers and prolonged droughts would further reduce the water availability and impact the surface water quality. Although, the larger water utilities have started adopting measures for adapting to climate change, examining both demand and supply-side solutions; such measures are yet to be undertaken by the smaller utilities.

Further, there are many different approaches within the game theory that could be applied to such issues. One of the drawbacks of the study is also the exclusion of transaction costs. This problem could be solved in the future by developing more complicated models where different game theory approaches are applied to general equilibrium type models including various costs.

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4.8 Appendix

4.8.1 The First-Order Conditions

The Demand System

$$\delta_i \alpha_i (A_i^{D(\alpha_i - 1)})(C_i^{D(1-\alpha_i)}) - \mu_i P_{Ai} = 0$$

$$\delta_i (1-\alpha_i)(C_i^{D(-\alpha_i)})(A_i^{D(\alpha_i)}) - \mu_i = 0$$

$$W_i - C_i^D - P_{Ai}A_i^D = 0$$

Production Sector

- Agricultural Sector

$$r_x - \lambda_{Ai}\gamma_i\beta_{Ai}(x_{Ai}^{(\beta_{Ai}-1)}l_{Ai}^{(1-\beta_{Ai})} = 0$$

$$r_l - \lambda_{Ai}\gamma_i(1-\beta_{Ai})x_{Ai}^{\beta_{Ai}}l_{Ai}^{-\beta_{Ai}} = 0$$

$$A_i^S - \gamma_i x_{Ai}^{(\beta_{Ai})}l_{Ai}^{(1-\beta_{Ai})} = 0$$

- Composite Sector

$$r_x - \lambda_{Ci}\theta_i\beta_{Ci}(x_{Ci}^{(\beta_{Ci}-1)}l_{Ci}^{(1-\beta_{Ci})} = 0$$

$$r_l - \lambda_{Ci}\theta_i(1-\beta_{Ci})x_{Ci}^{\beta_{Ci}}l_{Ci}^{-\beta_{Ci}} = 0$$

$$C_i^S - \theta_i x_{Ci}^{(\beta_{Ci})}l_{Ci}^{(1-\beta_{Ci})} = 0$$

CHAPTER 5

SUMMARY AND CONCLUSIONS

This dissertation contributes to a better understanding of the current literature by analyzing various aspects of water transfers and water-sharing using both the application of econometric and numerical simulation techniques to examine the impacts and the feasibility of such transfers.

The first essay analyzes the impacts of the water transfer on the economic growth and manufacturing sector of Los Angeles. Our findings show that the Gross Domestic Product per Capita and Manufacturing Product per capita are higher in the presence of the water transfer. In addition, we observe no impact on the Agricultural Product per Capita in Los Angeles. These results suggest that the increase in economic growth was higher in the presence of a water transfer. A key solution to the water allocation problems could be a careful examination of the impacts and cost-benefit analyses to ensure fairness, equity, and efficiency. The main contribution of the essay is an empirical analysis of a water transfer that began a century ago and has continued to the present day. We aim to provide critical evidence on the impacts of a water transfer which created an aversion towards future agricultural to urban or rural to urban water transfers.

The second essay extends the previous study by observing the impact of the transfer on urban sprawl. The negotiations related to water transfer have been based on lobbying by the government officials instead of research and careful examination of the facts. This study intends to emphasize the importance of the impact of resource allocation on urbanization in an economy. We use various difference-in-differences specifications and robustness checks based on subsets of the main dataset based on i)similarity to the treatment unit based on the percentage of urban population and ii) geographic location. We also include a model with lagged independent variables as a part of the robustness check. Our results show that the coefficient of our treatment effect is positive and significant throughout all models indicating that there was indeed a rise in the degree of urban sprawl as a result of the water transfer.

The third essay applies the Nash bargaining theory to a general equilibrium model computing the welfare impacts from sharing water between Cache County and Wasatch Front. We derive the compensating variation as a social welfare measure and compare it to the costs proposed under the Bear River Development Project. The project is seeking to develop additional water resources in Cache County and Box Elder County and divert a share of additional resources from both the counties to the Wasatch Front region. Our findings indicate that such a transfer would be beneficial only if the generating capacity of additional resources is much higher than the current water supply. As an alternative strategy, we suggest an equitable sharing of the total costs of the project. However, the implications of such a water development program on the worsening conditions of Utah Snowpack must be taken into consideration. The essay aims to make a contribution to the literature by applying a game-theoretic approach to a general equilibrium model and a cost-benefit type analysis for water allocation.

To conclude, water trade and water sharing are inevitable in the near future. Currently, such negotiations are based on persuasions and campaigns by government officials even after the existence of water markets in the Western US. A scientific method for water allocation is essential to avoid further water conflicts and wars in the future.

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Book Chapters

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