Title
Drought and Disparity: Labor Market Spillover in the 2012 to 2016 California Drought

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Drought and Disparity: Labor Market Spillover in the 2012 to 2016 California Drought*

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Abstract

Natural events such as drought can sometimes create ripple effects within closely related industries in local economies, reducing income and welfare. From 2012 to 2016 California experienced its most hydrologically severe occurrence of drought in the last 1,200 years. I investigate the impact of this drought by comparing heavily impacted agricultural counties to agriculturally similar counties in the Central Valley of California. Using a difference in difference strategy to analyze changes during the occurrence of the drought, I find substantial decreases in agricultural employment and wages in the affected counties. Despite this, I find no relative contractions overall in closely related tradable or non-tradable industries. When this impact is dissected, I observe substantial reductions in Hispanic worker employment and income. I also find evidence of a proportionate increase in construction employment, raising the possibility that these occupations were substituted to reduce impact during the drought.

Keywords: Agriculture, Drought, California, Labor

JEL Codes: Q110, J430, J110,

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1 Drought and Spillover Background

While there is evidence that drought causes individuals to reduce water consumption, household demand remains somewhat inelastic (Pint 1999). In periods of drought, the majority of water reallocation falls to industrial consumers and in particular the agricultural industry which consumes 80% of non-environmental allocated water in California (PPIC). While this may spark scarcity innovation through investing in new technology or selling and trading water permits, there are substantial costs from unexpected changes to a water supply.

In this paper, I investigate whether drought can create local spillovers into sectors closely related to the agricultural industry, using the distinct variation in drought intensity to compare compositionally similar counties. Empirical evidence suggests that price volatility in times of crisis creates considerable spillover in closely related industries (Kang et al. 2017). I attempt to test this hypothesis with the 2012 to 2016 California drought, a hydrologically significant event that primarily impacted the Central Valley. I use cross-sectional data to analyze outcomes utilizing a difference in difference methodology to compare the counties in the Central Valley that experienced a greater intensity of drought with those that narrowly evaded costly impacts.

Drought creates reductions in water supply that cause farmers to employ large-scale shifts to groundwater usage, less water per crop and increased reliance on water-conserving technology (Zilberman et al. 2011). Over pumping groundwater has the potential to create unquantifiable long-run impacts on the environment and permanently reduce the natural ability to replenish available aquifer levels.[1] In future drought occurrences, lower levels of groundwater will increase pumping costs, particularly in Central Valley counties that relied heavily on groundwater from 2012 to 2016 (MacEwan et al. 2017).

Although groundwater pumping is common, farmers that require more water than what is available from either state allocated water contracts or pumping face several choices. They can sell state allotted water permits to industrial consumers to recover a portion of losses, switch to drought-tolerant crops, or fallow portions of farmland.[2] Fallowing is often the last choice, as farmers forgo all profit generated from owning and operating the property and are

[1] Aquifers are underground layers of rock holding groundwater accumulated from rainfall. Aquifers can be reached and drained by wells or natural flow into springs.

[2] When a piece of land is fallowed this means it is left with no crops. This practice is typically utilized by farmers to allow the land to recover fertility after intensive farming. In this case the fallowing is not a choice but rather a lack of water or resources to farm any crop in this particular season.

likely to reduce the hours their employees work. Fallowing creates sizeable direct costs to the industry in productivity and job loss (CDWR).

1.1 The California Agricultural Economy

California agriculture is the national leader in terms of food sales, making up 11% of total exports in 2012. The lucrative industry was valued at $37.5 billion in 2012 and has been growing rapidly. Despite the drought, agricultural exports had a valuation of $46 billion in 2016 (CDFA). Estimates suggest output would have been much higher if the drought had not occurred. Total direct statewide economic losses to agriculture from the drought were $3.8 billion solely from 2012 to 2016 (Lund et al. 2018).

We know the 2012 to 2014 drought in Southern and Central California was the most severe occurrence in the last 1200 years by paleoclimate reconstructions of past droughts (Griffin and Anchukaitis 2014). The impact of the drought in terms of crop losses and job layoffs manifested primarily in the Central Valley, an inland area consisting of 18 counties. An estimated 72% of the crop losses in the height of the drought were contained in the San Joaquin valley and Tulare River basin (Lund et al. 2018).

Although agriculture statewide did not sustain extreme losses, job losses and pumping costs were distributed unequally. After using groundwater pumping to recover the majority of the water shortage, the remaining 10% shortage in statewide agricultural water use was accommodated by fallowing half a million acres of farmland. Approximately 90% of that fallowed land was in the San Joaquin Valley and the Tulare river basin. Other compositionally similar areas such as the central coast depend on different water sources that were not similarly impacted by the drought (Howitt et al. 2017).

1.2 Impact of the Drought

The 2012 to 2016 California drought highlighted the inadequacy of rural well and water systems, particularly in certain rural communities that lacked running water at the height of the drought. Tulare county suffered one of the greatest losses in crop production as well as bearing one of the highest costs of groundwater pumping. Due to reduced groundwater levels in Tulare, there were approximately 2,000 domestic well failures solely in 2015 (Lund et al. 2018). These small and often low-income areas are not always required to have contingency plans or links to larger water supply systems. Related literature has shown that rural and low-income individuals have less tolerance for natural disasters. A similar drought occurred in Australia from 2001 to 2004 and was estimated to be equivalent to an annual reduction of $18,000 (AUD) in income. However, this impact appeared only for individuals living in rural areas (Carroll et al. 2009). This result emphasizes differences in responses between demographic groups to natural disasters. Current literature aims to understand this differential to effectively implement welfare programs such as the relatively new Drought Housing Relocation Assistance Program implemented in 2015 (CDHCD).

While the negative impacts of drought are often disproportionately spread to low-income individuals, we have seen that windfall gains to agriculture create short-run spillovers to other industries (Hornbeck and Keskin 2015). This spillover is likely to impact closely related industries in terms of input-output and exchange the most (Moretti 2004). In the case of agriculture, we understand this to be industries that directly rely on agricultural output such as food manufacturing and wholesale.

When we consider the spillover impacts of a crisis event such as drought, there is evidence that the volatility of agricultural input exerts significant spillover effects on the volatility of agricultural output and retail food prices (Nazlioglu et al. 2013). There is also evidence of a strong spillover impact during a crisis period on commodities (Kang et al. 2017). I treat drought as a crisis event that creates volatility in the agricultural input price of water. Hornbeck and Keskin found that windfall gains to the agricultural industry can create short-run spillover to other local industries. While they found no evidence of long-run sustained spillover, as my data does not include ex-post results, this does not pose a threat to the scope of my study. In general, spillover is likely to be strongest in closely related industries and exert significant impact in times of crisis or in instances of volatile input prices. I observe the crisis period of the 2012 to 2016 California drought and the volatility it created in agricultural input and outputs to evaluate how drought impacts local incomes and employment. To the best of my knowledge, this is the first study utilizing individual data to analyze possible spillover impacts of the 2012 to 2016 California drought.[3] Previous studies focus on statewide impacts of the recent California drought or analyze different aspects of labor market impacts for either this or other historical droughts. Literature suggests that I would identify a significant negative impact on the agricultural industry and closely related industries during this time period.

[3]My paper builds off of research done in Lund et al. 2018 and focuses on and within counties instead of aggregate research on California conditions.

I estimate a difference in difference regression comparing outcomes in San Joaquin and Tulare, the two counties that experienced 90% of farmland fallowing, with outcomes in similar Central Valley counties [2]. I find a significant 9% reduction in employment and an 11% reduction in individual income for those working in agriculture.[4] Although I expected to discover contractions in closely related industries, I observe almost no impact on these industries' employment and incomes. There were also no significant differences in the impact of the drought between males and females when my regression was run with a gender interaction [3]. However, an additional interaction [4] shows a significant and highly negative impact on Hispanic individual employment in agriculture by 12% and further reduction in wages by 13%. This signals that although the economy was resilient, the drought disproportionately impacted Hispanic agricultural workers. Additionally, the small spillovers that occurred into related industries had impact only on Hispanic workers.

This result represents a departure from traditional intuition that observes spillover between closely related industries, particularly during a crisis. Although these results are unusual, further robustness checks and a statistically optimized control group would be necessary to confirm the lack of spillover effects. This instance of limited spillover could reflect the recent popularization of water permit trading amongst farmers and the introduction of new drought-related welfare programs (Cooley et al. 2015). Data on water trading rates and prices are not currently aggregated or publicly available but would be an area for potential further study. Prior research finds that water management policy coordinated with farmers has the potential to increase environmental and economic gains to all parties (Kousky 2015). A detailed input-output study would also further improve the validity of my results. These models are commonly used to analyze changes in farmer behavior in reaction to price changes among other purposes and could be fit to the scenario of a drought (Greenstone et al. 2010).

2 Literature Review

2.1 Research on Drought Impact

Lund et al. (2018) synthesize their past research on drought with contributions from other prominent researchers in the field to create a full picture of the impact in "Lessons from California's 2012-2016 Drought". I draw from components focusing on employment and revenue losses. In their preliminary findings, agriculture was the industry primarily impacted

[4] These results are drawn from Model 2 detailed in my Empirical Strategy section, that includes all controls: sex, race, education, and age.

through increased pumping costs of $600 million per year and half a million acres of fallowed crop area. When water supplies reached a low in 2012 to 2015, certain negotiated contracts with water projects received zero deliveries. Lund et al. touch on the uncertainty for future strength during drought caused by overdraft of groundwater, first reported by MacEwan et al. This will most likely hit rural areas the hardest as they have the least access to water and lower aquifer elevations available for groundwater pumping. The paper finds that overall resilience was due to strong prices for key specialty crops, ability to rely on groundwater, effective water management, and the beginnings of a robust water trading market. Despite this, they acknowledge that these costs were likely concentrated in areas with a lack of easily accessible groundwater. There is no detailed analysis of county level impacts on these rural and dry counties in the San Joaquin Valley and Tulare River Basin due to the 2012 to 2016 drought. Cooley et al. (2015) similarly find that overall impacts were mitigated, but discuss the need for local variability estimates for areas that experienced intense fallowing. Related literature has indeed shown that rural and low-income individuals have less tolerance for natural disasters. A drought of a similarly intense magnitude occurred in Australia from 2001 to 2004. Carroll et al. (2009) used life satisfaction survey data to estimate that the occurrence of the drought was equivalent to an annual reduction in income of $18,000 (AUD). Using fixed effects to control for unobserved area characteristics, this impact appeared only for individuals living in rural areas. While the Australian economy suffered more heavily due to a lack of drought infrastructure, the divide between rural and urban individuals in this case is clear.

I use a similar regression with fixed effects and demographic controls to look at labor market outcomes for the California Drought from 2012 to 2016. As with the Australian drought, this recent California drought has been proven to be hydrologically severe and sustained marked losses within the agricultural sector (Griffin and Anchukaitis 2014). Following the focus on rural and low-income individuals I estimate differences between the hydrologically dry rural counties with counties that were able to mitigate most drought losses with groundwater and water project contracts. Based on further studies (Medellín-Azuara et al. 2015) I determine that San Joaquin and Tulare counties were the most heavily impacted during this time period and faced the heaviest groundwater pumping costs. My study differs in its approach, data and focus. I choose to use survey data and look at individual characteristics within the more closely focused county groups. Additionally, I test for differences in outcomes for Hispanic individuals and females. The 2012 to 2016 California drought was found to create emotional distress regarding food insecurity, particularly in Hispanic households (Rodriguez et al. 2015). My results and analysis provide further evidence of the harsher penalties imposed on rural and Hispanic agricultural households due to drought conditions.

I additionally confirm the question theorized by earlier research in this field that there indeed was variability in county level impact due to the drought.

2.2 Spillover Effect

"Does Agriculture Generate Local Economic Spillovers? Short-Run and Long-Run Evidence from the Ogallala Aquifer" by Hornbeck and Keskin (2015) is the most closely related and influential paper in the design and understanding of my topic. This paper analyzes the impact of new technology that allowed farmers to utilize a new groundwater source, the Ogallala Aquifer. This windfall gain to the agricultural sector allows Hornbeck and Keskin to estimate the differences between counties with a high proportion of areas with increased water access and those that largely missed the benefits of this new water source. They estimate a difference in difference regression controlling for various agricultural effects and time effects to estimate the spillover impact of increased water access. They find that areas with high exposure to the Ogallala had increased agricultural gains through land value and revenue. This also caused an exogenous increase in rural farm employment. Similar to my paper, they set manufacturing, wholesale, retail, and services as comparison industries for their economic closeness. While this did not extend to the long-run, Hornbeck and Keskin did find short-run (around 20 years) statistically significant expansions in these industries. While this result is different from the lack of spillover seen in my results, I attribute this limit of negative spillover to efficient water management and programs to limit contractions to the agricultural industry itself.

Notably, Moretti (2004) demonstrated that spillovers occur between closely related industries with greater frequency and intensity than in industries that are distant. Instead of focusing on measures of agricultural workers or rural areas, Moretti looks to the proportion of college-educated workers within a data set cataloging production plant productivity. He finds an increase in plant productivity as a result of the faster growth of the proportion of college-educated workers in an area. This effect is larger for economically close industries, reflecting the spillover of knowledge and physical capital accumulation. Additionally, Kang et al. (2017) find that there is a strong impact of spillover during and after the crisis period by estimating commodity futures returns. This reflects a premium on uncertainty and increased supply chain costs for closely related industries that rely on crude commodities. We would expect to see the greatest impact on industries purchasing and relying on outputs of the agricultural sector (Albino et al. 2002). My findings that closely related sectors were not impacted is a departure from this intuition and is reflective of the effective water management and drought mitigation techniques that contained heavy losses to parts of the agricultural industry while keeping agricultural produce prices stable.

Nazlioglu et al. (2013) find that after the occurrence of a crisis in oil markets there is significant market volatility on key agricultural commodities. Using a GARCH model they show that there is a growing linkage between agriculture and energy markets due to their similarities and investor profile. Further work done by Apergis and Rezitis (2003) delves further into the links between agricultural input prices and output commodities. They used agricultural commodity prices in Greece from 1985 to 1990 to test for links in equilibrium price patterns. The study finds that there are significant linkages in price variation between agricultural input and output prices, and between agricultural output prices and retail food output prices. They also find evidence of imperfect price transmission among the three categories so that exogenous shocks would create disparate welfare changes among market participants. Since output prices were observed to be more flexible than input and retail prices, this indicates that general price decreases in a crisis would create short term losses for farmers as their prices decrease faster than input prices. This aligns with my findings that agricultural earnings had large short-run decreases due to drought-related shocks.

3 Data

3.1 Data Source

The main purpose of this study is to quantify how economic spillovers between industries impacted individuals living in areas severely affected by the 2012 to 2016 drought. I chose to use U.S. government survey data to have access to one of the largest data sources on my target counties while retaining other significant data measures on the socio-economic profile of the individuals. The American Community Survey (ACS) collects cross-sectional data on individuals with attached characteristics and publishes annually to the Integrated Public Use Microdata Series (Ruggles et al. 2020). The ACS uses a series of monthly samples on 250,000 addresses to produce an annual estimate of data for the same small areas on 3,000,000 addresses. My data extract is limited to individuals in the California Central Valley in the years 2006 to 2017 for sample size consistency. I use the California Research Bureau classification of the 18 Central Valley counties.[5]

[5]Central Valley counties: Butte, Colusa, Glenn, Placer, Sacramento, Shasta, Sutter, Tehama, Yolo, Yuba, San Joaquin, Stanislaus, Merced, Madera, Fresno, Tulare, Kings, and Kern (Umbach 1997)

To ensure the accuracy of my results I used the IPUMS provided CPI adjustment factor to convert income to 2005 dollars, so estimates are standardized to the beginning of the observed time period. Additionally, only individuals in the age range of 20 to 65 that did not reside in group quarters were kept, to ensure individuals not typically in the labor market did not distort income estimates. Before performing analysis, observations with missing values for labor industry classification or income were removed. After these modifications, the data includes 435,996 individual observations on individuals living in counties categorized as the Central Valley.

I used sex, educational attainment, and race control variables to add accuracy to the estimate without overfitting my model.[6] My outcomes of interest are individual income, usual weekly hours worked, industry employment rate and welfare income received. This allows me to account for all sources of reduced individual welfare that could occur as a result of this negative market shock. When appropriate, these outcomes were logarithm transformed so as to capture the relative impact when looking at an industry with a small percentage of the population.

I utilized the North American Industrial Classification System (NAICS) codes that were provided by the ACS survey in order to define my own classifications of individuals' labor industry to better fit the purpose of my study. These redefined industry classifications are used both as a binary outcome measure of the employment rate and as categorical regressors to look at differences in income and hours worked. Prior literature suggests a spillover impact between closely related labor industries (Moretti 2004). I redefined both closely related and distant occupations of interest into six groups as follows: agriculture, food product manufacturing, food product wholesale, local food industry, transportation, and construction. The food manufacturing category includes processing or production of animal food, produce, grain, sugar, bakery goods, dairy and animal byproduct. The food wholesale industry refers to groceries, farm products, and farm supplies. The local food industry category consists of grocery stores and restaurants.

These categories are designed so that primary impacts show in the closely related categories of food wholesale or manufacturing that directly purchase for input the agricultural sector's output. This reasoning follows selected industry classifications utilized by Hornbeck

[6]Education is a categorical variable that increments education by each year up to 12 years and above. Race is a categorical variable breaking down to White, Black, Hispanic, Asian and other. These both are used to hold constant possible effect to each outcome that isn't a result of drought.

and Keskin (2015) to observe agricultural spillover. Less significant changes should occur in the local food industry as it is higher in the supply chain. The distant industries such as transportation and construction, among others not included in this study, should experience the smallest or no impact. This follows the supply chain input-output process model documented by Albino et al. (2002).

To define my treatment group and time horizon, I looked at the hydrological impacts of the drought. An estimated 90% of drought-related farmland fallowing was restricted to the Tulare Lake Basin and some parts of the San Joaquin River Basin ensuring these areas sustained the greatest direct income differences due to drought (Lund et al. 2018). I defined San Joaquin and Tulare County as treatment counties because they comprise the majority of impacted land area both in terms of fallow unusable land and the need for extensive groundwater pumping. All remaining 16 Central Valley counties are set as the control group due to their compositional similarities without extreme drought impact. Although the drought began in 2012, water supplies reached a low in 2014 and 2015 (Howitt et al. 2017). The event time period is set as 2015 to 2017 to capture the fallout. This paper uses an interaction term between the treatment counties and drought horizon so that the impact of the drought is captured from the coefficient on the interaction. The difference in difference method also relies on an assumption that there is not frequent mobility between the two groups so that accurate values for income and employment changes can be reported. This is assured by checking population in my treatment and control counties in 2012 and 2016. I observe less than a 1% increase in population in my control counties, which have a much larger area, and a 0.04% increase in population in my treatment counties. This does not suggest that there was significant mobility between these two groups or outside of these areas.

3.2 Summary Statistics

Table 1 reports summary statistics in 2012 for both heavily impacted counties [7] by measure of extensive fallowing and other Central Valley counties.[8] This is to show that both groups follow a similar parallel growth trend in 2012 before the onset of the drought. There are level differences in the amounts of agricultural and food wholesale workers in the pre-drought time period, however, the two groups have followed a similar path over time. This satisfies the parallel trend assumption necessary for performing a difference in difference regression

[7]Hereafter referred to as treatment counties.

[8]Hereafter referred to as control counties

to test outcome differences.[9]

Table 1: Summary Statistics for County Groups in 2012 (pre-drought)

	Treatment	Control
Agriculture		
Employment Rate	0.089	0.049
Income	23,517	19,841
Hours Worked	40.7	40.4
Food Manufacturing		
Employment Rate	0.026	0.021
Income	29,865	30,398
Hours Worked	38.3	37.3
Food Wholesale		
Employment Rate	0.018	0.009
Income	25,100	27,193
Hours Worked	37.0	37.7
Food Industry		
Employment Rate	0.063	0.062
Income	16,561	16,561
Hours Worked	27.6	27.6
Transportation		
Employment Rate	0.037	0.032
Income	31,105	34,972
Hours Worked	37.8	36.2
Construction		
Employment Rate	0.047	0.052
Income	33,238	31,241
Hours Worked	31.7	32.7
Total Population	6,148	30,152

Note: Treatment counties consists of San Joaquin and Tulare. Control are all other Central Valley designated counties.

When considering the impact of an event with a time horizon and units that were impacted differently, using a difference-in-difference approach is standard. I interact the time horizon of the drought with the counties that experienced the harshest impact. Although ACS survey data is commonly used for such analysis, there are some key limitations in my application. One of the limitations of the study is that the difference in difference regression technique relies upon the parallel trend assumption. While we can verify this trend graphically [Appendix: Figure 1], it has the potential to lend imprecise results. Although ACS survey data is commonly used for such analysis, there are some key limitations in my application. Any study focusing on relatively removed phenomena such as drought faces difficulties with attrition. For survey privacy purposes individuals cannot be linked over time, so I am prevented

[9] The parallel trend assumption requires that in the absence of treatment, the difference between the treatment and control group outcome or characteristic is constant over time.

from using synthetic control to perfect my control group and better ensure both county groups follow parallel trends. I counter this by performing robustness tests by both changing the time horizon for the drought treatment and changing the combination of control groups. These regressions were also run on an interaction with gender and race [10] to ensure the reliability of my findings on spillover within all groups.[11] Additionally, without data that extends to the time period after the 2012 to 2016 drought it is impossible to analyze long-run spillover effects. This study is limited to data from the years 2006 to 2017. The lack of an ex post study is a potential avenue for research in the future. The addition of a hydrological framework would also help to improve the study.

4 Empirical Strategy

I use a difference in difference ordinary least squares regression to analyze the variation in outcomes for individuals living in severely impacted counties with those living in similar Central Valley counties that evaded the impact of the 2012 to 2016 drought. For empirical specifications, outcome Y for individual i is regressed on fixed time period effects δ_t, status as an individual in a highly impacted county Dr_i, and an interaction where α represents the causal impact of the drought on an individual. Based on earlier explanation of the high costs of land fallowing, Dr_i is a dummy variable equal to 1 if individual i resides in Tulare or San Joaquin County. Dr_i is set equal to 0 if the individual resides in any other Central Valley county. This variable serves to represent residence in an area highly impacted by drought. Because water supplies hit a low in 2014, indicator variable $Post_t$ is a binary, set equal to 1 if the individual observation falls after 2014. $Post_t$ is equal to 0 if the observation is from 2014 or prior. The interaction formed between these two indicators $Dr_i * Post_t$ has a coefficient α that represents the combined impact.

The models include other individual-specific control predictors: F_i is a dummy equal to 1 if the individual is female, ED_i controls for differences in education, A_i controls for age, and R_i controls for race-related differences in outcomes. My first attempt Equation 1 utilizes female and race base controls. Equation 2 makes the addition of education and age as further controls. For notational simplicity, all four control predictors are aggregated into the variable $\mathbf{X}$ in the second form of Equation 2. This notation is used going forward.

[10] Specifically this test was done on the Hispanic agricultural population as they make up 51% of all agricultural workers in California.

[11] Further description of robustness checks and data tables included in Appendix.

$$Y_{it} = \beta_0 + \beta_1 F_i + \beta_2 ED_i + \beta_3 R_i + \beta_4 A_i + \beta_5 Dr_i + \delta_t + \alpha Dr_i * Post_t + \epsilon_{it} \tag{2}$$

$$Y_{it} = \beta_0 + \beta_1 \mathbf{X}_i + \beta_2 Dr_i + \delta_t + \alpha Dr_i * Post_t + \epsilon_{it} \tag{2}$$

I use a triple interaction to separate welfare impacts for different groups. In this case, the additional interaction serves to observe differences between females and males. To differentiate the impact of the drought for each gender, the dummy variable F was interacted with county and the difference in difference value in Equation 3. γ represents the causal impact of the drought for females. This again uses the notation of $\mathbf{X}$ to aggregate all four control variables. The α coefficient still represents the causal impact of being an individual living in the treated counties during the height of the drought.

$$Y_{it} = \beta_0 + \beta_1 \mathbf{X}_i + \beta_2 Dr_i + \delta_t + \alpha Dr_i * Post_t + \beta_3 F_{it} * Dr_i + \gamma F_{it} * Dr_i * Post_t + \epsilon_{it} \tag{3}$$

As Hispanic agricultural workers make up 51% of all agricultural workers (USDA), I create a triple interaction to observe the causal impact of the drought on the Hispanic population in Equation 4. I refrain from testing other groups as non-white workers comprise only 6% of the total agricultural employment. The θ coefficient on the triple interaction represents the additional impact of the drought on Hispanic individuals. The alpha coefficient and $\mathbf{X}$ retain the same interpretation as in Equation 2.

$$Y_{it} = \beta_0 + \beta_1 \mathbf{X}_i + \beta_2 Dr_i + \delta_t + \alpha Dr_i * Post_t + \beta_3 Hi_{it} * Dr_i + \theta Hi_{it} * Dr_i * Post_t + \epsilon_{it} \tag{4}$$

I again estimated these interaction regressions with income, employment rate and usual hours worked per week as the outcomes. In each regression other than employment rate, I limited the sample pool to one of my 6 specified industry categories to separate the impact and isolate spillover impact. Both triple interacted regressions, female and Hispanic, serve to test the validity of my results and find if any individual group faced greater impact.

This model has foundations on a similar difference in difference regression run by Hornbeck and Keskin (2015) when analyzing the windfall gains of the Ogalla aquifer on counties with varying degrees of exposure. They followed a similar strategy of comparing non-agricultural industries within each county to observe the spillover in productivity seen from an agricultural stimulus. It is a widely accepted model for evaluating the impact of a sudden change that is applied to a subset of units observed. I circumvent typical biases by running robustness tests and including fixed effects to control for error in my model.

These equations use a time effect variable δ_t to control for the invariant presence of time trends in the data. Other similar models utilize state, time and group fixed effects (Apergis and Rezitis 2003). Because my study is confined to a region within California, there is no need for state fixed effects. The difference in difference equation I estimate utilizes differences between counties' outcomes based on locational effects of drought. County cluster effects are typically used on data sets with more groups and in this case could potentially remove the effect that is isolated by my regression. To ensure that the populations had normal distributions, I performed iterations of my regressions with bootstrapped error and found no significant differences from previously estimated outcomes. All results are reported with robust error to account for serial autocorrelation.

I believe that the other Central Valley counties provide the best approximation of parallel pre-drought trends in income and employment. The region has a similar composition in the sector, crop type, and incomes [Table 1]. Although synthetic control was not available to me with this data set, I ran my regressions on different treatment groups and with an earlier time period to ensure robust results. The model and question face limitations of data that do not allow for complete, precise identification of the causal impact of drought. Further analysis of a greater range of data would be necessary to confirm these results definitively.

5 Results

This section reports estimates of the impact of the 2012 to 2016 California drought on income, hours worked, and employment rate. I breakdown regressions by industry ranging from sectors closely related to agriculture to more distant industries to look for a heterogeneous change in welfare. Table 2 reports results obtained from estimating Equations 1 and 2 for only the agricultural industry. This table reports α, from my difference in difference interaction, and its standard error to represent the impact the drought had on each outcome. This table reports the base model controlling only for gender and race in column 1. Column 2 reports the model from equation 2, adding in additional controls for education and age.

I use multiple outcomes as dependent: employment rate, hours worked weekly, log income, and income. The percent change listed is the change in employment in each regression scaled by the population. The individual industry regressions for employment are run on binary indicators for each industry. The interpretation is that this coefficient shows a change in individuals categorized within an industry each year. Any change comes from individuals either switching to a different industry or losing their jobs and becoming unemployed.[12] Each time I regressed on income instead of the sector binary mentioned above I limited the sample to each industry to see the impact in that industry.[13]

Table 2: Estimated Differences in Coefficient due to Drought

Agricultural Outcome	(1) Basic Model	(2) Controls Added	Observations
Employment Rate	-0.00665**	-0.00802***	435,996
	(0.00247)	(0.00236)	
Percent Change	-7%	-9%	435,996
Hours Worked	-0.853	-0.881	22,864
	(0.555)	(0.555)	
Log Income	-0.0928*	-0.113**	21,863
	(0.0372)	(0.0347)	
Income	-703.0	-1378.2	22,864
	(1368.5)	(1246.4)	

Robust Standard error in parentheses.
Notes: This table reports coefficients on the interaction coefficient of drought occurrence and drought exposure. Column 2 adds controls education and age. Percent change is scaled from employment to visualize impact and has no standard error.

The first row in Table 2 reports the decreases seen in agricultural employment as a direct impact of the drought. When scaled, we observe an estimated 7% reduction in the agricultural employment rate in column 1. This comes with a significant 9.3% reduction in agricultural income. The average hours worked per week does not drop by a large or significant amount. This means that when faced with drought and land fallowing, many agricultural workers living in the counties heavily impacted by the drought lost jobs or had large reductions in income. When observing the changes from column 1 to column 2 when adding controls for education and age, we can see these results become more significant and negative. The agricultural employment drops to -9% and income for agricultural workers, all else constant, drops by 11.3%. In both regressions we do not observe any significant level declines in in-

[12]The effect of becoming unemployed is picked up in the regression by a lack of a NAICS industry classification code.

[13]The sample is similarly limited to each of the six defined industries when regressed on log income or hours worked.

come, however this is due to a reduction in growth rates of the agricultural industry due to drought, rather than absolute declines in productivity. In both we also see no significant change in hours worked implying workers left the industry or faced pay cuts rather than fewer hours.

Table 3 reports estimates obtained from the equations including a triple interaction (female or Hispanic). Column 3a reports estimates of the previous coefficient α on the interacted variable for Equation 3. This equation also includes a triple interaction coefficient γ with female to determine the impact of drought on females. This coefficient γ is listed in column 3b. When we look at the female interaction that is added in column 3a, the reduction in income rises slightly to 13%. However, when looking at the triple interaction coefficient in column 3b representing the female minus male difference in drought impact, there was no significant or large additional impact on females either in employment or income. This signals that the drought did not disproportionately impact females in agriculture.

Table 3: Estimated Differences in Coefficient due to Drought for Triple Interacted Equations

Agricultural Outcome	(3a) Male Only Interaction	(3b) Female-Male Difference	(4a) Non-Hispanic Interaction	(4b) Hispanic Interaction	Observations
Employment Rate	-0.0093*	0.0026	0.00014	-0.0218***	435,996
	(0.0039)	(0.0047)	(0.0020)	(0.0052)	
Percent Change	-17.6%	4.9%	0.1%	12.2%	435,996
Hours Worked	-0.623	-0.664	1.135	-2.504	22,864
	(0.635)	(1.160)	(1.406)	(1.497)	
Log Income	-0.129**	0.065	-0.006	-0.131	21,863
	(0.040)	(0.072)	(0.086)	(0.092)	
Income	-1629.4	869.0	546.9	-2305.1	22,864
	(1632.1)	(2060.4)	(5389.1)	(5386.4)	
Triple Interaction Coefficient	No	Yes	No	Yes	

Robust Standard error in parentheses. Percent change is scaled from employment rate.
Notes: Column 3b reports the coefficient on the drought triple interaction with female, while column 3a reports the regular drought interaction coefficient from the same equation 3. Columns 4a and 4b follow the same pattern with an interaction on Hispanic.

We observe very different results when using a Hispanic interaction. Column 4a reports estimates of the coefficient α on the interacted variable for Equation 4. This equation also includes a triple interaction coefficient θ with Hispanic to determine the impact of drought on Hispanic individuals in agriculture. This coefficient θ is listed in column 3b. When observing the change in employment rate in column 4a, the regression observes no significant changes to agricultural employment as result of the drought. Column 4b reveals that virtually all of the reduction in agricultural employment due to the drought was for Hispanic individuals. This aligns with literature observing high rates of food insecurity among Hispanic agricultural families during the drought (Rodriguez et al. 2015).

Table 4 attempts to report estimated spillover effects. This table uses Equation 2 as the only source for coefficients as it included all control variables. The addition of female interaction in Equation 3 tended not to significantly change coefficients, so it was not displayed for ease of viewing. Table 4 displays the most important outcomes for determining changes in each industry. This is repeated for each of my selected industries: agriculture, food manufacturing, food wholesale, food industry workers, transportation, and construction. These are arranged by ascending economic connection from agriculture.

Table 4: Spillover Effects on Outcomes by Sector

Industry	Employment Rate	Hours Worked Weekly	Log Income	Income
Agriculture	-0.00802***	-0.881	-0.113**	-1378.2
	(0.00236)	(0.555)	(0.0347)	(1246.4)
Food Manufacturing	-0.00143	0.0421	0.0779	629.8
	(0.00143)	(0.916)	(0.0560)	(2076.9)
Food Wholesale	-0.00194	1.990	0.0273	1370.0
	(0.00109)	(1.311)	(0.0785)	(2397.5)
Food Industry	0.00273	-0.746	-0.0808	-2074.7**
	(0.00218)	(0.620)	(0.0418)	(695.7)
Transportation	0.00288	0.241	0.00804	-1424.4
	(0.00187)	(0.831)	(0.0448)	(1420.1)
Construction	0.00591**	1.261*	-0.0493	-2071.6
	(0.00207)	(0.581)	(0.0412)	(1435.9)

Robust Standard error in parentheses.
Note: Equation (2) is used to report coefficient estimates. Each row is a different Industry.

I observe significant reductions in agricultural income and employment, however, when looking at closely related industries such as food manufacturing and wholesale there are no significant reductions in either employment or income. There is a significant drop in food industry incomes, but when this is logarithm adjusted to account for trends in incomes the effect is absent. This suggests that negative spillovers from agriculture due to drought did not occur. I also observe large significant increases of 12% in construction employment accompanied by small increases of hours worked. This suggests that agricultural workers who lost jobs due to drought possibly began working in construction, which experienced relative expansion. This indicates that construction and agricultural jobs were treated as substitutes as the percentage of jobs lost in agriculture was fully recovered in construction.

Table 5 scales the results from Table 4 to show the true impact of the drought on employment, hours worked, and income. I do this by using the IPUMS provided individual person weights to account for their true representation in the population, and scale these up by the percent of individuals in each industry. These are standardized to the change from 2012 pre-drought levels of each outcome. Hours worked weekly is scaled to show the aggregate change in hours worked per week in each industry due to the drought. Since these changes are often marginal, this scale helps to better observe the way these incremental changes impacted California's Central Valley overall.

Table 5: Spillover Effects Scaled to Population

Industry	Employment Rate	Hours Worked Weekly	Total Income	Change in Income
Overall				
Agriculture	-9%	-52640	-11%	-$82,347,419
Food Manufacturing	-5%	725	8%	$10,847,674
Food Wholesale	-9%	26857	3%	$18,489,476
Food Industry	4%	-32931	-8%	-$91,583,433
Transportation	8%	5949	1%	-$35,162,774
Construction	12%	40603	-5%	-$66,703,500
Hispanic				
Agriculture	-12%	-131703	-13%	-$121,241,373
Food Manufacturing	-5%	7086	5%	-$16,466,415
Food Wholesale	-18%	-9140	-3%	-$32,693,496
Food Industry	15%	12688	5%	$3,861,614
Transportation	7%	-30409	2%	$18,490,717
Construction	22%	-24460	0%	-$47,127,814
Non-Hispanic				
Agriculture	1%	8119	-1%	$3,911,976
Food Manufacturing	-2%	-1432	5%	$8,480,192
Food Wholesale	4%	12221	4%	$17,762,660
Food Industry	-3%	-24838	-10%	-$52,749,661
Transportation	4%	29319	-1%	-$39,983,432
Construction	3%	31287	-5%	-$12,776,452

Note: The industry spillover effects are scaled to 2012 pre-drought levels to observe changes. Overall estimates are scaled from Table 4 estimates. Hispanic and Non-Hispanic estimates are scaled from estimates in Table 8 in the Appendix using coefficients on the non-Hispanic and Hispanic interactions.

We can see that almost all of the spillover impact is limited to Hispanic workers.[14] It also seems that upon further breakdown, spillovers that better fit the typical framework from input-output models can be seen in the Hispanic interaction, however these are not always

[14] A table and description of the spillover impact for only Hispanic individuals is included in the appendix.

significant differences. What is striking is that we can see clear evidence suggesting that Hispanic construction work increased proportionately with agricultural decreases.

6 Discussion

I attempted to measure the spillover impact of California's drought from 2012 to 2016 from agriculture into closely related sectors. In prior difference in difference estimation of agricultural spillovers, short-term expansion was found in other sectors (Hornbeck and Keskin 2015). We have seen that volatility in agricultural inputs and markets as a whole creates volatility in prices of outputs, impacting businesses that purchase agricultural products (Apergis and Rezitis 2003). There is also evidence suggesting that closely related industries experience the greatest spillover effects in the presence of positive or negative change (Moretti 2004).

I estimate a difference in difference regression that tests the interaction between counties severely impacted by the drought and the time period of the event to find the causal impact of drought for individuals in each industry. I define severely impacted counties as San Joaquin and Tulare as they collectively contained 90% of fallowed land and experienced the highest groundwater pumping costs. The severity of the 2012 to 2016 California drought and its unique status as the most severe occurrence in recent state history would suggest that this event would have a severe impact on both agricultural incomes and employment. I find an estimated 9% reduction in agricultural employment and 11% reduction in agricultural wages. There were reductions in Hispanic agricultural employment of 12% and 13% income decreases.

I find no evidence of negative spillover in employment rate or income in closely related industries. While there was evidence of limited spillovers when analyzing Hispanic interactions, these were not always significant. This is particularly striking as it contrasts with the intuition from prior literature, and by empirical design the spillover impacts would be overstated (Hornbeck and Keskin 2015). While the closely related industry spillover did not appear as in prior literature, there are many possible reasons to consider when questioning the lack of spillover. In the height of the drought, the state of California pushed an agenda to limit household water usage and provide aid to individuals living in rural areas. The Emergency Community Water Assistance Grant (ECWAG) provided water to communities experiencing significant declines in availability or quality of water available. The Drought Housing Relocation Assistance Program was funded in 2015 to provide assistance and compensation to families forced to relocate due to a lack of access to water (CDHCD).

There are also programs serving industrial interests. A 2014 Federal Farm bill requires farmers to rely on crop insurance as part of their contingency plan in case of drought to recover losses. In another novel way to mitigate losses, farmers began to trade their rights to water permits (Cooley et al. 2015). Allowances are given to each plot of land, based roughly on seniority and size. In the face of the drought, some farms sold their water rights to other farms to recover losses from reduced crop sales. In some cases water was trading at $\$1.7/m^3$. Even at averages of $\$0.8/m^3$ for the duration of the drought, prices were approximately three times regular non-drought water prices (Lund et al. 2018). There have been documented instances of farmer led water innovation in the face of mounting financial pressure. Kousky shows that when financially incentivized correctly through policy, farmers voluntarily implemented water management that created economic and environmental gains for all parties. This new form of drought mitigation likely reduced the decline in farm incomes and prevented a sharper spillover by stabilizing output prices. There is also evidence that the California agricultural industry was forced to invest in new water-saving technology and more efficient methods as a result of the drought (Cooley et al. 2015).

When analyzing the interactions with female and Hispanic individuals to see the difference in impact for these groups we see varied results. There was no additional causal impact from drought on either employment or wages for females, however there were substantial contractions in Hispanic employment and wages within agriculture. This aligns with prior literature that finds that rural and low-income households experience the greatest detrimental impact during crisis and natural disaster (Carroll et al. 2009). As Hispanic individuals make up the largest proportion of agricultural workers, this is a disparity that must be addressed by further research. The estimated impact to Hispanic individuals is likely to be understated in my results due to an uncertain amount of undocumented Hispanic agricultural workers that undoubtedly experienced labor market tightness during the drought. There are limitations to this data set because of issues with reporting undocumented labor in census data, but some estimates have attempted to solve this problem (Passel et al. 2005). There is also evidence that some agricultural labor switched to the construction sector as the increase in construction labor more than matched the agricultural decrease. This labor substitution has potential to further mitigate contraction in times of crisis. When we look at spillovers for Hispanic individuals [Appendix: Table 8] we can see some significant declines in food wholesale. While these results are more closely aligned to traditional assumptions about spillovers, the lack of consistent significant results prevents conclusions about Hispanic spillovers. Similar to previous regressions, when limited to Hispanic interactions we also observe significant increases in construction employment. This gives further credibility to the idea that construction was a substitute occupation for Hispanic individuals who lost or left jobs in the agricultural sector.

While my study finds interesting evidence of policy and innovation working to limit negative spillovers from this shock, there are limitations to the data available. Without ex post data, there is a possibility that a more refined control group could be created to match pre-drought trends more accurately. This also prevents long-run impact analysis. Additionally, a wider range of data with more characteristics and a larger sample would improve the accuracy and validity of my result. For example, more granular data on the level of farm employment that distinguishes between farm workers and managers would allow me analyze welfare impact at a deeper level.

This paper suggests that contractions due to drought have the potential to display limited local spillovers, despite having substantial impact on the local agricultural sector. As the frequency and extent of droughts increase, there is potential for adequate policy responses and a better framework for resource trading to continue to mitigate agricultural and local losses. These policy responses must account for the disproportionate contractions to employment and income of Hispanic agricultural workers to best serve the welfare of the agricultural and Hispanic communities. The beginnings of a network created by farmers to trade water rights and the ability of farm labor to switch to substitute industries are interesting topics for further investigation into the lack of spillovers as a result of the 2012 to 2016 California drought.

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Appendix: Tables

Table 6: Alternative Drought Time 2013-2017: Estimated Differences in Coefficient

Agricultural Outcome	(1) Basic Model	(2) Controls Added	Observations
Employment Rate	-0.00535*	-0.00551**	435,996
	(0.00213)	(0.00208)	
Hours Worked	-0.370	-0.396	22,864
	(0.446)	(0.447)	
Log Income	-0.0757**	-0.0869**	21,863
	(0.0274)	(0.0269)	
Income	-1152.6	-1517.8	22,864
	(977.4)	(958.9)	

Robust Standard error in parentheses.
Notes: This table reports similar results to Table 2 in Results but with 2013 and later as the drought horizon instead of 2015.

I perform a robustness check by changing the drought impact time period from 2015 and after, to 2013 and after. This table presents similar results to the table analyzing the impact of the drought in my results in Table 2. The interaction coefficients on employment rate and income in the agricultural sector show significant decreases, yet not at the same magnitude because of the lag from the drought onset to when water supplies became scarce.

This justifies my selection of 2015 as the onset of the drought for analysis in the paper.

Table 7: Alternative Drought Time 2013-2017: Estimated Differences in Coefficient for Triple Interacted Equations

Agricultural Outcome	(3a) Male Only Interaction	(3b) Female Only Interaction	(4a) Non-Hispanic Interaction	(4b) Hispanic Interaction	Observations
Employment Rate	-0.00616	0.000473	-0.00251	-0.00965*	435,996
	(0.00346)	(0.00419)	(0.00178)	(0.00485)	
Hours Worked	-0.591	0.302	-1.482	1.321	22,864
	(0.509)	(1.044)	(1.149)	(1.256)	
Log Income	-0.115***	0.0838	-0.0139	-0.0941	21,863
	(0.0313)	(0.0623)	(0.0683)	(0.0748)	
Income	-2084.7	1716.2	-1228.2	110.9	22,864
	(1274.4)	(1668.6)	(4113.0)	(4143.4)	
Triple Interaction Coefficient	No	Yes	No	Yes	

Robust Standard error in parentheses.
Notes: This table reports similar results to Table 3 in my Results section but with 2013 and later as the drought horizon.

Similarly the triple interaction table shows similar results at a lesser magnitude as Table 3 in my results. There is again no significant difference between males and females and almost all impact of the drought falls on Hispanic agricultural workers.

Table 8: Hispanic Impact: Spillover Effects on Outcomes by Sector

Industry	Employment Rate	Hours Worked Weekly	Log Income	Income
Agriculture	-0.0218***	-2.504	-0.131	-2305.1
	(0.00515)	(1.497)	(0.0921)	(5386.4)
Food Manufacturing	-0.00183	0.628	0.0496	-1459.4
	(0.00295)	(1.782)	(0.108)	(4345.1)
Food Wholesale	-0.00523*	-1.064	-0.0339	-3806.0
	(0.00229)	(2.553)	(0.152)	(5218.9)
Food Industry	0.0101*	0.645	0.0480	196.3
	(0.00432)	(1.200)	(0.0811)	(1243.4)
Transportation	0.00188	-3.723*	0.0240	2263.8
	(0.00365)	(1.585)	(0.0867)	(2641.7)
Construction	0.0117**	-1.585	-0.00493	-3053.9
	(0.00411)	(1.111)	(0.0792)	(2681.9)

Robust Standard error in parentheses.
Note: Equation (4) is used to report coefficient estimates from Hispanic triple interaction on γ. Each row is a different Industry.

When we analyze the spillover impact that occurred within only the Hispanic population, we can see better evidence of a spillover impact that somewhat follows traditional models of input-output spillover. There are decreases in food wholesale, however food manufacturing and food industry jobs did not have similar significant decreases in employment or wages. This table also mirrors the overall spillover table with an increase in construction employment for Hispanic individuals. This points again to the possibility that these workers substituted industries when there was tightness in the agricultural labor market.

Appendix: Figures

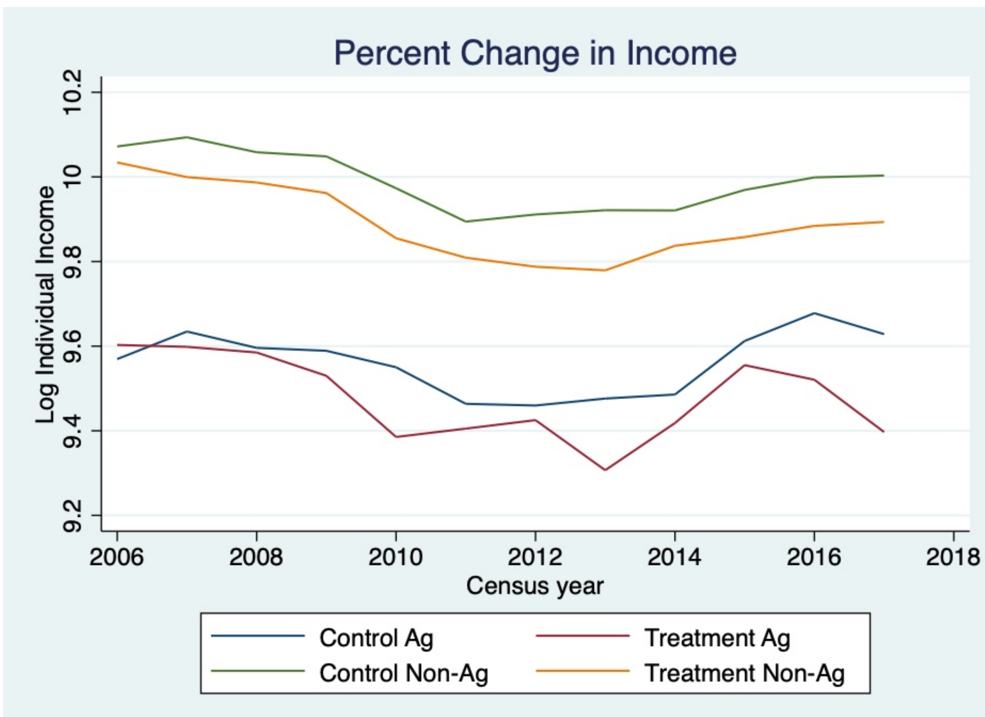

Figure 1: Parallel Trend Assumption

We can see from this graph that both the agricultural and non-agricultural sectors seem to follow parallel pre-trend levels in income. This means that after the event of the drought, the estimated change in income can be attributed to the drought.