DAM REMOVALS: AN

AGRICULTURAL ANALYSIS

by

Nathan Alexander Bush

A thesis submitted in partial fulfillment
of the requirements for the degree

of

Master of Science

in

Applied Economics

MONTANA STATE UNIVERSITY
Bozeman, Montana

May 2024

ACKNOWLEDGEMENTS

I would like to thank my parents, John and Katie, for their unwavering love and support throughout my graduate school experience; my sister, Annie, for her lightheartedness and perspective whenever needed; the fellow members of my graduate cohort, for their passion and array of perspectives that consistently challenge my own; my advisor, Melissa Lopalo, for her patience and guidance during each stage of my research process; and all my friends throughout the Gallatin Valley, both new and old, for providing reprieve, laughter, and new experiences.

TABLE OF CONTENTS

LIST OF TABLES

Table Page

LIST OF FIGURES

Figure Page

ABSTRACT

Dam removals are occurring with increased frequency throughout the United States. 77% of all dam removal projects in U.S. history have occurred in the 21st century and the number of dams being removed each year is rising. Dams often play a key role in agricultural production, making it important for agricultural producers and policymakers to understand the effects of these removals as they become more common. This paper explores the causal effects of dam removal on agricultural productivity in the United States using a two-way fixed effects event study and an instrumental variable framework. Primary results of the analysis are mixed and differ based on exact specifications used but show initial evidence of per acre crop productivity increases and cash receipt declines following a removal. Further research is needed to explore the fine-scale effects of dam removals on individual agricultural producers and to expand on the preliminary causal relationships observed in this paper.

INTRODUCTION

There are an estimated 91,815 dams on rivers and streams throughout the continental United States which impede over 600,000 miles of free-flowing riverway (Federal Emergency Management Agency [FEMA], 2022). The average life expectancy of a dam, the number of years it can safely hold water without a significant risk of failure, is 50 years (United States Army Corps of Engineers [USACE], 2019). The average age of a dam in the United States is 61 years old, and by 2030, 80% of dams will be more than 50 years old (National Inventory of Dams, 2024). Aging dam infrastructure in conjunction with a growing body of literature illuminating the harmful ecological effects of dams (Foley et al., 2017; Chen et al., 2017, Tullos et al., 2016**)** has greatly increased public support for dam removal in the United States. More than 900 dams were removed in the last decade alone (United States Geographical Survey [USGS], 2023). As large-scale dam removals occur more frequently[1], the impacts of dam removal will be broadcast to wider audiences and likely catalyze the removal of smaller, more easily removable dams nationwide.

Environmental scientists and ecologists are rapidly reaching the consensus that dams have negative effects on the health of native ecosystems, migratory fish populations, and water quality **(**Cooper et al. 2017, Larinier 2001, Stanley and Doyle 2003**)**. Economists assessing the impact of several potential large dam removals determined that the enhanced agricultural output, hydroelectric power generation, and improved transportation infrastructure provided by the dams are outweighed by the removal benefits of improved ecological health, greater recreational

[1] The Elwa Dam Removal project, completed in 2014 was the largest dam removal project in history and will be eclipsed by the Klamath Dam Removal project in 2024.

opportunities, and substantial non-use values (ECONorthwest 2019, Loomis 1996). Additionally, as dams near the end of their reliable 50-year lifespan the likelihood of a failure increases exponentially, and dam owners are being forced to choose between renovation or removal.

The elimination of a dam triggers substantial alterations to the landscape surrounding a removal site, especially in terms of the volume and regularity of surface water (Dillon and Fishman, 2019). A fundamental understanding of these impacts is crucial not only for agricultural producers seeking to optimize their production, but also for policymakers tasked with making informed decisions regarding the design and implementation dam removal projects. Understanding the environmental and economic effects of dam removal is important for agricultural producers to better anticipate and adapt to future changes while ensuring the long run sustainable management of their natural capital and water resources.

This paper exploits variation in the timing and location of dam removal projects within the contiguous United States to estimate a causal relationship between dam removal and measures of agricultural productivity and economic output. I create a novel panel dataset using publicly available data and implement a two-way fixed effects events study framework and find generally non-precise, mixed results with some evidence that per-acre crop yields exhibit slight increases following a removal while cash receipts for crops decline. My paper is the first in the literature seeking to identify a causal relationship between dam removal and agriculture production. I follow methods laid out in previous studies which seek to estimate causal relationships between dam construction and various agricultural and economic factors (Duflo and Pande, 2007; Hansen et al., 2009).

BACKGROUND

Dams have been used to supplement agricultural production and regulate water supply for thousands of years and date as far back as ancient Mesopotamian society (Gabrielli, 2022). Today, dams are primarily used to provide irrigation, generate hydroelectric power, store municipal water supplies, control flooding, and provide recreational opportunity (Cybersecurity and Infrastructure Security Agency [CISA], 2021). While dams often provide these myriad benefits, they also incur potentially serious environmental ramifications (Foley et al., 2017). By inhibiting the traditional flow of water through its natural riverine system, dams disturb the original landscape within a watershed, which can affect wildlife populations, inhibit the passage of androgenous fish species to their traditional upstream spawning locations, and degrade upstream and downstream water quality (Bellmore, 2016).

Dam Removal History

Over the last 40 years, the removal of dams has begun to occur with increased frequency. Figure 1 shows the number of dam removal projects that have occurred throughout the US since 1980. Half of all dams in the US were built between 1950 and 1979 (CISA, 2021). As stated earlier, a vast majority of these dams have surpassed or are nearing the end of their traditionally reliable 50-year lifespan (USACE, 2019). At the time of this writing, a dam built in 1979 is now 45 years old. Figure 2 shows a chart depicting the frequency of dam removal based on its year of construction. As shown, a majority of the dams that have been removed were built sometime between 1900 and 1960, indicating that they were likely beyond their reliable lifespan when removed.

As dams age and close in on their 50-year anniversary, their risk of failure[2] increases dramatically (USACE, 2019). The American Society of Civil Engineers handed out a 'D' grade for the collective state of US dam infrastructure in 2017. Since 2000, there have been 289 dam failures nationwide and an average of 28 dams fail annually (McCann Jr., 2018). A majority of these failures occur on small dams[3] with relatively minimal impacts to downstream infrastructure and human life, but large-scale dam failure has occurred in the past and is likely to occur again[4].

As more dam owners and government officials are faced with the decision between restoration of their dam's infrastructure or complete removal, a fundamental understanding of the costs and benefits of each option is necessary. Dam safety requirements vary by state, but all dams in the US are required pass minimum safety and viability requirements which are becoming increasingly strict as the threshold for maximum precipitation events rises in accordance with climate change (Kunkel et al. 2013). Upgrading out-of-date dams or modifying dams that do not meet maximum precipitation event standards often includes an enlargement of the main spillway, the structure used to control the incremental release of water downstream, and is typically cost prohibitive (Gonzales and Walls, 2020). The mean cost of a dam removal project

[2] Dam Failure is referred to as the united release of water stored in a dam's reservoir or a breach in the dam's embankment infrastructure resulting in any release of water or sediment downstream.

[3] Small dams are defined as those with a height of less than 6 feet or a storage capacity of less than 100,000 m^3.

[4] In 1928, 450 lives were lost due to the St. Francis Dam failure in California. In 2020, the Edenville Dam failure in Michigan caused thousands of people to be evacuated from their homes and cost upwards of $140 million in repairs. The Oroville Dam failure in 2017 displaced 188,000 California residents, washed massive amounts of sediment downstream, and cost the California Department of Water Resources over $1.1 billion in repairs (Four Lakes Task Force, 2024; Independent Forensic Team Report, 2018).

in the United States is $994,478[5]. This number fluctuates significantly based on removal size; an additional foot of dam height is associated with an estimated cost increase of $30,620, but is typically considered lower than an infrastructure rehabilitation project and much less costly than a potential dam failure (Walls 2020, Blachly and Uchida 2017, Magilligan et al., 2016).

Agricultural Impacts

Dams provide benefits to agricultural producers in three primary ways: a) increasing the security of water availability such that farmers are less dependent on natural precipitation cycles and weather patterns throughout the growing season, b) increasing the total amount of water available to use on their crops throughout the growing season, and c) by protecting their agricultural plots from the impacts of potential flooding (Duflo and Pande, 2007). The theory behind irrigation dams is that water is stored in the reservoir behind a dam is distributed to agricultural producers within a viable range of the dam on a more frequent and reliable basis than would be possible with a free-flowing river system. This increase in water stability and provision increases the total amount of land feasible for agricultural production and the productivity of affected agricultural land. Inversely, the removal of irrigation dams should decrease both the amount of land feasible for agricultural production and the agricultural productivity of affected land. Controlling the available water supply has been shown to help farmers overcome typical agricultural obstacles associated with drought, insufficient or excessive precipitation, and unpredictable weather patterns (Hansen et al., 2014).

---

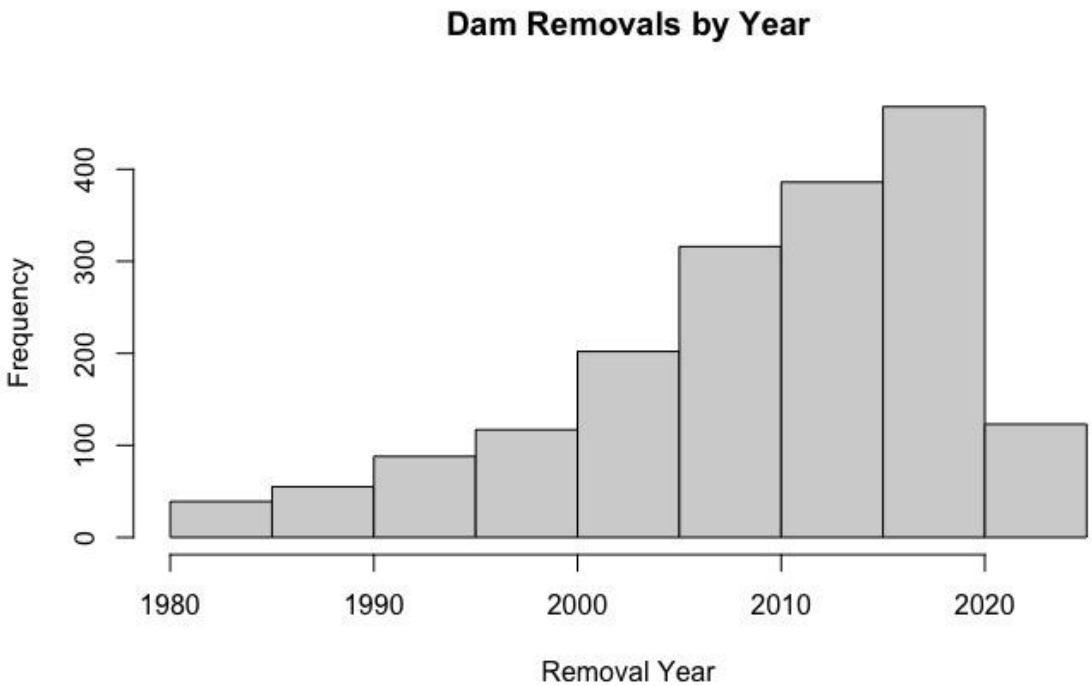
[5] This number is estimated using the 415 dam removals in the American Rivers Dam Removal Database for which cost data is available. Dollar values are indexed to 2020.

Farmers typically access the additional water made available from dams via irrigation infrastructure that draws water from the reservoir created upstream of a dam onto their respective agricultural plots. This type of irrigation system and access to regulated water sources such as a reservoir can substantially increase a farmers' production possibilities frontier and is the most effective irrigation method (Xie and Zilberman, 2017). Additionally, agricultural producers who do not directly access water from a dam's reservoir may still experience spillover benefits from the saturation of the water table, which leads to improved soil fertility and an expansion of viable agricultural acreage upstream from a dam as surface water is more readily available (Celík, 2018). Irrigation gives farmers the ability to use water in the amount and timing of their discretion, resulting in increases for both crop yields and market prices (Dillon and Fishman, 2019). Over 10% of US cropland is directly irrigated by dams, and 43% of cropland is identified as protected from flood risk due to dam construction (CISA, 2023).

Farmers may react to a dam removal in two fashions. First, they can rely on the natural systems of the land to provide the necessary amount of water needed for crop production. Second, they can adapt technologically to obtain the amount of water necessary for crop production. In this context, technological adaption can occur in two forms: 1) accessing groundwater through the drilling of new wells, or 2) developing infrastructure that draws water directly from the riverine system itself (Bednarek, 2001**).** This is similar to traditional irrigation infrastructure that draws water directly from a reservoir, but will be more dependent on seasonal streamflow levels and likely subject to stricter regulations and capacity constraints (ECONorthwest, 2019). The overall impact of a dam removal on agricultural producers will thus depend on their pre-existing agricultural production system. Producers that are heavily reliant on existing irrigation infrastructure will be more affected by a dam removal than producers who are less reliant on their pre-existing irrigation systems.

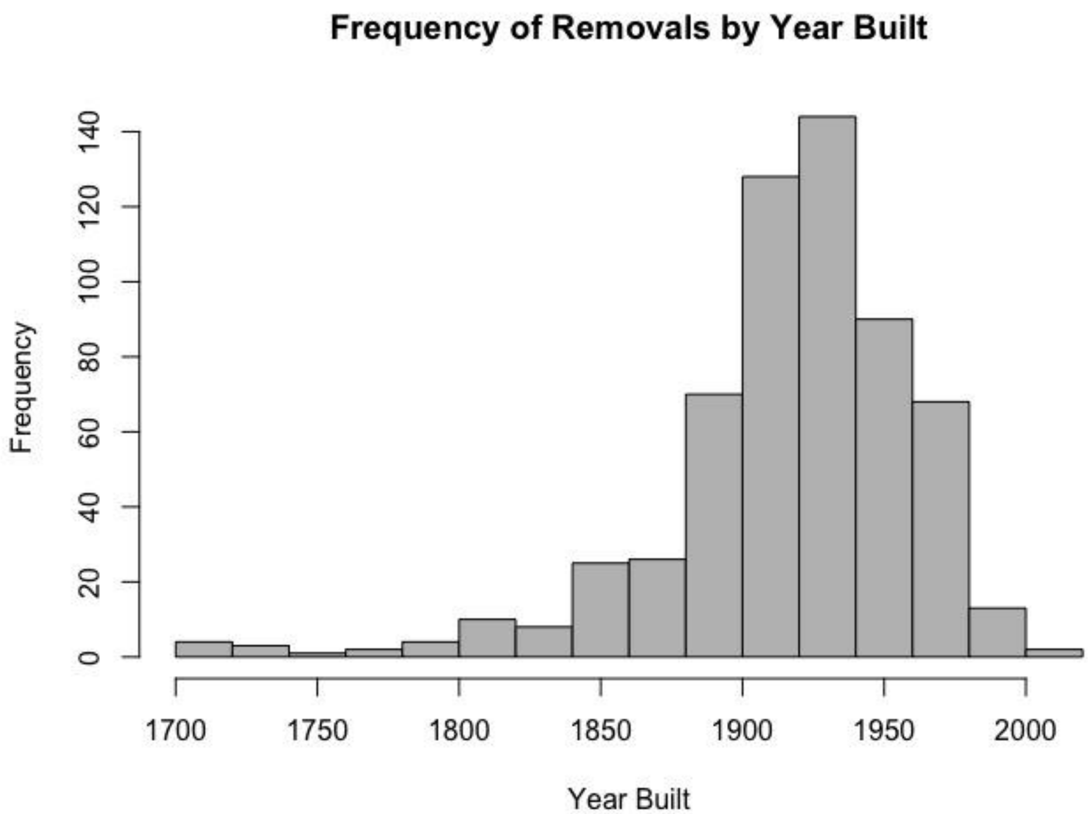
Dam owners include federal, state, and local governments, public utility companies, and private entities. Private entities own the majority of dams, 63%, while local governments own 20%, and the federal government 4% (CISA, 2021). In general, removals occur when a dam is no longer in compliance with environmental regulations, at a substantial risk of failure, no longer serving its intended purpose, is a significant threat to aquatic life and ecosystem health, or interferes with tribal rights (American Rivers, 2022). Often, dams fall under several of these categories simultaneously. In general, the rule of thumb is that when the economic costs of ownership outweigh the benefits, a dam is removed. However, the decision-making process is often extremely complex involving dozens of interdependent cultural, fiscal, and legal influences. It is not uncommon for removal and restoration plans to develop slowly across several years (Wall, 2020).

Figure 1. Dam Removals by Year



Notes: The figure above depicts the number of dam removals by year for the 1980-2022 time period. Bars indicate five-year time spans.

Figure 2. Dam Removal Frequency by Year Built



Notes: The figure above depicts the number of dam removals by year of construction for all removals in my primary dataset. Bars indicate twenty-year time spans.

LITERATURE REVIEW

Literature on the economic impacts of dam removals is sparse. This is largely due to significant identification challenges such as selection bias, distributional outcomes, and the difficulty of obtaining balanced panel datasets to estimate long run effects (Dillon and Fishman, 2009). The scarcity of previous research can also be attributed to the fact that 72% of all dam removals in the U.S. have taken place over the last 20 years (American Rivers, 2024). Much of the relevant economic literature focuses on the construction of new dams in developing countries where these projects are undertaken to stimulate economic growth and enhance agricultural productivity (World Bank, 2023). This contrasts the current situation in the United States where dam removals are becoming increasingly frequent due to aging infrastructure and a growing recognition of their ecological consequences (Perera & North, 2021; USGS, 2023).

Ecological Impacts

There exists an extensive body of literature published on the ecological impacts of dam removal over the last 20 years. Several studies have shown that the removal of dams effectively rehabilitates river systems by restoring traditional physical and ecological function to the environment (Pohl, 2002; Pess et al., 2014; Magilligan et al., 2016). Fish populations typically exhibit swift and significant changes post-removal and the restoration of upstream connectivity often increases the biodiversity of fish species (Kornis et al., 2015, Burroughs et al., 2010). The primary ecological concern with dam removal is the release of sediment that has accumulated against the upstream wall of a dam. These sediment deposits are often substantial and if released improperly can have adverse consequences for downstream aquatic organisms, alter the mineral composition of watersheds, and pose toxicity risks to human, plant, and animal life (Tullos et al., 2016, Foley et al., 2015).

Costs and Benefits

Literature on the costs and benefits of dam removal and restoration projects is limited. The current average cost estimate for a dam removal project in the United States is $994,478 for a 14.7-foot-high dam and increases by $30,620 with each additional vertical foot (Gonzalez and Walls, 2020; Blachly & Uchida, 2017). The average rehabilitation cost for a 15-foot dam in fair condition over fifty years old is $2.67M (Association of State Dam Safety Officials [ASDSO], 2023). Costs of dam failures vary widely, but often exceed the cost estimates for both removal and restoration projects (McCann Jr, 2018). In general, the literature indicates that the cost of removal projects are typically lower than rehabilitation and failure costs.

Literature on the benefits of dam removal typically focuses on recreational and passive use values. An *ex-post* analysis of the Edwards Dam removal on the Lower Kennebec River in Maine shows significant benefits to recreationalists in the form of increased spending to visit and access the fishery, as well as an increased willingness to pay for more frequent fishing opportunities on the river (Robbins and Lewis, 2008). A similar survey-based study estimates households' willingness to pay (WTP) for two proposed dam removal projects on the Elwha River in Washington and concludes that the general public's aggregate benefits from the removal of both dams would exceed the estimated costs of the combined removals (Loomis, 1996).

Dam Construction Literature

The seminal paper in dam-related economic literature studies the distributional and productivity effects of large irrigation dams constructed throughout India (Duflo and Pande, 2007). Their analysis focuses on the construction of new dams and finds that in Indian districts (analogous to counties in the United States) located downstream from a dam, agricultural production increases while vulnerability to precipitation shocks and rural poverty decline. In the districts in which a dam is built, agricultural production remains largely unchanged and rural poverty increases. These results imply there are distributional impacts of dam construction and that considering the spatial framework of analysis is important. Their study exploits variation in dam construction by Indian district and implements an instrumental variable based on river gradient to solve identification challenges.

Hansen et. al (2009) and Hansen et. al (2014) are the two predominant papers seeking to estimate a causal relationship between dams and agriculture in the United States. Hansen et al. (2009) studies the effect of dams built in the last century on agricultural crop selection and harvest productivity. Their analysis is conducted at the county level and an instrumental variable technique is also employed to account for identification challenges. Results show that dam construction has little impact on agricultural production in normal precipitation years, but a significant effect during drought years.

Hansen et al. (2014) isolate their study area to the state of Idaho to analyze the effect of dam placement on crop productivities, crop mixes, and agricultural land values at the county level. They show that dams enable the spatiotemporal transfer of water resources which significantly aids crop production and indicate that dams increase total crop acreage, shift crop mixes toward more valuable and water intensive crops, increase crop productivity during drought periods, have little to no effect on land values.

Dam Removal Literature

Economic literature focusing specifically on dam removals predominantly centers around hedonic pricing analyses. A study by (Lewis and Bohlen, 2008) shows property owners pay a 16% premium for the privilege to live on the waterfront, but this premium declines as the property approaches active dam sites. A hedonic property value analysis for land near hydropower dam removal sites along the Kennebec River in Maine found an increase in property values following removals (Lewis et al., 2009). A third study examines the impact of small dam removals in south-central Wisconsin to and finds that shorefront properties near small dams are not significantly different in value compared to shorefront residential properties along free-flowing streams (Provencher et al., 2008). Other dam removal literature discusses the recreational and passive use values of dam removals (Robbins and Lewis, 2008; Loomis, 1996).

To the best of my knowledge, my paper is the first study seeking to estimate a causal relationship between dam removal and agricultural production. I use counties as my unit of analysis and apply panel data methods, including an instrumental variable approach, to address identification challenges in accordance with (Duflo and Pande, 2007; Hansen et al., 2009).

DATA

This study combines data on agricultural statistics, climatic conditions, and dam removals to create a novel, unbalanced, county-year dataset for the 2000-2022 time period.

Dam Removal Data

Data regarding the removal of dams is obtained from the American Rivers Dam Removal Database. This is a comprehensive dataset of all dam removals officially recorded in the United States, and to my knowledge is the only available historical record of dam removals in the United States. Information on dam removals is collected as far back as 1912 and is continuously updated as dam removal projects occur in real time. This dataset is compiled with support and assistance from the United States Geological Survey (USGS) Dam Removal Information Portal (DRIP). Relevant data includes the latitude and longitude coordinates of each removal, original year of dam construction, year of removal[6], dam height, dam length, restored free-flowing river miles, and the dam's intended purpose. All data is not available for each removal in the dataset.

Table 1 shows summary statistics for relevant variables in the unmodified American Rivers dam removal dataset and indicates how many observations are present for each descriptive variable. Data that is available for all removals includes the latitude and longitude coordinates of each removal, the name of the removed dam, and the body of water on which the removal occurred. Dam removals are aggregated up from the precise coordinate level to the

[6] Some removal projects take several years to complete. There is no explicit information in the American Rivers Dam Removal Database specifying whether the year of removal is recorded at the start or end date of a removal project. However, based upon a cross-reference of multiple large removal projects and their de-construction timelines, it is assumed that the year of removal is recorded at the inception of a removal project.

county level for analysis. Figure 3 shows a map of the dam removals in my panel dataset weighted by the number of removals per county.

Dam Removals included in the American Rivers Dam Removal Database are those where a significant portion of the full original height of the dam has been removed such that ecological function, natural river flow, and fish passage has been restored at the site. The Dam Removal Database is revised and updated annually with information discovered by American Rivers or provided by contributors throughout the US. This dataset is most comprehensive source of information on dam removals in the country and is the primary reference cited by previous studies referencing previous dam removal projects (Guilfoos and Walsh 2023, Gonzales and Walls, 2020, Magilligan et al., 2016).

Existing Dams Data

In addition to dam removals, I incorporate current dam infrastructure in the United States into my analysis using data from the US Army Corps of Engineers National Inventory of Dams (NID) database. This is a comprehensive database documenting all known dams in the United States that meet a set of relevant criteria[7] and is the most comprehensive dam infrastructure database available. This dataset includes 91,822 observations, nearly identical to the estimate of 91,815 dams in the United States by (FEMA, 2022), so it is reasonable to assume that the dataset

[7] 1. Downstream flooding would likely result in loss of human life (high hazard potential).
2. Downstream flooding would likely result in disruption of access to critical facilities, damage to public and private facilities, and require difficult mitigation efforts (significant hazard potential).
3. Dams that meet minimum height and reservoir size requirements. These dams are typically equal to or exceed 25 feet in height and exceed 15 acre-feet in storage, or equal to or exceeding 50 acre-feet storage and exceeding 6 feet in height.

encompasses all existing dam infrastructure in the US. I download the GPS coordinates of current dams, year built, and dam size from this database. I use this data to develop an estimate of the age of current dam infrastructure within each county as well as the total number of dams by county. Figure 1 shows summary statistics for the number of dams within each county, the median being 13.

Agricultural Data

Agricultural data is downloaded from multiple sources. Crop-specific productivity statistics are obtained from the United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) Quick Stats database, a comprehensive public archive compiling agricultural information for assorted time periods, commodities, and scales. Data is taken at the county level for all years in which the data is available in the sample time frame (2000 – 2022). Agricultural yields are downloaded for three crops; winter wheat, corn grain, and soybeans and are reported in terms of bushels per acre.[8] For some counties, crop yield data is available for all years in the sample time frame, while for other counties data is more sporadic. It is important to note that crop yield measurements are a barometer of agricultural productivity and not total output. Figures 4, 5, and 6 show maps of the average crop yields by county and are a useful depiction of the availability of these variables within my dataset.

---

[8] Crop yields are calculated as the total amount of county-level production in a growing season divided by the total number of acres harvested.

I obtain net farm income[9] and cash receipts for crops[10] data from the Bureau of Economic Analysis CAINC45 Farm Income and Expenses dataset. This dataset contains farm income and expense data by county in the US for the years (1969 – 2023). This data is available at the county level on an annual basis for each year in my dataset. I include both net farm income and cash receipts as measures of the economic attainment of agricultural producers. While yield data is an important measure of agricultural productivity, net farm income and cash receipts for crops are useful indicators to assess how agricultural producer's total output and overall economic health are impacted by the removal of a dam. For example, it is plausible to imagine that if there is a decline in a county's total planted acreage, crop yields may increase as a result of higher per-acre productivity while total net farm income might simultaneously decline as a result of lower total crop output. These would be two differential and important findings to investigate. Figures 7 and 8 show maps of the average net farm income and cash receipts for crops by county and are a useful depiction of the spatial distribution of these variables within my dataset.

Indemnity claims data for drought and excess moisture is taken from the United States Department of Agriculture Risk Management Agency's Southwest Climate Hub AgRisk Data Viewer. This database contains information on indemnity claims and payments on a county level throughout the United States for numerous commodities and causes between the years (1989 – 2022). Specifically, I download the total amount of indemnity payouts in US dollars, for drought

---

[9] Net farm income is defined as the realized net income consisting of total cash receipts and other income less total production expenses.
[10] Cash receipts for crops are defined as the value of gross revenues received from the marketing of crop commodities such as corn, wheat, and soybeans; hay; vegetables; fruits and nuts; greenhouse and nursery products; tobacco; cotton; and other miscellaneous crops, during a given calendar year.

and excess moisture related claims. An indemnity claim is an insurance claim made by an agricultural producer regarding land that has been significantly damaged by non-ordinary weather or climatic events (USDA, 2012). A payment is then issued by the farmer's Approved Insurance Provider. It is useful to look at indemnity claims data in the context of my study since dam removals will affect the exposure of agricultural land plots to states of drought and floods; potentially affecting the amount of indemnity payments for drought and excess moisture related claims. Figures 9 and 10 show maps of the average indemnity payments for drought and excess moisture related claims. They are also a useful depiction of the spatial distribution of these variables within my dataset.

Weather Data

Weather and climate data are pulled directly from Oregon State University's Parameter-elevation Regressions on Independent Slopes Model (PRISM) Climate Group database.[11] PRISM weather data is available in a wide variety of spatial scales and time periods down to the 800-meter grid level on a daily basis. For the purpose of my analysis, I use data available at the county level on a monthly basis, which I then aggregate up to the yearly level to fall in line with the other variables of interest in my dataset. The PRISM database uses all available and relevant weather monitoring stations, meaning that as weather stations are built and come online, all new relevant information is incorporated into the PRISM weather monitoring model.

Relevant statistics derived from the PRISM climate database include precipitation totals, maximum temperature, minimum temperature, and the number of days in which the temperature

[11] This data was pulled directly from the Oregon State University PRISM dataset with code provided from https://asmith.ucdavis.edu/data/prism-weather.

reaches levels above the thresholds of twenty-nine, thirty, and thirty-two, and degrees Celsius respectively. There is evidence showing that temperature effects are strictly non-linear above certain temperature thresholds and the relative productivity of the crops included in my analysis are differential based upon their exposure to these given temperature thresholds, especially during the growing season. (Schlenker and Roberts, 2009) Degree days are thus incorporated into my dataset as a relative measure of the amount of time each county is exposed to temperatures above certain threshold values per month. I then aggregate these monthly index measures up to an annual total in order to derive a level of annual exposure within each county following the technique laid out by (Schenker 2008).[12]

I also implement the Palmer Drought Severity Index (PDSI) as a control variable for the level of relative drought severity within a county during a given month. The Palmer Drought Severity Index is based on the ecological balance between soil moisture supplied and soil moisture demanded. The index typically fluctuates within a range from -6 to 6, with negative values denoting dry spells and positive values indicating wet spells. [13] There are a few extreme values above the magnitudes of -7 to 7, but these indicate highly abnormal weather conditions. PDSI data is downloaded from the National Oceanic and Atmospheric Administration (NOAA)

---

[12] As shown in Table 2, maximum values for the above_29 and above_32 variables are larger than 365, indicating more than 365 days of exposure to these certain temperature thresholds. This is due to the manner in which these indexes are calculated. Degree days are calculated by giving weights to temperatures above a certain threshold, °C. For instance, if an entire day's temperature is above the relevant threshold, the index takes a value of 24, explaining why some county year observations in the dataset are above 365.

[13] The categorical definitions for PDSI measurements are defined as follows: 0 to -.5 = normal; -0.5 to -1.0 = incipient drought; -1.0 to -2.0 = mild drought; -2.0 to -3.0 = moderate drought; -3.0 to -4.0 = severe drought; and greater than -4.0 = extreme drought. Similarly, values of 0 to .5 = normal; 0.5 to 1.0 = incipient wet spell; 1.0 to 2.0 = mild wet spell; 2.0 to 3.0 = moderate wet spell; 3.0 to 4.0 = severe wet spell; and greater than 4.0 = extreme wet spell.

New Divisional Dataset (nCLIMDIV) where PDSI data is available at the county level for the years (1895 – present). I incorporate these variables to control for climatic variation and shocks within counties. Years of abnormal temperatures or precipitation levels are likely to substantively affect agricultural production. If not controlled for, these omitted variables would bias my results.

Table 1. Dam Infrastructure Summary Statistics

Variable	**N**	**Min**	**Max**	**Mean**	**Median**	**Unit of Measurement**
Year of removal	1531	2000	2022	2013	2013	
Dam height	1508	1	210	13	9	Feet
Dam length	976	2	7500	233	113	Feet
Original use	646					
Restored river miles	743	0	1132	24.76	2	Miles
Current Dams	3103	0	312	24	13	County

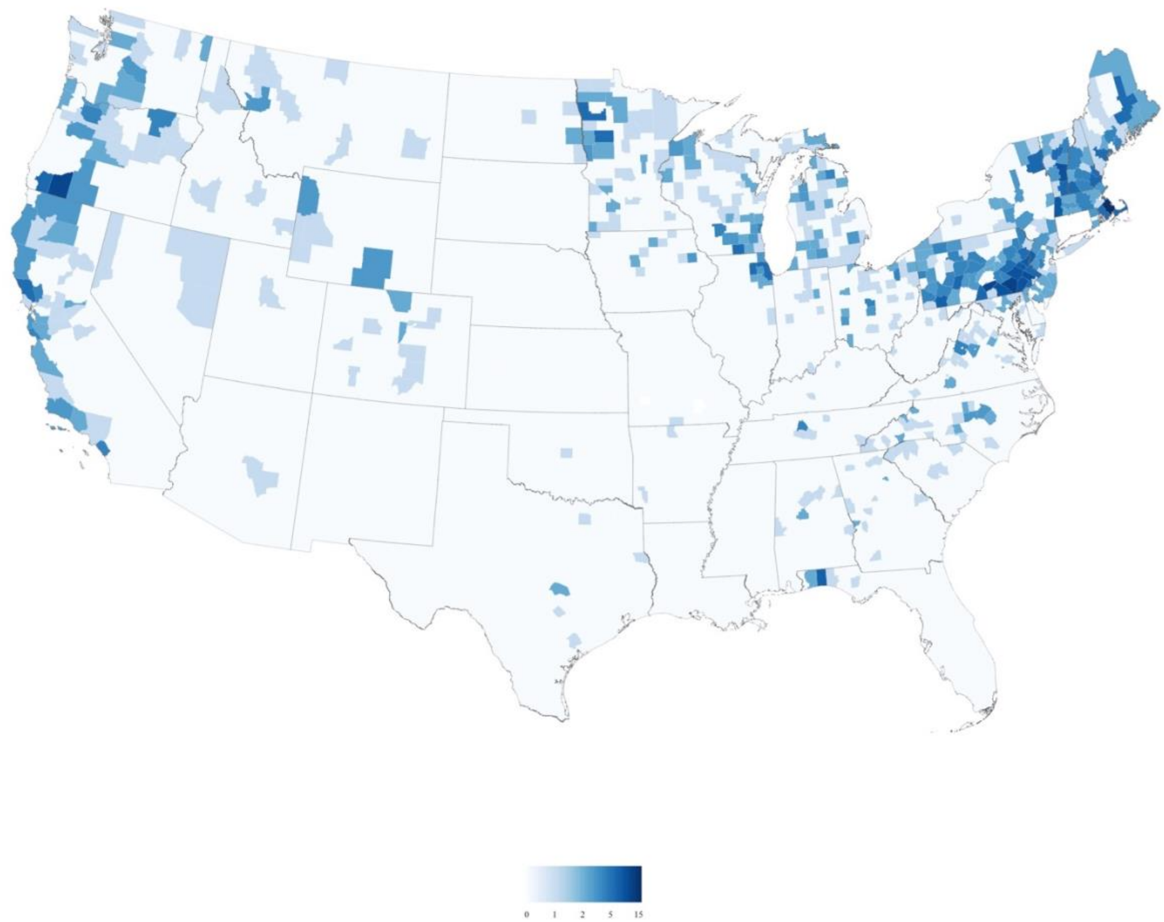
Notes: The table above includes descriptive statistics for characteristics of the dam removals included in my final dataset and current dam infrastructure.

Table 2. Dependent Variable Summary Statistics

Variable	Unit of Measurement	N	Min	Max	Mean	Median
Winter Wheat Yield	Bushels/acre	27,917	0	153.80	51.82	51.30
Corn Grain Yield	Bushels/acre	37,309	0	277.1	134.3	138.0
Soybean Yield	Bushels/acre	31,740	0.7	80.4	40.7	41.2
Net Income	US ($)	67,164	-176,859	2,337,023	21,080	7,393
Cash Receipts	US ($)	67,164	0	5,037,065	54,829	20,074
Drought	US ($)	42,621	-42,373	148,773,023	1,175,356	128,063
Excess Moisture	US ($)	45,734	-86,320	105,518,970	829,170	118,066
Drought Severity		68,266	0	12	0.40	0
Flood Severity		68,266	0	12	0.87	0
Above 29		68,266	0	797.65	68.58	43.59
Above 32		68,266	0	496.87	19.08	6.73
Year			2000	2022		

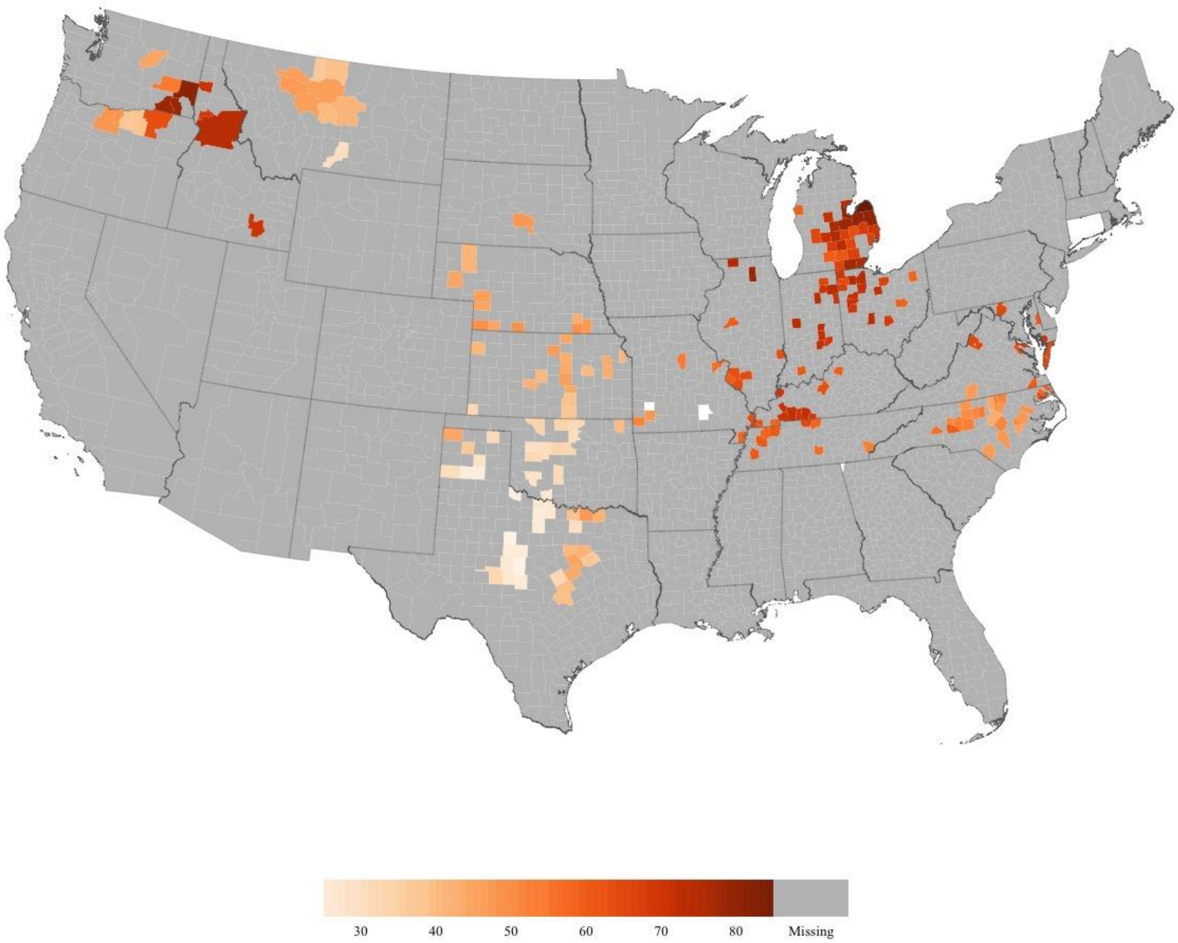
Notes: The table above includes descriptive statistics for outcome and control variables in my final dataset.

Figure 3. Dam Removal Map



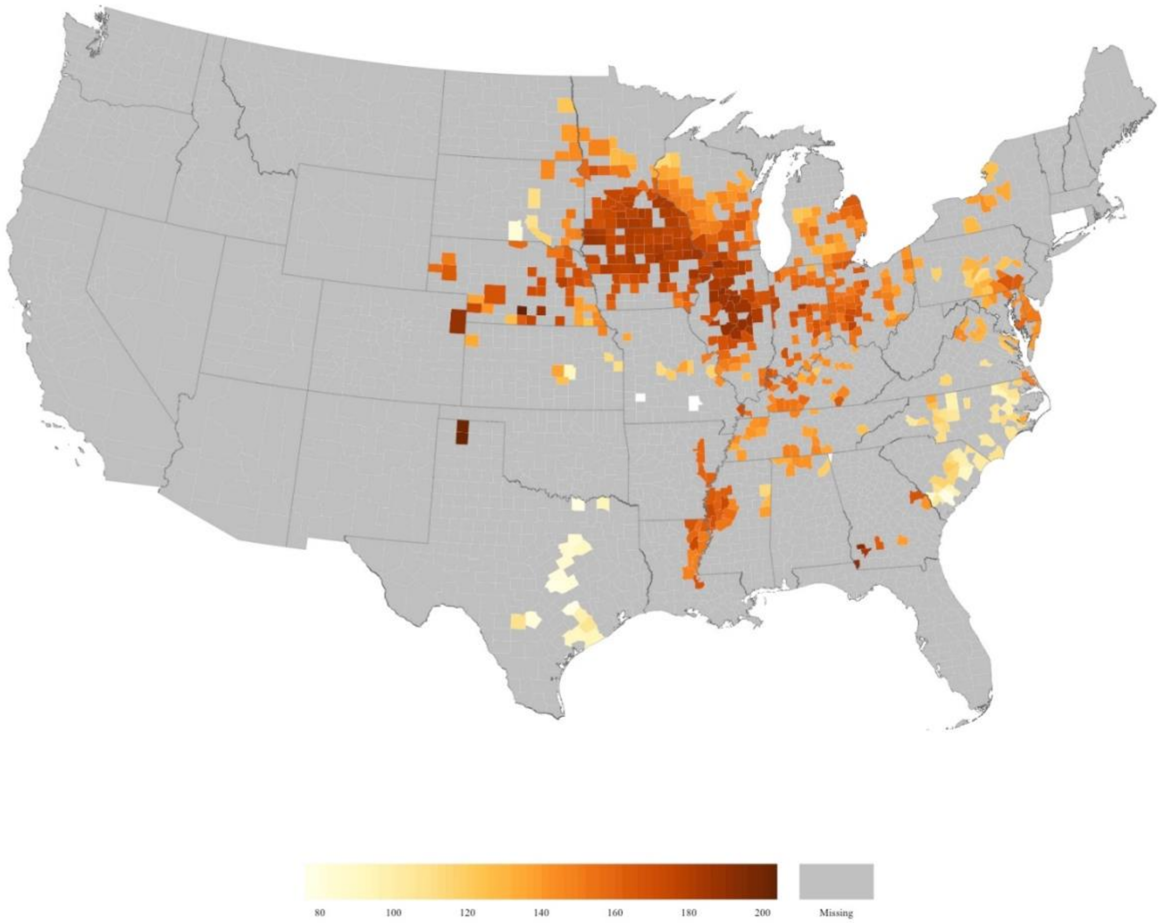
Note: The figure above shows the number of dam removals in each county in the U.S. from 2000-2022.

Figure 4. Winter Wheat Yield Map



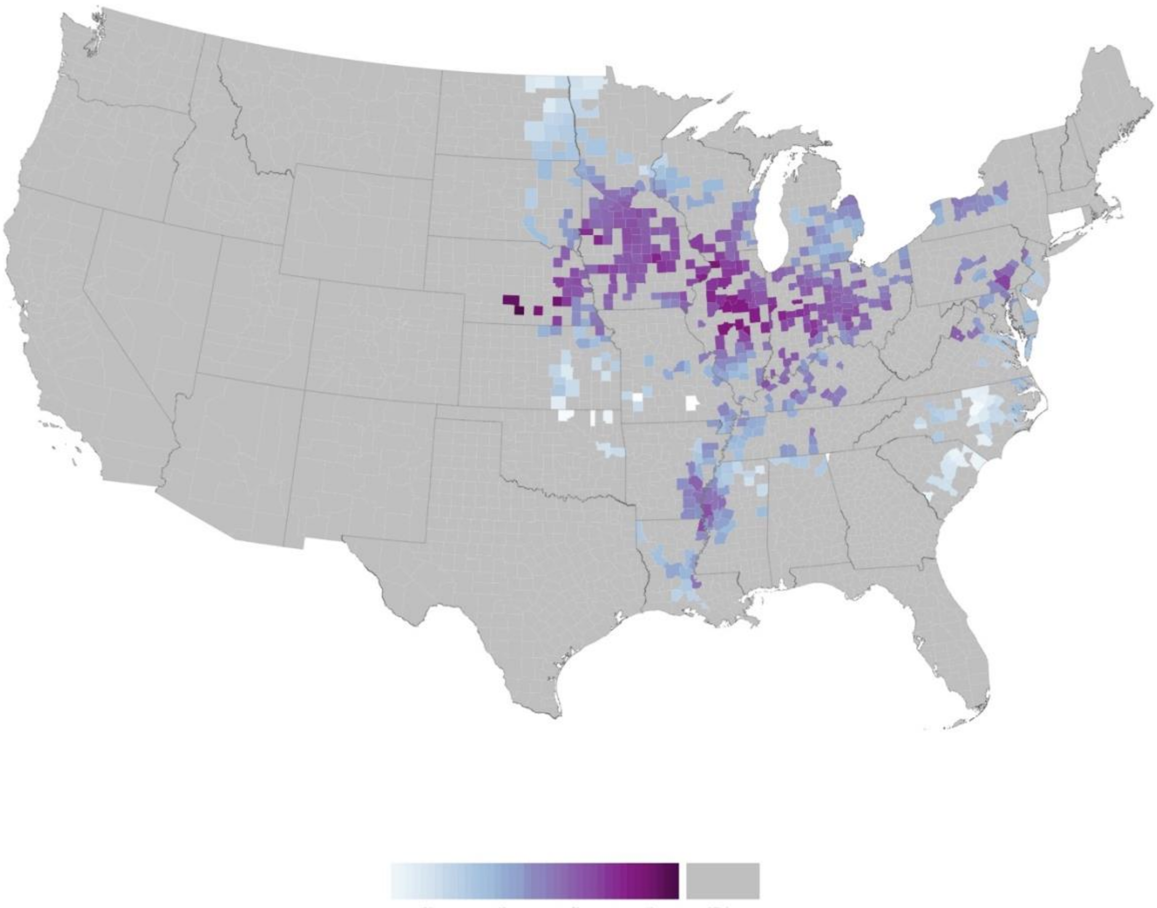
Note: The figure above shows the average winter wheat yield by county in the U.S. from 2000-2022.

Figure 5. Corn Grain Yield Map



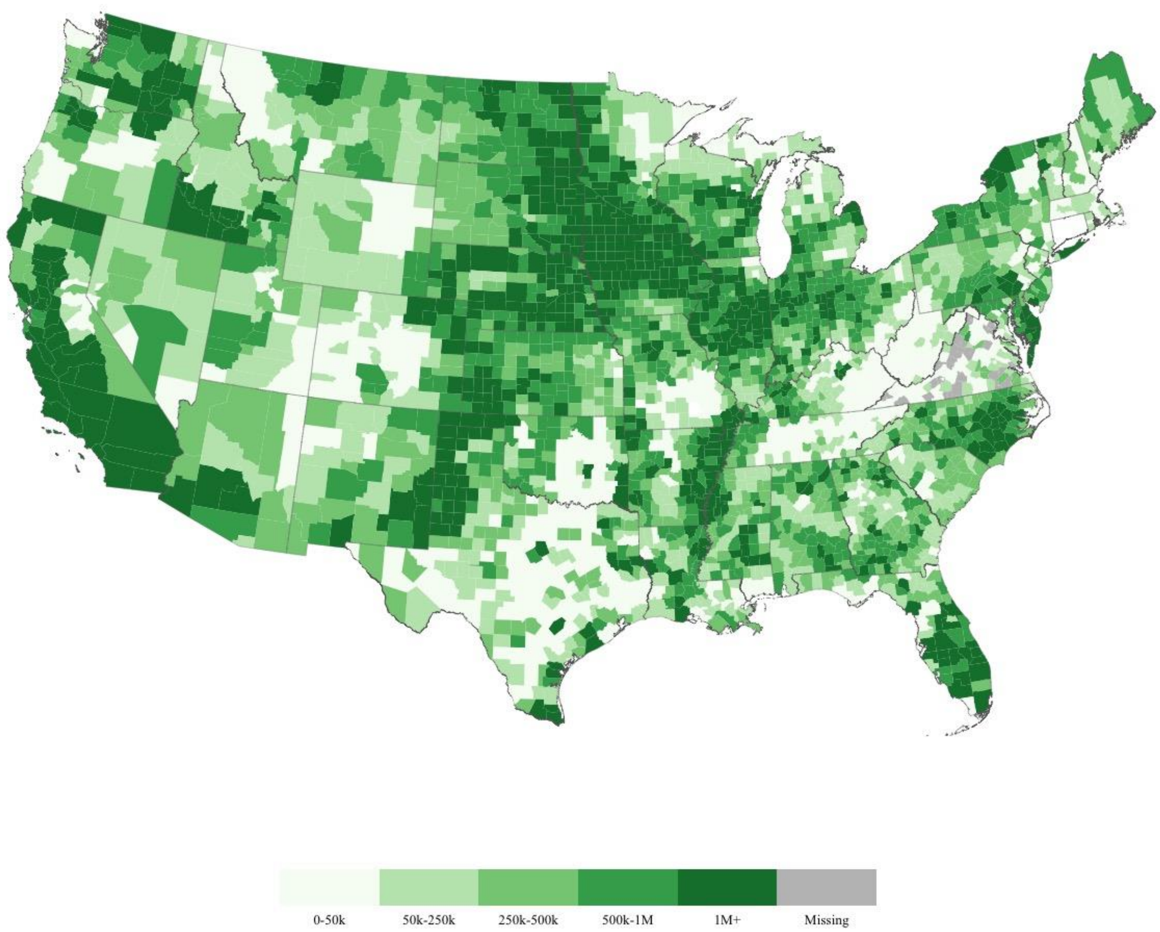
Note: The figure above shows the average corn grain yield by county in the U.S. from 2000-2022.

Figure 6. Soybean Yield Map



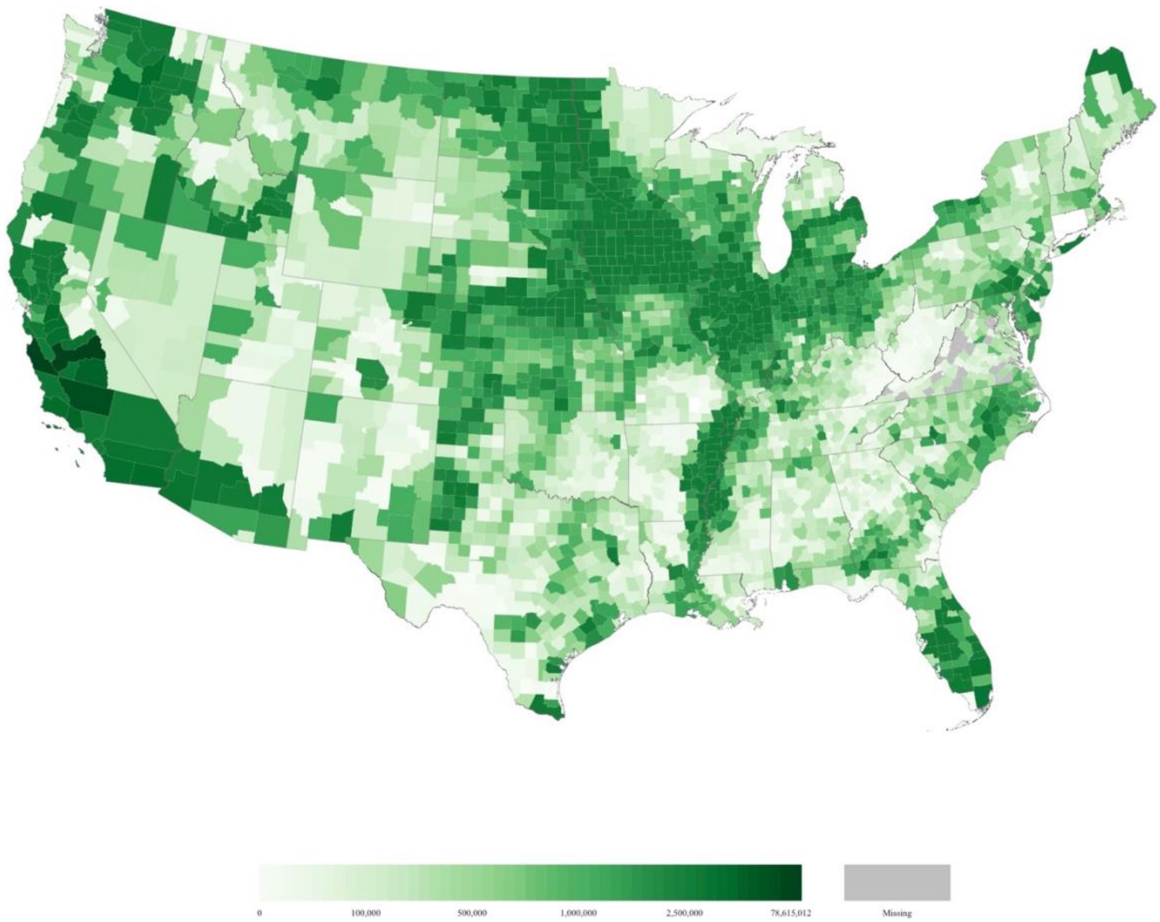
Note: The figure above shows the average annual soybean yield by county in the U.S. from 2000-2022.

Figure 7. Net Farm Income Map



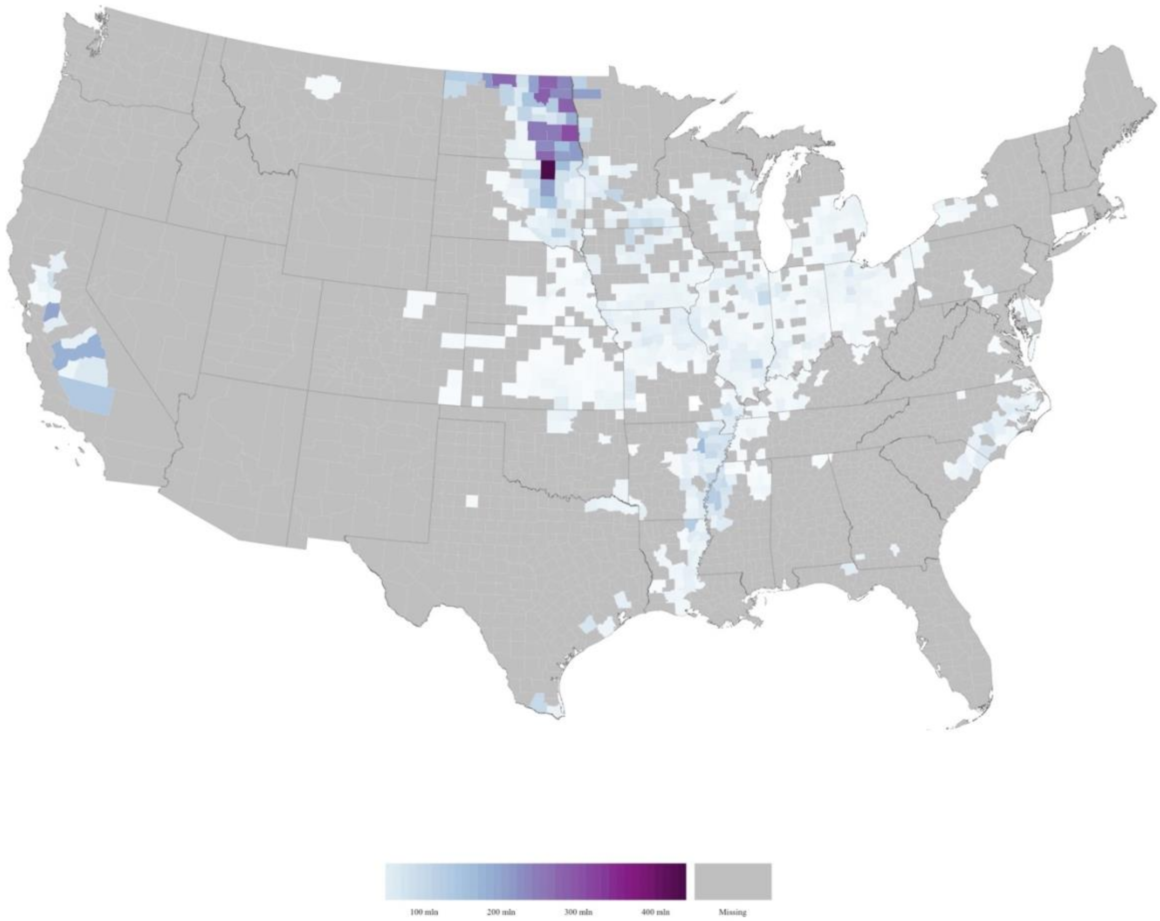
Note: The figure above shows the average annual net farm income by county in the U.S. from 2000-2022.

Figure 8. Cash Receipts Map



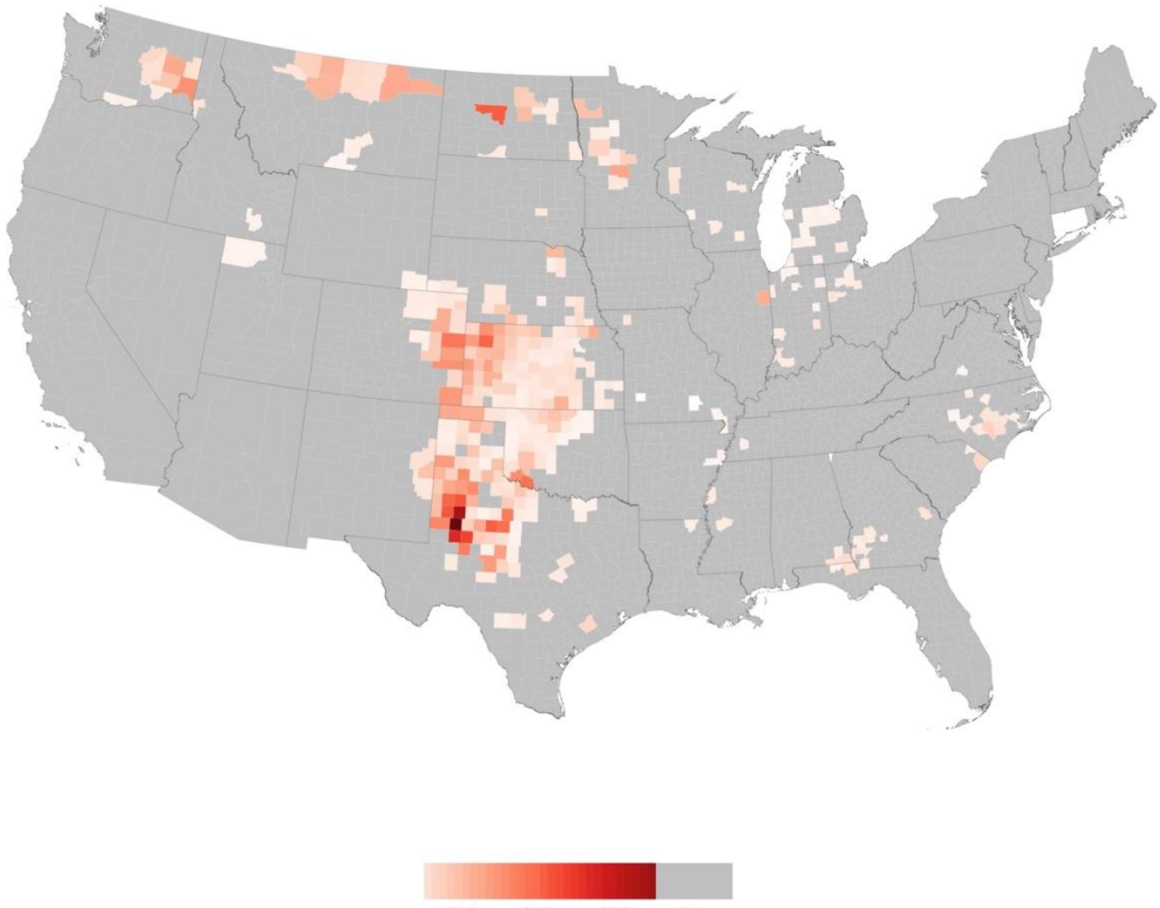
Note: The figure above shows the average annual cash receipts for crops by county in the U.S. from 2000-2022.

Figure 9. Indemnity Excess Moisture Payments Map



Note: The figure above shows the average annual indemnity payments for excess moisture related claims by county in the U.S. from 2000-2022.

Figure 10. Indemnity Drought Payments Map



Note: The figure above shows the average annual indemnity payments for drought related claims by county in the U.S. from 2000-2022.

METHODOLOGY

An exact identification of the causal effect of dam removals on agricultural productivity would require the observation of exogenously determined dam removals on spatially-weighted individual agricultural plots before and after removals occur across a multi-year balanced data panel. It would then be necessary to assess the effects of dam removals on precise agricultural units across time, interpret the distributional effects of dam removals on precise agricultural units based on proximity to the removal site and appropriate downstream or upstream location, and further examine the heterogenous effects based on the characteristics of specific agricultural plots. Thus, the ideal experiment would be to compare independent agricultural plots that are equivalent in relevant factors affecting productivity: soil fertility, precipitation, average temperature, crop choice, water usage, etc... , and randomly assign times and locations for dam removals which would directly affect the treated agricultural plots. With this experiment, agricultural outcomes and farming decisions at both plots, assumed to be identical in the pre-treatment period, could then be assessed based upon their varying responses to the dam removal.

This paper attempts to emulate the ideal experiment using publicly available data and appropriate econometric techniques. I implement a staggered two-way fixed effect events study framework to estimate the causal effect of dam removals on agricultural production. Fixed effects are employed at the county and year levels to absorb time-invariant characteristics of counties and year-specific trends, assisting with the isolation of results to the causal impact of dam removals. I implement an event study framework to analyze the differential impacts of removals across time. The event study approach allows me to assess the effects of a removal on agricultural outcomes before and after the event on an annual level, providing a more descriptive representation of the effects of removals over time. My baseline estimating equation in this paper is the panel event study model shown in equation (1) presented below:

$$(1)\ Y_{c,t} = \sum_{j\in-3,5}^{J}(\delta_j * D_{c,t-j}) + \alpha_c + \lambda_t + \beta\boldsymbol{X}_{c,t} + \varepsilon_{c,t}$$

This equation evaluates the overall effect of dam removals on seven categories of agricultural production and economic indicators in county *c* during time *t*. The summation $\sum_{j\in\{-3,5\}}^{J}(\delta_j * D_{c,t-j})$ represents a set of lag and lead indicator variables for event time. $D_{c,t-j}$ is an indicator variable for event time j, meaning that the event took place j periods before or after a particular observation's unit of recorded time and a distinct term is included for each particular event. The coefficients following the occurrence of a removal (for $j \geq 0$) designate the evolving impacts of a removal, reflecting the dynamic effects as they unfold over the years following a removal. Conversely, the coefficients preceding the event (for $j < 0$) serve as both a falsification test, assessing any potential spurious correlations before the treatment event occurs, and as a measure of the level of the potential anticipation effect regarding an agricultural producer's decision-making process. $\beta\boldsymbol{X}_{c,y}$ is a vector of time-variant controls including categorical variables for drought and flood severity and a weighted monthly temperature index variable. α_c are county-level fixed effects, λ_t are year fixed effects, and $\varepsilon_{c,t}$ is the error term.

Within my panel dataset, 588 counties experience a dam removal and 2,515 counties experience no dam removals. 301 counties experience two or more removals. This creates an econometric circumstance where there are multiple treatment periods among treated units in addition to the presence of never treated units. This framework requires a specific interpretation of estimated coefficients as partial effects that hold constant over time and fails to demonstrate potential differential impacts of subsequently occurring events. This includes events whose likelihood of occurrence may be influenced by previous events at a constant or non-constant level (Miller, 2023). To account for these issues, I estimate two distinct regression specifications.

Regression [1] incorporates all dam removals in my sample to estimate an equation without modifying the number of treatments in the dataset. This methodology is suggested by Sandler and Sandler (2014) and allows the event dummy, $D_{c,t-j}$, to occur in any period where an event takes place; permitting its occurrence across multiple time periods t, and within the same unit, c. In the context of my study, this allows the 301 counties with multiple removals to experience multiple treatments across the sample time frame.

Regression [2] is estimated by restricting the treatment exclusively to the first dam removal per county. This technique is employed to account for the issues pertaining to the interpretation of event time coefficient estimates when using multiple treatments per unit by isolating the treatment exclusively to the first dam removal per county and follows the approach suggested by Jacobson, LaLonde, and Sullivan (1993). Restricting my treatment to the first event per unit also serves to evaluate the potential differential impacts of treatments by the order in which they occur. It could be the case that the first dam removal in a county is more or less impactful than subsequent removals due to human and ecological factors. For instance, counties may tend to remove a small dam prior to a large dam in order to assess the feasibility and outcomes of removal projects before undergoing a large dam removal project[14]. It may also be the case that

[14] In Table A5, I examine the average size of a dam removal within counties based upon the order of removal and find that the first removal is typically slightly larger than subsequent removals. This supports the idea of using a county's first removal as the single treatment unit to test differential effects and implies that results will likely be most substantial for the first removal.

the first removal on a riverine system or in a given watershed will have a larger impact than subsequent removals within the same system.

Identification Challenges

There are a number of identification assumptions that need to hold in order for the results of my study to represent a true causal effect. The basic event study assumptions necessary include, 1) both treatment and control groups would have experienced parallel trends in the outcome variables of interest in the pre and post treatment time periods in the absence of a treatment; 2) no anticipation effects; and 3) no spillover effects in the untreated group. In the context of my paper these assumptions contextualize to 1) parallel trends among agricultural yields and measures of economic activity for relevant treatment and control groups before and after a dam removal; 2) no anticipatory behavioral responses, such as adapting water supply techniques or altering crop mixes in a way that would affect yields or economic indicators; and 3) no spillover effects of dam removals into neighboring counties.

The event-study design of this paper helps to prove the validity of assumptions 1 and 2 by examining and reporting pre-treatment trends and impacts of removals. I also estimate alternative regression specifications by restricting and unrestricting my sample population to counties with and without removals, which helps to serve as a check for the no spillover effects assumption. Additionally, it is generally found empirically that the downstream impacts of a dam removal decrease as the distance from the removal increases, generally fading out around 2.9 miles (Colaiacomo, 2014). Thus, it can be generally assumed that removal effects are typically isolated to the county in which they are removed.

In complement to the basic event study identification assumptions, my methodology assumes exogenous determination of dam removal sites. That is to say, after accounting for the impact of covariates and fixed effects, the timing of dam removals within counties is methodologically random. This assumption would not be violated if dams are removed with differing frequencies in geographic areas based upon relative agricultural productivities since my county-level fixed effects would absorb these unit-level differences. However, if dams that are less important agriculturally are more likely to be removed than dams whose agricultural impacts are especially critical, this could cause a reverse causality problem and violate a critical assumption of my empirical strategy. As such, I implement an instrumental variable technique described below which aims to alleviate this concern.

Preferred Specifications

My preferred baseline model estimates equation (1) using the regression specifications, [1] and [2], outlined above. Both regression [1] and [2] allow us to compare lagged and lead coefficient estimates for counties with dam removals to the estimates for these counties in the year preceding a removal. In both models, $D_{c,t-1}$ is selected as the excluded event time comparison group in accordance with standard event study procedure (Miller, 2023). In each of these model specifications, I use cluster-robust standard errors that are clustered at the county level.

Each of these baseline specifications are ran on a subset of my sample that is restricted to counties which experience a dam removal within my sample time frame. This restriction is done to: a) simplify the comparison group and the interpretation of event time coefficients, b) simplify the interpretation of heterogeneity analyses and c) make the sample counties more homogenous as there may be unobserved differences between treatment and control counties that vary differentially across time and are not captured by my unit or time fixed effects. Figure 3 shows dam removals to be concentrated in the north-east, mid-west, and western parts of the US, so restricting my sample exclusively to counties with removals effectively isolates these sub-regions. The benefits gained by excluding the never-treated units outweighs the penalty of lost statistical power, thus the restricted sample is used in my baseline estimates. I do show the robustness of my primary results to a set of secondary results where never-treated units are included in the sample for regressions [1] and [2] below.

RESULTS

The primary results I find using regression specifications [1] and [2] with my baseline model specification in equation (1) are shown in Table 3 for my three primary agricultural variables of interest; winter wheat, soybean, and corn grain yields. Table 4 presents results for my four economic variables of interest; cash receipts from crops, net farm income, indemnity drought payments, and indemnity excess moisture payments. In Table 3, results are presented in terms of bushels per acre and are a measure of agricultural productivity. Table 4 shows results in terms of percentage change.[15]

The results of my baseline specifications are mixed. Table 3 shows generally insignificant and economically inconsequential results across event time periods. In regression [1], I find that winter wheat yields in the five or more years following a dam removal are 1.15 bushels per acre higher on average compared to yields during the year before a removal, significant at the 10% level. This is an increase of 1.8% from the group mean of 61.11 bushels per acre. This would imply that as the effects of a dam removal are realized by winter wheat producers, their per acre productivity rises. One possible explanation for this could be that agricultural producers might plant less total acreage and focus primarily on their most productive plots of land as they lose water availability from a dam removal. This would be inversely consistent with the results found by (Hansen et al. 2009). However, since this result is found exclusively for winter wheat in the 5+ years lagged coefficient and is not shared by other lagged event years or crops, I cannot rule

[15] I log-transform my key economic variables of interest to account for the rightward skew present in each of my four economic variables of interest shown in Figure A1. I use an inverse hyperbolic sine transformation due to the presence of zeros and negative values in these variables. Table A1 shows the results the same regression before the functional form transformations.

out this result being driven primarily by statistical noise or type 1 error. All other event-time coefficient estimates for winter wheat, soybean, and corn grain yields using regression [1] are statistically insignificant with relatively large standard errors, often causing the 95% confidence interval to straddle 0. Coefficient plots for this baseline model specification [1] are shown in Figure 11.

When implementing regression [2] by restricting the treatment to the first dam removal in each county, I find slightly different results. In general, there is an increase in coefficient values and standard errors when restricting the treatment units when using this updated specification. I find that the effects on corn grain and soybean yields are positive and statistically significant at the 10% level in the year of a dam removal. However, the signs on the lagged event time coefficients for both these crops are inconsistent across time, and the 95% confidence interval often contains zero. I no longer find significance for winter wheat yields in the 5+ years lagged coefficient.

It is worth noting that the 5+ year lagged coefficient estimates for soybeans, corn grain, and winter wheat are all statistically insignificant in specification [2] and the F-tests for joint significance of the lagged coefficients are all insignificant in both specifications. Soybean yields are 0.95 bushels per acre higher on average in the year of a removal and 0.94 bushels per acre larger the year following a removal, both statistically significant at the 10% level.

Table 4 shows results using regressions [1] and [2] on the economic outcome variables of interest: net farm income, cash receipts for crops, indemnity drought payments, and indemnity excess moisture payments. Primary findings using regression [1] show statistically significant declines for cash receipts in the year of a dam removal and for all years following. These results are statistically significant at the 10% level 5+ years after a removal and at the 1% level in the year of a removal and 1 through 4 years following a removal. The lagged coefficient values for cash receipts are jointly significant and fairly similar in magnitude, all indicating between a 4% and 5.8% decline in cash receipts in the years following a removal. This could be another indicator that total crop production may decline following a dam removal. Since cash receipts are a measure of crop related revenue, declines in this outcome variable post-removal could indicate declines in total crop production, and therefore total cash receipts in accordance with lower total output. However, regression [1] also shows a statistically significant decline for cash receipts in the two years prior to a dam removal at the 10% level. This is a puzzling result that may suggest these results are subject to bias and statistical noise.

Other findings using regression [1] indicate no meaningful results for net farm income, indemnity drought payments, or indemnity flood payments. Standard errors are very high relative to the coefficient estimates for these three variables, and despite some significant results for indemnity drought payments, relevant event time coefficient estimates fluctuate between positive and negative values, and F-statistics all indicate joint insignificance.

When restricting the treatment to first removals using regression [2] on my economic variables of interest I find substantially different results. I now find statistically significant positive effects on cash receipts at the 5% level in the 3+ years prior to a removal and no statistical significance on any of the lagged event time coefficients. This result is likely driven by the restriction of the treatment group. Now that the treatment is defined as the first removal per county, there are no instances of contamination in of the 3+ year lead variable where there may have been when allowing for multiple treatments.[16] However, due to the inconsistency of these results and issues with multiple hypothesis testing in this model, coefficient estimates should continue to be interpreted cautiously. I find no results for net farm income or either indemnity payment category. Standard errors are generally larger across the board when using this restricted estimation technique due to the loss of identifying variation from latter dam removals.

The inconsistency in results between regressions [1] and [2] suggests that a) subsequent dam removal impacts are important and their effects are captured more consistently when using regression [1] and b) there is substantial variation among my outcome variables of interest not identified by my model. Thus, coefficient estimates are subject to change when altering the definition of the treatment. Given the significant amount of noise present in the estimates of both regressions [1] and [2], alternating positive and negative coefficient estimates, and the discrepancy of results based upon which specification is used, the results of my baseline model specifications should be interpreted cautiously and further research should be done to establish reliable causal interpretation.

Heterogeneity Analysis

To further parse out the mechanisms behind the effects of dam removals displayed by my baseline model, I examine the potential heterogenous effects of removals based upon various characteristics of a dam removal. First, I estimate my baseline model specifications on a subset of counties with large dam removals and compare these results to a subset of counties with small dam removals. Large dams are considered those that are 6 feet or greater in height and have

[16] For example, with multiple treatments within counties there could be a dam removal 4 years from now, but also 2 years ago, allowing both event time coefficients to equal 1.

larger widespread impacts than smaller dams when removed (USACE, 2019). It is important to note that within my sample, there are 690 large dam removals, 122 small dam removals, and 243 dam removals with no recorded information about dam size. The results of this analysis are shown for my agricultural variables of interest in Table 5.

My findings from this analysis are generally too noisy to interpret with confidence, particularly among the small removal subsample. However, there is some evidence from the subset of large removals that supports the results from my baseline model specification indicating winter wheat yields experience a significant increase after a removal has taken place in the long run; suggesting that these results may be driven disproportionately by the removal of large dams. Results from the subset of small removals indicate the opposite effect, the coefficient for the five-plus-years following a removal is statistically significant and negative, potentially indicating that small dam removals are less constraining to the water availability of farmers in the long run.

Additionally, I compare dam removals based upon the original intended purpose of the dam. Specifically, I compare the removal of agriculturally related dams[17] to the removal of dams that were not originally built for agricultural purposes.[18] In my dataset, there are 55 dams whose original purpose was agriculturally related, 591 dams whose original purpose was something

[17] There are a large number of original uses written into the original dam removal dataset which have been interpreted as agriculturally related or not. A full list of these interpretations can be found in the data section of the appendix.
[18] It is worth noting that the original purpose of a dam and its current or most recent use are not necessarily the same, and that agricultural producers also benefit from dams whose primary purpose is not specifically agriculture.

other than agriculture, and 409 dams with no information regarding their original purpose. Results from this analysis are shown in Table 6.

This analysis is limited in scope due to the lack of dam removals whose original intended purpose is designated as agriculture-specific. The 55 agriculturally focused dam removals in this context does not provide enough statistical power to make valid comparisons when restricting the sample to counties with an agriculturally related dam removal. Standard error estimates are very high, and each model specification has less than 400 observations for my main agricultural variables of interest using this sample subset. As such, no impactful conclusions can be drawn from this particular heterogeneity analysis.[19]

Robustness Checks

To assess the validity of my baseline model estimation results, I implement a number of robustness checks. First, I re-estimate regressions [1] and [2] using my original estimating equation (1) including all counties within my dataset to specifically incorporate counties that never experience a dam removal into the analysis. This unrestricted model adds never treated units into the sample population and substantially increases the number of observations available in the regression specification. For continuity, both regressions exclude the prior year event time coefficient. Results from regressions [1] and [2] on my unrestricted sample of counties differ

[19] I also examine potential heterogenous impacts of removals during drought years, flood years, and by the number of free-flowing river miles removal restores. I do not find differing results for removals in drought or flood years, and do not have enough statistical power to reliably estimate the effects of removals based upon the number of restored river miles. Results from these analyses are shown in the appendix.

slightly but do not impact overall findings of my study. Results and are shown in appendix Tables A3 and A4.

Sun and Abraham Method

First, I implement the Sun and Abraham method as suggested in the event study literature to account for potential issues with the already treated units being included in the comparison group (Miller, 2023; Sun and Abraham, 2021). In particular, I include this robustness check to assess the estimation problem that can occur in situations in which the timing of a treatment varies across different units and corresponding lead or lag coefficient estimates may be influenced by effects from other time periods. Figure 12 shows coefficient plots for my baseline model specification overlaid with the Sun and Abraham model estimates to compare event study coefficients and standard errors. As shown, there are no large discrepancies between the models, illustrating that my baseline specification estimates are robust to the issues presented above.

Pooled Difference-in-Difference

In order to gain statistical power by increasing the intensity of the signal for a dam removal and simplify the interpretation of event time coefficients, I implement a pooled difference-in-difference methodology. With this method, my estimating equation is now shown by equation (2) below:

$$(2)\ Y_{c,t} = \phi + \alpha_c + \lambda_t + \gamma D_{c,t} + \beta \boldsymbol{X}_{c,t} + \varepsilon_{c,t}$$

where $D_{c,t}$ represents a county with a removal in the post treatment time period and, γ is my key coefficient of interest. The key change in the interpretation of this model is that the effects of a dam removal are now assumed to be constant across the post treatment time period. Results using this pooled difference-in-difference specification are shown in Table 7 for my crop yield variables. Results differ based upon which sample restriction is used as the comparison group changes and statistical power increases in conjunction with the number of available observations. Thus, I include the never treated units using the sample of all counties for my primary results using this pooled difference-in-difference methodology.

The primary results shown in Table 7 show positive, statistically significant coefficients for winter wheat and corn grain yields at the 1% and 5% levels respectively. These results indicate that, on average, winter wheat yields are 1.15 bushels per acre higher in the years after a dam removal compared to yields in the years before a removal and in counties without any removal. This finding is generally consistent with the results from the event study models presented above. Corn grain yields are 2.14 bushels per acre higher on average. It is worth noting that these results become smaller and insignificant when restricting the sample to counties with removals exclusively. This may indicate that these results are driven primarily by the comparison to never-treated counties.

Table 8 shows results using equation (2) on my four economic outcome variables of interest. I find statistically significant negative coefficient estimates for cash receipts and indemnity payments for excess moisture at the 1% level using the sample of all counties. I find an 8% decline in cash receipts following a dam removal and a 15% decline in indemnity excess moisture payments. This result is consistent with my event study estimates for cash receipts, but is a new finding for indemnity excess moisture payments. This result is not in line with economic or institutional intuition and does not hold when restricting the sample to counties with removals only. As such, this finding is likely due to estimation bias or subject to type 1 error. It is worth noting that my primary findings for cash receipts are generally robust to the restricted sample estimates.

Instrumental Variable

In order to address potential reverse causality issues driven by the endogeneity of dam removal decisions, I employ an instrumental variable approach. I instrument for the likelihood of a county having a dam removal using the age of dam infrastructure; dam age would affect the likelihood of dam removal, but plausibly not the agricultural productivity of a county. This is a final econometric strategy I implement to address the possible endogeneity problem and potential spurious correlation present in my baseline specifications. The concern being that counties which do not have substantial agricultural production, irrigation, or gains from existing dams would be more likely to remove their dam infrastructure.

I use the percentage of old dam infrastructure in a county as an instrument affecting the relative likelihood of dam removal events in a county while not directly influencing the agricultural yields or economic outcomes in that county.[20] The first stage relationship between the percentage of old dam infrastructure in a county and the likelihood of a dam removal is strong, with F-statistic of 75.1[21]. The exclusivity of this instrument cannot be tested since this model is exactly defined[22], but it is plausible that the general age of dam infrastructure would not be correlated with agricultural production in a county. While the age of a dam directly correlates

---

[20] This variable is the number of old dams in a county (>50 years old) divided by the number of total dams.
[21] Three instruments were created and tested as shown in appendix table A2.
[22] Number of instruments = number of endogenous variables.

to its likelihood for removal due to increased risk of failure, need for costly maintenance, and regulatory compliance costs, a dams age should not directly affect agricultural production. Old dams still create reservoirs for irrigation, increase total arable land, provide flood protection, and generally function in much the same way that newer dams do. Additionally, a dam's age is unlikely to correlate with the level of agricultural production in a county. Since dams are implemented for a wide variety of purposes, agriculture being one of many, it is unlikely that dams in agriculturally focused counties were built prior to dams in the average county at a disproportionate rate. Counties with higher proportions of old dam infrastructure should not indicate counties with higher or lower agricultural output.

The results of my instrumental variable approach are shown in Tables 9 and 10 below. To retain statistical power and simplify the comparison of coefficients, I continue to use the pooled difference-in-difference methodology. My key findings do change slightly when instrumenting for dam age in this methodology. In Table 9, the coefficient estimate for corn grain increases from 2.14 to 15.28 bushels per acre, significant at the 5% level. This is a substantial increase and suggests that the average increase in per acre productivity for corn grain fields is larger than originally estimated. I also find an increase in soybean yields form 0.03 bushels per acre to 2.52, significant at the 10% level, and a change in winter wheat yields from 1.15 to 2.19. These changes are relatively small in magnitude, but the changes in these coefficient estimates generally suggest that my previous findings were subject to some level of bias from the endogeneity of dam removals.

Table 10 depicts results from the instrumental variable approach on my four economic outcome variables. Results for these variables change substantially. Significant results for cash receipts disappear and the coefficient estimate changes from a decline of 8% to an increase of 52% following a removal. Other economic variables of interest change with similar magnitudes. Focusing on variation from the removal of old dams with this IV approach often switches the sign of key coefficients and suggests that the previously estimated negative results may have been driven by endogeneity of removals. Again, these results should be interpreted cautiously.

CONCLUSION

This paper has shed light on the complex relationship between dam removals and agricultural productivity. As dam infrastructure in the United States ages and public support for removals rises, dam owners and policymakers will face a new set of challenges and understanding the impacts of dam removal becomes essential. This study provides insight into how dam removals can influence agricultural outcomes with regard to crop yields, indemnity claims, and farm earnings.

Although subject to data and identification challenges, my study finds initial suggestive evidence that per acre productivity of crops increases, while cash receipts for crops decline following dam removals at the county level. Both results are subject to the specific model specification used, and should be interpreted cautiously with an eye towards further research. The mechanism behind these results is open to speculation, but could indicate that agricultural producers cultivate less total acreage following a dam removal. My study does not include data on total planted acreage, so this discussion is purely speculative, but would be in line with that found by (Hansen et al. 2014). If farmers are cultivating less acreage, they are likely growing crops primarily on their most productive plots of land, driving up per acre productivity but decreasing the amount of total farm output, subsequently driving down cash receipts for crops. Again, this analysis is purely speculative and should be interpolated only after further research.

Additionally, my findings may be generally true at the county level, but a deeper analysis is needed to distinguish these high-level effects from the fine-scale impacts on agricultural producers at the farm or field level. While I find null or noisy results for many of my outcome variables at the county level, this does not rule out potentially substantial effects of dam removals to certain agricultural producers on an individual level. While the implications of my study may be useful on a broad scale for policymakers and county officials to understand the general impacts of dam removals on their geographic region, future research should seek to assess the impacts of dam removals on individual agricultural producers at finer geographic scales.

While dam removal offers potentially significant ecological benefits and can address risks associated with old or failing dams, the impacts on agricultural producers has the potential to be significant, particularly for those producers who rely on irrigation infrastructure. Policymakers and dam owners must weigh these trade-offs carefully when making dam removal decisions. Ultimately, my research contributes to the comprehensive understanding of how dam removals might shape the landscape of agricultural production and guides avenues for future research by emphasizing the need for additional fine-scale geographic analysis of the impacts of dam removals to agricultural producers at the field level.

Table 3. Baseline Specification Table (Crop Yields)

	[1] All removals, counties with removals			*[2] First removal, counties with removals*		
	Winter Wheat Yields	Corn Grain Yields	Soybean Yields	Winter Wheat Yields	Corn Grain Yields	Soybean Yields
Dam Removal 3+ Year Lead	0.37 (0.59)	-0.10 (1.24)	0.24 (0.33)	0.63 (0.95)	1.76 (1.69)	0.69 (0.47)
Dam Removal 2 Year Lead	-0.50 (0.53)	-0.91 (0.95)	0.11 (0.33)	0.02 (0.94)	-1.76 (1.70)	0.21 (0.53)
Dam Removal	0.66 (0.54)	1.16 (0.98)	0.16 (0.31)	0.88 (0.98)	3.06* (1.65)	0.95* (0.52)
Dam Removal 1 Year Lag	0.11 (0.60)	-0.42 (0.91)	-0.10 (0.30)	0.65 (1.12)	1.73 (1.79)	0.94* (0.55)
Dam Removal 2 Year Lag	-0.36 (0.61)	-0.14 (0.98)	-0.29 (0.32)	0.45 (1.03)	0.61 (1.86)	0.40 (0.54)
Dam Removal 3 Year Lag	-0.33 (0.55)	0.23 (1.06)	-0.35 (0.34)	-0.22 (1.10)	-0.44 (2.00)	-0.57 (0.57)
Dam Removal 4 Year Lag	0.62 (0.60)	1.54 (0.99)	0.03 (0.32)	0.45 (1.16)	0.96 (1.97)	0.43 (0.54)
Dam Removal 5+ Year Lag	1.15* (0.69)	-0.83 (1.14)	0.28 (0.32)	1.42 (1.01)	-0.50 (1.80)	0.61 (0.50)
N	3,903	5,906	4,800	3,903	5,906	4,800
Group Mean	61.11	132.9	41.6	61.11	132.9	41.6
F-Statistic of lagged coefficients	0.97	0.87	0.67	0.75	0.61	1.40
Unit of Measurement	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre
Adj. R^2	0.75	0.74	0.70	0.75	0.74	0.70
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table above shows results for the baseline event study specification on my agricultural outcome variables of interest. Standard errors are clustered at the county level.

Table 4. Baseline Specification Table (Economic Indicators)

	[1] All removals, counties with removals				*[2] One removal, counties with removals*			
	Cash Receipts	Net Income	Indemnity Payments (Drought)	Indemnity Payments (Excess Moisture)	Cash Receipts	Net Income	Indemnity Payments (Drought)	Indemnity Payments (Excess Moisture)
Dam Removal 3+ Year Lead	-142.8 (3933.4)	-216.1 (1887.3)	-78632.5 (123243.0)	-6905.6 (171203.4)	-1516.9 (5615.4)	-3205.6 (2814.3)	112199.1 (157598.1)	38515.2 (190379.9)
Dam Removal 2 Year Lead	467.9 (2467.8)	1014.3 (1404.1)	-43811.7 (114757.8)	-97691.8 (77545.1)	-588.4 (1381.5)	-506.8 (1092.3)	55683.1 (154578.1)	-168647.3 (162692.4)
Dam Removal	534.1 (2700.9)	654.7 (1483.5)	-107906.5 (103897.2)	-183699.3** (81708.3)	96.6 (910.1)	163.7 (930.5)	-266677.2** (134167.9)	-185495.3 (161489.9)
Dam Removal 1 Year Lag	-488.4 (2885.2)	-665.6 (1386.5)	35632.4 (115952.3)	-224011.7** (87424.7)	-2658.6** (1168.9)	-1410.6 (1148.7)	-248712.0* (128869.4)	-307768.3* (178889.5)
Dam Removal 2 Year Lag	-591.1 (3126.6)	-1255.0 (1315.8)	4145.1 (107656.6)	-164560.6* (88599.9)	-2635.3 (1826.0)	-3425.8** (1385.4)	34152.2 (185138.0)	-281379.8 (195957.1)
Dam Removal 3 Year Lag	121.3 (3497.1)	-218.3 (1368.6)	-78031.4 (117578.1)	-40317.7 (111427.1)	-3018.2 (2559.7)	-2859.1 (1866.0)	-59055.8 (196740.8)	9162.7 (240598.7)
Dam Removal 4 Year Lag	-529.5 (3580.69)	134.7 (1373.6)	-125918.7 (106877.0)	-279413.9*** (97234.2)	-5634.8* (3151.9)	-4037.6* (2207.6)	-108270.4 (181379.1)	-331948.5* (177127.3)
Dam Removal 5+ Year Lag	-1950.2 (4383.8)	-1806.74 (2045.3)	-77969.0 (113324.6)	-113398.4 (114887.0)	-4520.4 (5043.4)	-3446.8 (2802.2)	-190596.6 (158820.0)	-236492.8 (211971.4)
N	10,956	10,956	6,269	7,136	10,956	10,956	6,269	7,136
Group Mean	71,437	23,183	605,443	716,298	71,437	23,183	605,443	716,298
F-Statistic for lagged coefficients	0.24	0.80	0.46	2.78**	1.90*	1.37	1.26	1.47
Unit of Measurement	US/$	US/$	US/$	US/$	US/$	US/$	US/$	US/$
Adj. R^2	0.92	0.85	0.19	0.32	0.92	0.85	0.19	0.31
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table above shows results for the baseline event study specification on my economic outcome variables of interest. Standard errors are clustered at the county level.

Table 5. Dam Size Heterogeneity Analysis

	Large Dams			*Small Dams*		
	Winter Wheat Yields	Corn Grain Yields	Soybean Yields	Winter Wheat Yields	Corn Grain Yields	Soybean Yields
Dam Removal 3+ Year Lead	0.12 (0.68)	-0.83 (1.49)	-0.26* (0.37)	0.85 (1.61)	3.58 (2.51)	2.69*** (0.83)
Dam Removal 2 Year Lead	-0.60 (0.54)	-0.53 (1.02)	0.12 (0.37)	-0.35 (1.44)	-2.66 (2.62)	0.58 (0.67)
Dam Removal	0.84 (0.58)	1.45 (1.06)	0.14 (0.32)	0.07 (1.45)	0.15 (2.47)	0.69 (0.89)
Dam Removal 1 Year Lag	-0.26 (0.61)	-0.86 (0.99)	-0.05 (0.34)	1.17 (1.77)	3.54 (2.44)	0.19 (0.62)
Dam Removal 2 Year Lag	-0.66 (0.64)	0.12 (1.08)	-0.25 (0.35)	0.88 (1.95)	-0.68 (2.33)	0.09 (0.87)
Dam Removal 3 Year Lag	0.15 (0.57)	-0.04 (1.16)	-0.68* (0.38)	-2.96* (1.57)	1.93 (2.56)	1.82** (0.79)
Dam Removal 4 Year Lag	0.54 (0.60)	1.39*** (1.06)	-0.04 (0.36)	-0.20 (1.69)	3.02 (2.50)	0.94 (0.66)
Dam Removal 5+ Year Lag	2.12*** (0.76)	-1.26 (1.30)	0.24 (0.34)	-2.08*** (1.66)	1.20 (2.61)	0.89 (0.86)
N	2,941	4,631	3,751	962	1,275	1,049
Unit of Measurement	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre
Adj. R^2	0.75	0.74	0.70	0.76	0.74	0.68
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: The table above shows results for the baseline event study specification on my agricultural outcome variables of interest ran on two distinct subsets of my sample based on dam size. Large dam sub-sample is restricted to counties that have remove a dam greater than or equal to 10 feet. Small dam sub-sample is restricted to counties that remove a dam, but not one greater than or equal to 10 feet. Standard errors are clustered at the county level.

Table 6. Dam Purpose Heterogeneity Analysis

	Agricultural Dams			*Non-Agricultural Dams*		
	Winter Wheat Yields	Corn Grain Yields	Soybean Yields	Winter Wheat Yields	Corn Grain Yields	Soybean Yields
Dam Removal 3+ Year Lead	0.30 (2.45)	-3.09 (6.14)	2.52 (2.69)	0.32 (0.61)	0.10 (1.25)	2.69*** (0.83)
Dam Removal 2 Year Lead	-4.97** (1.94)	-4.67 (3.59)	-3.78*** (0.81)	0.01 (0.47)	-0.54 (0.98)	0.58 (0.67)
Dam Removal	1.84 (2.77)	-1.42 (4.75)	-0.43 (2.86)	0.54 (0.51)	1.25 (1.02)	0.69 (0.89)
Dam Removal 1 Year Lag	0.61 (1.58)	-1.26 (4.20)	0.24 (1.47)	-0.04 (0.64)	-0.40 (0.96)	0.19 (0.62)
Dam Removal 2 Year Lag	-3.82 (2.30)	-3.90 (5.76)	-2.91 (1.40)	0.04 (0.60)	0.02 (0.99)	0.09 (0.87)
Dam Removal 3 Year Lag	-2.29 (2.71)	0.99 (3.89)	-0.03 (0.96)	0.04 (0.53)	0.44 (1.10)	1.82** (0.79)
Dam Removal 4 Year Lag	1.54 (2.56)	4.04 (4.37)	-2.84 (1.90)	0.07 (0.60)	1.32 (1.02)	0.94 (0.66)
Dam Removal 5+ Year Lag	5.45* (3.00)	4.84 (9.71)	3.00 (2.09)	1.06 (0.70)	-1.03 (1.16)	0.89 (0.86)
N	361	271	148	3,542	5,635	1,049
Unit of Measurement	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre
Adj. R^2	0.81	0.88	0.80	0.75	0.72	0.68
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table above shows results for the baseline event study specification on my agricultural outcome variables of interest ran on two distinct subsets of my sample based on dam size. Agricultural dam sub-sample is restricted to counties that remove a dam in which its intended purpose is agriculturally related. Non-agricultural dam sub-sample is restricted to counties who remove a dam, but not one in which its intended purpose is agriculturally related. Standard errors are clustered at the county level.

Table 7: Basic Pooled Difference-in-Difference (Crop Yields)

	All counties			*Counties With Removals*		
	Winter Wheat Yields	Corn Grain Yields	Soybean Yields	Winter Wheat Yields	Corn Grain Yields	Soybean Yields
Dam Removal * Post-Treatment	1.15*** (0.43)	2.14** (0.84)	0.03 (0.24)	0.20 (0.56)	0.78 (1.04)	0.11 (0.28)
N	27,917	37,309	31,740	3,903	5,906	4,800
Group Mean	51.82	134.29	40.7	61.11	132.89	41.16
Unit of Measurement	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre
Adj. R^2	0.75	0.74	0.70	0.76	0.74	0.68
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table above shows results for my baseline pooled difference-in-difference methodology on my agricultural outcome variables of interest. Standard errors are clustered at the county level.

Table 8: Basic Pooled Difference-in-Difference (Economic Indicators)

	All counties				*Counties With Removals*			
	Cash Receipts	Net Income	Indemnity Payments (Drought)	Indemnity Payments (Excess Moisture)	Cash Receipts	Net Income	Indemnity Payments (Drought)	Indemnity Payments (Excess Moisture)
Dam Removal*Post-Treatment	-0.08*** (0.02)	0.46* (0.24)	0.10 (0.06)	-0.15*** (0.05)	-0.05** (0.02)	0.05 (0.30)	0.03 (0.08)	0.04 (0.07)
N	67,164	67,164	42,621	45,734	67,164	67,164	42,621	45,734
Group Mean	71,437	23,183	605,443	716,298	71,437	23,183	605,443	716,298
Adj. R^2	0.79	0.52	0.28	0.30	0.92	0.80	0.28	0.30
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table above shows results for my baseline pooled difference-in-difference methodology on my economic outcome variables of interest. Standard errors are clustered at the county level.

Table 9: Instrumental Variable Table (Crop Yields)

	All counties [IV]			*All Counties*		
	Winter Wheat Yields	Corn Grain Yields	Soybean Yields	Winter Wheat Yields	Corn Grain Yields	Soybean Yields
Dam Removal * Post-Treatment	2.19 (2.71)	15.28** (6.90)	2.52* (1.45)	1.15*** (0.43)	2.14** (0.84)	0.03 (0.24)
N	27,917	37,309	31,740	27,917	37,309	31,740
Group Mean	51.82	134.29	40.7	51.82	134.29	40.7
Unit of Measurement	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre
Adj. R^2	0.75	0.74	0.70	0.76	0.74	0.68
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table above shows the results for my pooled difference-in-difference instrumental variable methodology on my agricultural outcome variables of interest. Standard errors are clustered at the county level.

Table 10: Instrumental Variable Table (Economic Indicators)

	All counties (IV)				*All counties*			
	Cash Receipts	Net Income	Indemnity Payments (Drought)	Indemnity Payments (Excess Moisture)	Cash Receipts	Net Income	Indemnity Payments (Drought)	Indemnity Payments (Excess Moisture)
Dam Removal*Post-Treatment	0.52 (0.37)	1.44 (4.54)	-1.67 (2.14)	-0.79 (0.67)	-0.08*** (0.02)	0.46* (0.24)	0.10 (0.06)	-0.15*** (0.05)
N	67,164	67,164	42,621	45,734	67,164	67,164	42,621	45,734
Group Mean	71,437	23,183	605,443	716,298	71,437	23,183	605,443	716,298
Adj. R^2	0.95	0.51	0.37	0.54	0.92	0.80	0.28	0.30
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table above shows the results for my pooled difference-in-difference instrumental variable methodology on my economic outcome variables of interest. Standard errors are clustered at the county level.

Figure 11. Baseline Event Study Coefficient Plots

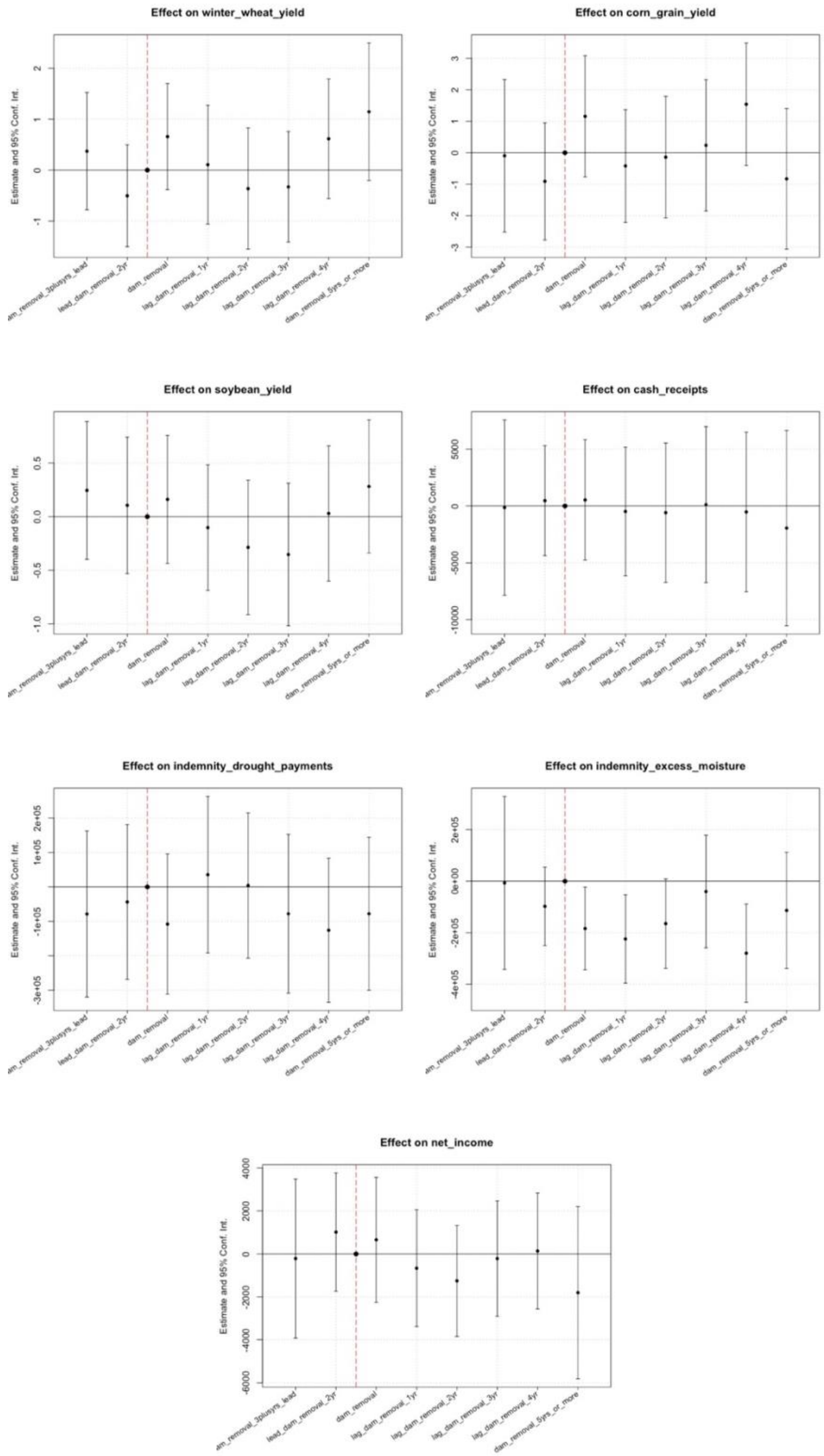
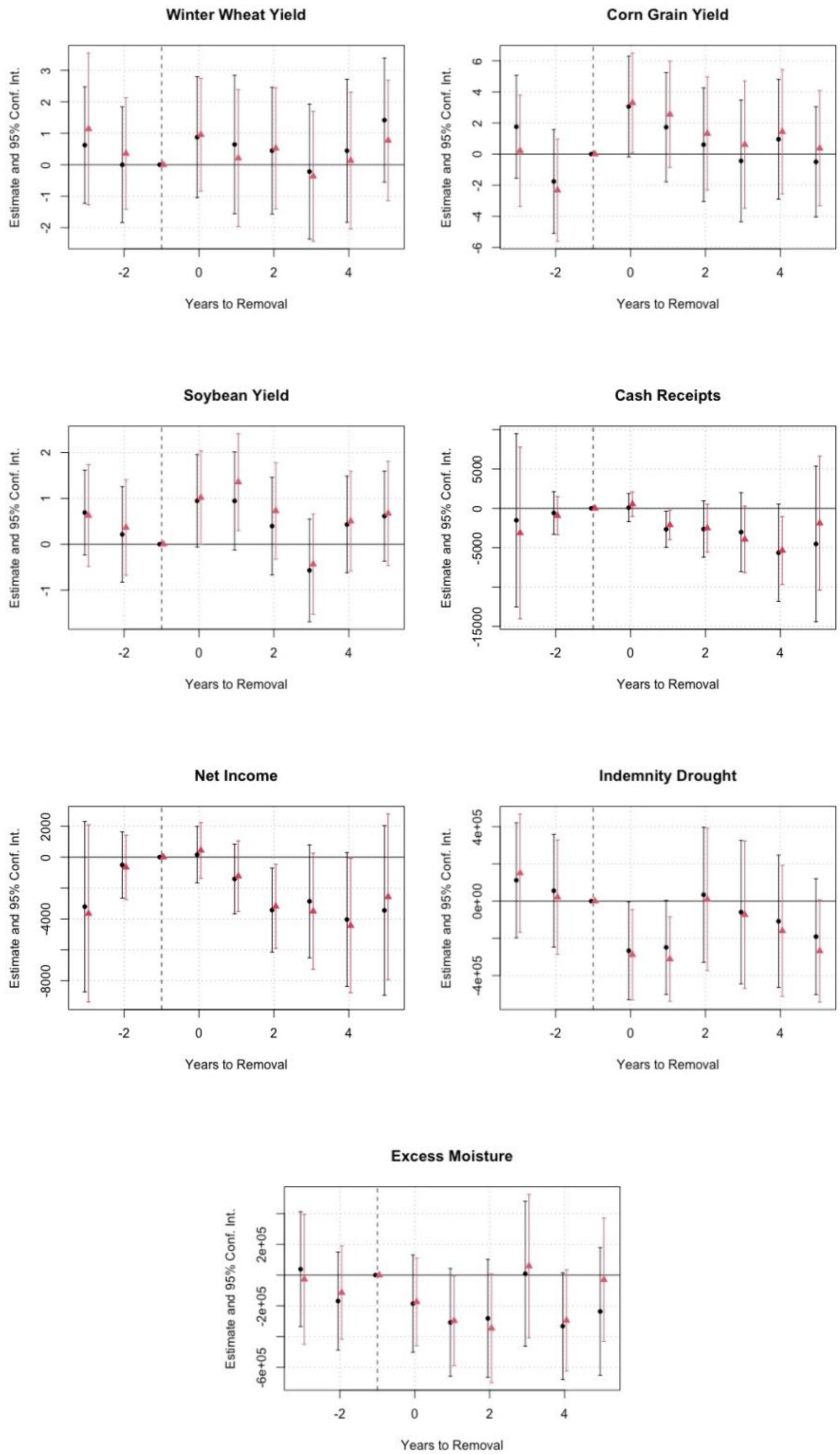


Figure 12. Sun and Abraham Coefficient Plots



REFERENCES

A big dam problem: The disaster in Michigan and solutions for the future —. (n.d.). Retrieved March 20, 2024, from https://www.americanrivers.org/2020/05/a-big-dam-problem-the-disaster-in-michigan-and-solutions-for-the-future/

Bednarek, A. T. (2001). Undamming Rivers: A Review of the Ecological Impacts of Dam Removal. *Environmental Management*, *27*(6), 803–814. https://doi.org/10.1007/s002670010189

Blachly, B., & Uchida, E. (n.d.). *Estimating the Marginal Cost of Dam Removal*.

Bohlen, C., & Lewis, L. Y. (2009). Examining the economic impacts of hydropower dams on property values using GIS. *Journal of Environmental Management*, *90*, S258–S269.

Bountry, J., Tullos, D., Duda, J., Randle, T., Jansen, A., McKay, K., Jumani, S., & Bailey, S. (n.d.). *Cost estimating dam removal: Databases and drivers*.

ÇeliK, R. (2018). Impact of Dams on Groundwater Static Water Level Changes: A Case Study Kralkızı and Dicle Dam Watershed. *Uluslararası Muhendislik Arastirma ve Gelistirme Dergisi*, 119–126. https://doi.org/10.29137/umagd.442483

Colaiacomo, E. J. (n.d.). *Downstream spatial and temporal response to dam removal, White Salmon River, WA*.

Commission On Dams, W. (2001). Dams and Development: A New Framework for Decision-Making. *Environmental Management and Health*, *12*(4), 444–445. https://doi.org/10.1108/emh.2001.12.4.444.2

Cooper, A. R., Infante, D. M., Daniel, W. M., Wehrly, K. E., Wang, L., & Brenden, T. O. (2017). Assessment of dam effects on streams and fish assemblages of the conterminous USA. *Science of The Total Environment*, *586*, 879–889. https://doi.org/10.1016/j.scitotenv.2017.02.067

Dillon, A., & Fishman, R. (2019). Dams: Effects of Hydrological Infrastructure on Development. *Annual Review of Resource Economics*, *11*(1), 125–148. https://doi.org/10.1146/annurev-resource-100518-093913

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

Foley, M. M., Bellmore, J. R., O’Connor, J. E., Duda, J. J., East, A. E., Grant, G. E., Anderson, C. W., Bountry, J. A., Collins, M. J., Connolly, P. J., Craig, L. S., Evans, J. E., Greene, S. L., Magilligan, F. J., Magirl, C. S., Major, J. J., Pess, G. R., Randle, T. J., Shafroth, P. B., … Wilcox, A. C. (2017). Dam removal: Listening in. *Water Resources Research*, *53*(7), 5229–5246. https://doi.org/10.1002/2017WR020457

Freyaldenhoven, S., Hansen, C., Perez, J. P., & Shapiro, J. M. (n.d.). *Visualization, Identification, and Estimation in the Linear Panel Event-Study Design*.

Gillette, D. P., Daniel, K., & Redd, C. (2016). Fish and Benthic Macroinvertebrate Assemblage Response to Removal of a Partially Breached Lowhead Dam. *River Research and Applications*, *32*(8), 1776–1789. https://doi.org/10.1002/rra.3017

Gonzales, V., & Walls, M. (2020). *Dams and Dam Removals in the United States*.

Gowan, C., Stephenson, K., & Shabman, L. (2006). The role of ecosystem valuation in environmental decision making: Hydropower relicensing and dam removal on the Elwha River. *Ecological Economics*, *56*(4), 508–523. https://doi.org/10.1016/j.ecolecon.2005.03.018

Hansen, Z. K., Lowe, S. E., & Xu, W. (2014). Long-term impacts of major water storage facilities on agriculture and the natural environment: Evidence from Idaho (U.S.). *Ecological Economics*, *100*, 106–118. https://doi.org/10.1016/j.ecolecon.2014.01.015

Hansen, Z., Libecap, G., & Lowe, S. (2009). *Climate Variability and Water Infrastructure: Historical Experience in the Western United States* (w15558; p. w15558). National Bureau of Economic Research. https://doi.org/10.3386/w15558

Hart, D. D., Johnson, T. E., Bushaw-Newton, K. L., Horwitz, R. J., Bednarek, A. T., Charles, D. F., Kreeger, D. A., & Velinsky, D. J. (2002). Dam Removal: Challenges and Opportunities for Ecological Research and River Restoration. *BioScience*, *52*(8), 669. https://doi.org/10.1641/0006-3568(2002)052[0669:DRCAOF]2.0.CO;2

Jaeger, W. K., Plantinga, A. J., Chang, H., Dello, K., Grant, G., Hulse, D., McDonnell, J. J., Lancaster, S., Moradkhani, H., Morzillo, A. T., Mote, P., Nolin, A., Santelmann, M., & Wu, J. (2013). Toward a formal definition of water scarcity in natural-human systems. *Water Resources Research*, *49*(7), 4506–4517. https://doi.org/10.1002/wrcr.20249

Jhunjhunwala, B. (2010). *Economics of River Flows: Lessons from Dam Removals in America*. Gyan Publishing House.

Kornis, M. S., Weidel, B. C., Powers, S. M., Diebel, M. W., Cline, T. J., Fox, J. M., & Kitchell, J. F. (2015). Fish community dynamics following dam removal in a fragmented agricultural stream. *Aquatic Sciences*, *77*(3), 465–480. https://doi.org/10.1007/s00027-014-0391-2

Kuby, M. J., Fagan, W. F., ReVelle, C. S., & Graf, W. L. (2005). A multiobjective optimization model for dam removal: An example trading off salmon passage with hydropower and water storage in the Willamette basin. *Advances in Water Resources*, *28*(8), 845–855. https://doi.org/10.1016/j.advwatres.2004.12.015

Lewis, L. Y., Bohlen, C., & Wilson, S. (2008). DAMS, DAM REMOVAL, AND RIVER RESTORATION: A HEDONIC PROPERTY VALUE ANALYSIS. *Contemporary Economic Policy*, *26*(2), 175–186. https://doi.org/10.1111/j.1465-7287.2008.00100.x

Loomis, J. B. (1996). Measuring the Economic Benefits of Removing Dams and Restoring the Elwha River: Results of a Contingent Valuation Survey. *Water Resources Research*, *32*(2), 441–447. https://doi.org/10.1029/95WR03243

Magilligan, F. J., Graber, B. E., Nislow, K. H., Chipman, J. W., Sneddon, C. S., & Fox, C. A. (2016). River restoration by dam removal: Enhancing connectivity at watershed scales. *Elementa: Science of the Anthropocene*, *4*, 000108. https://doi.org/10.12952/journal.elementa.000108

Miller, D. L. (2023). An Introductory Guide to Event Study Models. *Journal of Economic Perspectives*, *37*(2), 203–230. https://doi.org/10.1257/jep.37.2.203

Nolin, A. W. (2013). Toward a formal definition of water scarcity in natural-human systems. *Water Resources Research*. https://www.academia.edu/114209995/Toward_a_formal_definition_of_water_scarcity_in_natural_human_systems

Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. (n.d.). https://doi.org/10.1073/pnas.0906865106

Perera, D., & North, T. (2021). The Socio-Economic Impacts of Aged-Dam Removal: A Review. *Journal of Geoscience and Environment Protection*, *09*(10), 62–78. https://doi.org/10.4236/gep.2021.910005

Pohl, M. M. (2002a). Bringing down Our Dams: Trends in American Dam Removal Rationales1. *JAWRA Journal of the American Water Resources Association*, *38*(6), 1511–1519. https://doi.org/10.1111/j.1752-1688.2002.tb04361.x

Pohl, M. M. (2002b). Bringing down Our Dams: Trends in American Dam Removal Rationales1. *JAWRA Journal of the American Water Resources Association*, *38*(6), 1511–1519. https://doi.org/10.1111/j.1752-1688.2002.tb04361.x

Provencher, B., Sarakinos, H., & Meyer, T. (2008). Does Small Dam Removal Affect Local Property Values? An Empirical Analysis. *Contemporary Economic Policy*, *26*(2), 187–197. https://doi.org/10.1111/j.1465-7287.2008.00107.x

Robbins, J. L., & Lewis, L. Y. (2008). Demolish it and They Will Come: Estimating the Economic Impacts of Restoring a Recreational Fishery1. *JAWRA Journal of the American Water Resources Association*, *44*(6), 1488–1499. https://doi.org/10.1111/j.1752-1688.2008.00253.x

Ryan Bellmore, J., Duda, J. J., Craig, L. S., Greene, S. L., Torgersen, C. E., Collins, M. J., & Vittum, K. (2017). Status and trends of dam removal research in the United States. *WIREs Water*, *4*(2), e1164. https://doi.org/10.1002/wat2.1164

Sandler, D. H., & Sandler, R. (n.d.). *Multiple Event Studies in Public Finance and Labor Economics: A Simulation Study with Applications*.

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences*, *106*(37), 15594–15598. https://doi.org/10.1073/pnas.0906865106

Schmitt, R. J. P., Rosa, L., & Daily, G. C. (2022). Global expansion of sustainable irrigation limited by water storage. *Proceedings of the National Academy of Sciences*, *119*(47), e2214291119. https://doi.org/10.1073/pnas.2214291119

Smith, L. W., Dittmer, E., Prevost, M., & Burt, D. R. (2000). Breaching of a Small Irrigation Dam in Oregon: A Case History. *North American Journal of Fisheries Management*, *20*(1), 205–219. https://doi.org/10.1577/1548-8675(2000)020<0205:BOASID>2.0.CO;2

Stanley, E. H., & Doyle, M. W. (2003). Trading off: The ecological effects of dam removal. *Frontiers in Ecology and the Environment*, *1*(1), 15–22. https://doi.org/10.1890/1540-9295(2003)001[0015:TOTEEO]2.0.CO;2

Sun, L., & Abraham, S. (2021). Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics*, *225*(2), 175–199. https://doi.org/10.1016/j.jeconom.2020.09.006

Tonitto, C., & Riha, S. J. (2016). Planning and implementing small dam removals: Lessons learned from dam removals across the eastern United States. *Sustainable Water Resources Management*, *2*(4), 489–507. https://doi.org/10.1007/s40899-016-0062-7

Tullos, D. D., Collins, M. J., Bellmore, J. R., Bountry, J. A., Connolly, P. J., Shafroth, P. B., & Wilcox, A. C. (2016). Synthesis of Common Management Concerns Associated with Dam Removal. *JAWRA Journal of the American Water Resources Association*, *52*(5), 1179–1206. https://doi.org/10.1111/1752-1688.12450

Walls, M. (n.d.). *Aligning Dam Removal and Dam Safety: Comparing Policies and Institutions across States*.

Watts, R. J., Richter, B. D., Opperman, J. J., & Bowmer, K. H. (2011). Dam reoperation in an era of climate change. *Marine and Freshwater Research*, *62*(3), 321. https://doi.org/10.1071/MF10047

Winter, B. (2008). Making the Case for Ecosystem Restoration by Dam Removal in the Elwha River, Washington. *Northwest Science*, *82*, 13–28. https://doi.org/10.3955/0029-344X-82.S.I.13

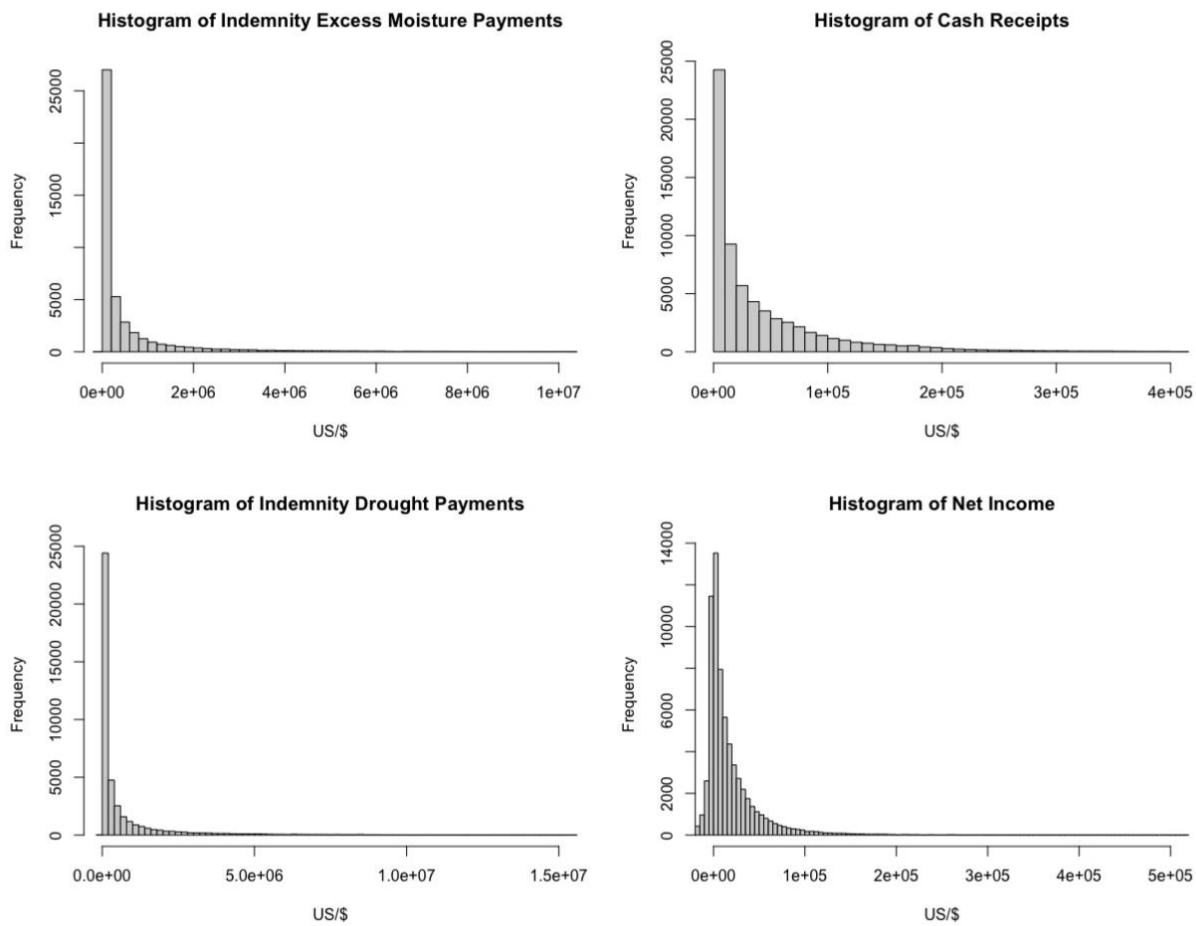
Woodward, A., Schreiner, E. G., Crain, P., Brenkman, S. J., Happe, P. J., Acker, S. A., & Hawkins-Hoffman, C. (2008). Conceptual Models for Research and Monitoring of Elwha

APPENDICES

APPENDIX A

ADDITIONAL TABLES AND FIGURES

Figure A1. Histogram Chart of Economic Indicators



Note: The table above shows histogram plots for my four key economic variables of interest.

Table A1. Dam Height by Removal Order

	1st Removal	2nd Removal	3rd Removal or Later
Avg. Dam Height (ft.)	15.22	12.74	11.43

Notes: The table above shows average height of a dam that is removed based upon the order in which it is removed by county.

Table A2. Instrumental Variable F-Statistics

Instrument	**1st Stage F-Statistic**
Average dam age in county	9.22
Binary old dam presence variable	7.18
Percentage of old dams in county	75.1

Notes: The table above shows results for instrument relevance F-tests for each of the instrumental variables attempted in this analysis.

Table A3. Unrestricted Sample Event Study (Crop Yields)

	[3] All counties, all removals			*[4] All counties, one removal*		
	Winter Wheat Yields	Corn Grain Yields	Soybean Yields	Winter Wheat Yields	Corn Grain Yields	Soybean Yields
Dam Removal 3+ Year Lead	0.41 (0.51)	-0.02 (1.01)	0.48* (0.27)	0.47 (0.903)	0.03 (1.614)	0.69 (0.444)
Dam Removal 2 Year Lead	-0.40 (0.52)	-0.10 (0.93)	0.13 (0.32)	-0.01 (0.955)	-1.97 (1.698)	0.09 (0.539)
Dam Removal	1.01* (0.53)	1.93* (1.00)	0.26 (0.31)	1.17 (0.995)	3.49** (1.644)	0.97* (0.522)
Dam Removal 1 Year Lag	0.57 (0.59)	0.41 (0.92)	-0.13 (0.30)	1.09 (1.121)	2.31 (1.798)	0.75 (0.553)
Dam Removal 2 Year Lag	0.24 (0.62)	0.87 (1.01)	-0.19 (0.33)	1.26 (1.041)	1.29 (1.850)	0.39 (0.545)
Dam Removal 3 Year Lag	-0.13 (0.57)	1.33 (1.05)	-0.25 (0.35)	0.09 (1.118)	0.87 (1.944)	-0.53 (0.596)
Dam Removal 4 Year Lag	0.99 (0.60)	2.64*** (0.97)	0.20 (0.32)	1.04 (1.152)	2.31 (1.918)	0.46 (0.540)
Dam Removal 5+ Year Lag	1.91*** (0.60)	0.80 (0.98)	0.44 (0.27)	2.28*** (0.879)	1.55 (1.550)	0.63 (0.452)
N	27,917	37,309	31,740	27,897	37,309	31,740
Group Mean	51.82	138.0	41.2	51.82	138.0	41.2
F-Statistic of lagged coefficients	2.61**	1.76	1.02	2.19*	0.45	1.30
Unit of Measurement	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre
Adj. R^2	0.77					
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table above shows results for my baseline event study specification on my agricultural variables of interest when using all counties available in my sample. Standard errors are clustered at the county level.

Table A4: Unrestricted Sample Event Study (Agricultural Indicators)

	[3] All counties, All removals				*[4] All counties, One removal*			
	Cash Receipts	Net Income	Indemnity Payments (Drought)	Indemnity Payments (Excess Moisture)	Cash Receipts	Net Income	Indemnity Payments (Drought)	Indemnity Payments (Excess Moisture)
Dam Removal 3+ Year Lead	-4036.02 (4332.36)	-1111.76 (1743.24)	-47766.40 (104722.10)	33414.42 (119520.19)	-4951.70 (5615.46)	-4491.85 (2849.85)	205762.50 (137032.44)	43431.96 (175115.13)
Dam Removal 2 Year Lead	577.60 (2320.92)	1724.70 (1477.19)	-132202.83 (118384.96)	-105895.68 (75935.58)	-881.44 (1381.53)	-663.44 1011.1392)	86407.80 (163325.12)	-212435.08 (165369.69)
Dam Removal	745.37 (2707.75)	1207.23 (1554.55)	-204642.18* (112677.90)	-160572.23** (81799.48)	176.77 (910.16)	38.32 (849.28)	-304317.00** (145345.32)	-160254.12 (160906.83)
Dam Removal 1 Year Lag	-54.79 (2935.23)	-96.89 (1427.09)	-44377.21 (126005.08)	-210634.59** (86063.43)	-1785.64* (1168.93)	-1310.21 (1015.72)	-278729.30* (148507.72)	-294166.27* (178502.01)
Dam Removal 2 Year Lag	-76.22 (3182.57)	-627.42 (1346.02)	-71848.07 (110427.66)	-145331.96* (85402.44)	-1010.62 (1826.04)	-2975.08** (1218.37)	25124.50 (188030.01)	-261260.87 (194033.15)
Dam Removal 3 Year Lag	487.02 (3408.28)	316.42 (1345.50)	-134416.71 (122131.05)	-23282.00 (112887.15)	-1130.25 (2559.79)	-2299.88 (1532.01)	-46881.80 (209093.94)	12594.33 (237449.16)
Dam Removal 4 Year Lag	384.18 (3672.49)	1032.64 (1434.78)	-236684.01** (111790.03)	-267943.40*** (95912.25)	-2862.32 (3151.97)	-3069.94* (1851.37)	-211892.50 (193902.75)	-315022.96* (172767.61)
Dam Removal 5+ Year Lag	1885.23 (4392.08)	131.11 (1962.73)	-264377.47** (106085.61)	-143018.49 (96030.98)	1346.56 (5043.44)	-1990.34 (2027.15)	-234937.70 (145229.87)	-245590.64 (189398.24)
N	67,164	67,164	42,621	7,136	67,164	67,164	42,621	7,136
Group Mean	71,437	23,183	605,443	716,298	71,437	23,183	605,443	716,298
F-Statistic of lagged coefficients	0.10	0.35	2.87**	3.09***	2.01*	1.25	1.34	1.47
Unit of Measurement	US/$	US/$	US/$	US/$	US/$	US/$	US/$	US/$
Adj. R^2	0.92	0.80	0.28	0.30	0.92	0.80	0.28	0.30

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: The table above shows results for my baseline event study specification on my economic variables of interest when using all counties available in my sample. The results in this tables are in terms of US/$. Standard errors are clustered at the county level.

Table A5: River Miles Restored Heterogeneity Analysis

	>10 miles restored			*<10 miles restored*		
	Winter Wheat Yields	Corn Grain Yields	Soybean Yields	Winter Wheat Yields	Corn Grain Yields	Soybean Yields
Dam Removal 3+ Year Lead	1.40 (0.92)	2.30 (2.51)	-0.44 (0.56)	0.07 (1.40)	0.82 (2.48)	-0.50 (0.79)
Dam Removal 2 Year Lead	-1.10 (0.90)	0.94 (1.49)	-0.16 (0.54)	-1.29 (1.13)	-2.19 (1.68)	0.48 (0.67)
Dam Removal	1.00 (1.01)	2.55 (1.67)	-0.07 (0.50)	0.22 (1.24)	-0.85 (2.04)	-0.29 (0.89)
Dam Removal 1 Year Lag	0.09 (0.91)	1.03 (1.54)	-0.25 (0.47)	-0.40 (1.40)	-2.91* (1.58)	-1.17* (0.62)
Dam Removal 2 Year Lag	0.10 (0.96)	2.78 (1.68)	-0.43 (0.61)	-2.60* (1.24)	-2.05 (1.65)	-0.18 (0.87)
Dam Removal 3 Year Lag	0.10 (0.96)	-0.02 (1.64)	-0.65 (0.55)	-0.26 (0.96)	0.28 (1.81)	-0.05 (0.79)
Dam Removal 4 Year Lag	-0.51 (0.93)	1.41 (1.44)	0.27 (0.53)	-0.26 (0.96)	-0.54 (1.79)	-0.15 (0.66)
Dam Removal 5+ Year Lag	-0.70 (1.29)	-2.24 (1.95)	0.03 (0.03)	1.78 (1.28)	-1.99 (2.00)	-0.23 (0.86)
N	1,434	1,887	1,604	862	1,475	1,070
Unit of Measurement	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre	Bushels Per Acre
Adj. R^2	0.75	0.79	0.72	0.70	0.72	0.68
County FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes

* p < 0.1, ** p < 0.05, *** p < 0.01

Notes: The table above shows results for my baseline event study specification on my economic variables of interest when comparing dam removals by river miles restored. Standard errors are clustered at the county level.

Table A6 – Pooled Difference-in-Difference Regression (Drought Year)

	All counties						
	Winter Wheat	Corn Grain	Soybeans	Cash Receipts	Net Income	Indemnity Payments (Excess Moisture)	Indemnity Payments (Drought)
Dam Removal*Post Treatment*Drought Year	0.73 (2.93)	6.65 (7.18)	-0.66 (1.74)	-0.12* (0.06)	0.44 (0.63)	-0.33 (0.36)	-0.18 (0.34)
N	67,164	67,164	42,621	45,734	67,164	67,164	42,621
Group Mean	71,437	23,183	605,443	716,298	71,437	23,183	605,443
Adj. R^2	0.95	0.51	0.37	0.54	0.92	0.80	0.28
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table above shows results for my pooled difference-in-difference specification on all outcome variables when interacted with a drought year indicator variable. Standard errors are clustered at the county level.

Table A7 – Pooled Difference-in-Difference Regression (Flood Year)

	All counties						
	Winter Wheat	Corn Grain	Soybeans	Cash Receipts	Net Income	Indemnity Payments (Excess Moisture)	Indemnity Payments (Drought)
Dam Removal*Post Treatment*Flood Year	0.18 (1.08)	0.33 (1.10)	0.22 (0.33)	-0.06* (0.02)	0.53 (0.35)	-0.18* (0.08)	0.12 (0.14)
N	67,164	67,164	42,621	45,734	67,164	67,164	42,621
Group Mean	71,437	23,183	605,443	716,298	71,437	23,183	605,443
Adj. R^2	0.95	0.51	0.37	0.54	0.92	0.80	0.28
County FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Notes: The table above shows results for my pooled difference-in-difference specification on all outcome variables when interacted with a flood year indicator variable. Standard errors are clustered at the county level.

APPENDIX B

DATA CLEANING APPENDIX

The numerous steps and procedures I took during my data collection and cleaning process are outlined below.

Data Cleaning

First, the American Rivers Dam Removal Database is downloaded[23] and cleaned so that dam removals before 2000 and columns with information irrelevant to my analysis are taken out. County fips codes are added based upon on the latitude and longitude coordinates of each removal. An updated year of removal is added for two removals, 'Sultan Mill Pond Dam' and 'Mill Creek Settling Basin Dam', where was available online but not present in the dataset. All fips codes for removals in Connecticut were re-assessed based upon their latitude and longitude coordinates because Connecticut changed from traditional counties to county-equivalent 'planning regions' in 2022 which included the re-drawing of county boundaries. As such, the fips codes for the county equivalents of multiple Connecticut dam removals did not match their counterparts among the agricultural outcome variables. Any dam removals with no information available for year of removal were taken out. For counties with multiple dam removals within the same year, removals are collapsed and retain the characteristics from the largest removal. Removals in Alaska and Hawaii are removed from the dataset.

Next, agricultural economic data is downloaded for relevant economic statistics. Unnecessary columns are omitted, state and county codes are merged to match relevant fips codes, and this data is merged with the original dam removal dataset so that dam removal observations are present exclusively in the county and year of their removal. Climate data is

[23] Downloaded from: https://figshare.com/articles/dataset/American_Rivers_Dam_Removal_Database/5234068?file=39240698.

downloaded and merged based on fips codes. Winter wheat yields, soybean yields, and corn grain yield data is downloaded, NA values are removed, unnecessary columns are removed, and this data is merged to the main dataset. Indemnity excess moisture and drought data is added and merged to the main dataset for payment acreage, number of payments, and payments in US/$.

Palmer Drought Severity Index (PDSI) data is downloaded and state codes are adjusted accordingly as there were slight discrepancies between the state codes in this dataset and the traditional fips codes used in my dataset. Dummy variables for ‘severe drought’ and ‘severe flood’ are created that take 1 if monthly PDSI data index variables are less than -4 and greater 4 respectively. An index variable totaling the number of flood months and drought months is created. If there are seven months in a year where the severe drought dummy is equal to 1, the drought severity index variable equals 7, if there are 4 months in the year where the severe flood dummy is equal to 1, the flood severity index variable equals 4. Monthly temperature data is downloaded and aggregated up to an annual index for temperature thresholds of 29, 30, and 32 degrees Celsius.

County observations that were abolished or absorbed by another county during my sample time frame include “Dade County", "Yellowstone National Park", "Bedford city", "Clifton Forge city", “Shannon County”, "Lexington city", and "South Boston city" and were removed from my dataset. Observations for US islands and territories such as “Guam”, “Puerto Rico”, “Virgin Islands”, “American Samoa”, and “Northern Mariana Islands” and “Minor Outlying Islands” were removed.

For counties with multiple dam removals within the same year, removals are collapsed into one specific removal and retain the characteristics from the largest removal. A dummy variable is created indicating which counties had multiple removals in a year and another is created indicating any county with a removal in that year. Additional lag and lead dummy variables are then created for counties which have multiple removals in the sample and for the first removal in a county. A column indicating the number of years to a removal is then created based off these two columns. One column indicates the number of years to the closest removal in the case of multiple removals per county and the other indicates the number of years to the first removal in a county.

When cleaning the Year Built variable, any observation where the value was “pre-*year”* was changed to the year immediately prior. For example, an observation stating a dam removal occurred ‘pre-1920’ was changed to ‘1919’. Observations stating a removal occurred in the early or late part of a century is adjusted to the appropriate quarter of the century. ‘Late 1900’s’ is changed to ‘1975’ and ‘early 1900’s’ is changed to ‘1925’. Observations stating a removal occurred in the ‘mid-1990’s’ for example are changed to ‘1995’.

When creating the dummy variable for agriculture as the original purpose of a dam, observations with the following uses are included as agriculturally related dams: "Agricultural", "Agricultural Pond", "Agricultural pond", "Agriculture", "Irrigation", "Irrigation & Recreation", "Farm", "Farm pond", "Farm pond for irrigation", "Farm ponds", "Farming", "Irrigation Diversion", "Irrigation Dam", "Irrigation diversion" Irrigation Diversion", "Irrigation diversion/canal", "Irrigation/frost protection", "Irrigation/recreation", "Irrigation/water supply", "USDA Project/Agriculture".