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The Impact of Federal Drought Assistance on the U.S. Cattle Herd^{*}

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1 Introduction

Drought conditions are a major concern for global agricultural productivity affecting both crop and livestock production. The increasing intensity and duration of drought has catalyzed policy-makers and stakeholders to develop novel policy mechanisms to insure producers against economic losses incurred due to drought (Wallander et al., 2013; MacLachlan et al., 2018). The success of these mechanisms is reflected in its capacity to mitigate the negative effects of drought and the cost associated with such mitigation. However, questions remain regarding whether government programs enable or distort producer incentives for adaptation to changing weather conditions (Annan and Schlenker, 2015). This paper contributes to this literature by assessing the impacts of a government program designed to compensate U.S. livestock producers for forage production losses arising from persistent drought conditions. Specifically, we analyze the U.S. Department of Agriculture’s (USDA) Livestock Forage Program (LFP), which provides financial compensation to livestock producers affected by drought.

The impact of drought on the U.S. crop and livestock sectors is well documented (Kuwayama et al., 2019; Countryman et al., 2016). For the livestock sector, drought conditions can prompt herd liquidation as producers respond to higher feed costs and diminished forage availability. These short-run responses have long-run implications as breeding stock inventories decline, restricting future livestock supplies. Figure 1 documents the relationship between drought conditions in the continental U.S., as reported by the U.S. Drought Monitor, and the U.S. beef cattle herd size as reported by the the USDA’s National Agricultural Statistics Service (NASS). Periods of more intense drought are generally associated with reductions in the aggregate beef cattle herd size. The LFP was designed to partially mitigate the negative effects of drought by providing payments to livestock producers to partially covering feed costs affected by drought. Since 2008, more than \$9 billion in LFP payments have been distributed to livestock producers in

the U.S. LFP payments compensating livestock producers for drought related losses arising from historically dry conditions occurring between 2012 and 2013, constituted more than 19% of total Federal Government direct farm program payments during 2012-13 (MacLachlan et al., 2018).

[Figure 1 about here.]

Despite the relatively large Federal Government expenditures on the LFP, to our knowledge no research has characterized the impacts of the program on livestock sector outcomes. Our paper addresses this gap in the literature by empirically modeling how LFP payments impact key livestock agriculture outcomes, notably county-level herd sizes. Specifically, we use a quasi-experimental research design based on discrete program eligibility criteria to assess the impact of the LFP. This approach compares livestock sector outcomes in LFP eligible counties to counties that nearly reached LFP eligibility status based on their drought classification as documented by the U.S. Drought Monitor. We leverage a novel weighted matching two-way fixed effect estimator to assess the impact of LFP eligibility on livestock sector outcomes (Imai et al., 2021). This empirical approach provides a means to estimate treatment effects in scenarios where units of observation move in and out of the treatment group through time (i.e., treatment reversal). This is important in the context of this paper as LFP eligibility is based on annual drought conditions and a given county may be LFP eligible for multiple non-sequential years in our time period of analysis.

Our results indicate that LFP eligibility increases subsequent county-level beef cattle herd size by approximately 1% compared to similar counties also experiencing drought conditions but not eligible for LFP payments. These results demonstrate the efficacy of the program in mitigating the short- and long-run economic costs imposed by drought on the livestock sector. Specifically, by compensating producers whose forage production is negatively affected by drought, the LFP potentially reduces the likelihood that livestock producers liquidate some of their herd in response to drought. Decreased rates of

herd breeding stock liquidation in response to drought can increase producer current and future profits as a larger breeding stock can increase future calf crops. Additionally, diminished rates of herd liquidation in response to drought can mitigate future variation in consumer prices as large-scale herd liquidation decreases future supplies and increases price.

(Imai et al., 2021)’s estimator has been implemented in several context such as, macroeconomics (Hope and Limberg, 2022), health (Shiraef et al., 2022), political science (Kim and Li, 2023) and forest conservation (West et al., 2022). Our study contributes to the broader agricultural and applied economics literature by applying (Imai et al., 2021)’s estimator, which is capable of addressing scenarios of treatment reversal in panel data econometric models. Panel data methods are commonly used in the agricultural and applied economics literature to estimate treatment effects. Until recently most commonly employed estimators were unable to estimate treatment effects in contexts where treatment status changed through time. However, there are many scenarios relevant to agricultural and applied economics where treatment reversal is common or possible (e.g., changing Farm Bill programs, conservation program eligibility, etc.). As such, the methods outlined in this paper constitute an important contribution to the literature by providing a guide for estimating treatment effects with panel data when treatment status reversal is possible.

The paper proceeds as follows: in the next section we provide background and context on the LFP, in the third section we describe our research design and the empirical model used to estimate treatment effects, in the fourth and fifth sections we present our results and conclude by interpreting their importance for the broader agricultural policy-making landscape.

2 Background of the Livestock Forage Disaster Program

The Livestock Forage Disaster Program (LFP), which was initially established by the 2008 Farm Bill, provides compensation to livestock producers experiencing losses in forage due to drought or wildfire.¹ Figure 2 plots annual aggregate LFP payments between 2008 and 2022. LFP payments peaked in 2012 to more than \$2 billion as the majority of the major livestock production regions of the U.S. experienced unprecedented levels of drought (Rippey, 2015).

[Figure 2 about here.]

The LFP authorized in the 2008 Farm Bill funded the program through 2011 and imposed a previous risk management purchase requirement for eligibility. Specifically, producers must have purchased private insurance, a policy through USDA's Risk Management Agency, or coverage through the Noninsured Crop Disaster Assistance Program to be eligible for LFP payments (MacLachlan et al., 2018). The LFP was suspended after 2011 until the passage of the 2014 Farm Bill which allowed for retroactive payments to producers experiencing losses in 2012 and 2013. Additionally, the LFP authorized in the 2014 Farm Bill ended the previous risk management purchase requirements for eligibility, opening program eligibility to nearly all U.S. livestock producers regardless of enrollment in private or government insurance programs.

LFP payments cover livestock feed costs on a per-animal basis for eligible expected losses due to drought.² The USDA's Farm Service Agency (FSA) administers the LFP and annually sets species-specific per-animal payment rates as well as county-level eligible grazing periods. To be eligible for LFP payments, the county a livestock producer operates within must experience drought conditions exceeding a given threshold during the

¹Prior to the passage of the 2008 Farm Bill, forage losses were covered by Feed Indemnity Program, LFP's predecessor.

²LFP payments are also dispersed to livestock producers whose operations are affected by wildfire. However, these wildfire payments are only available to cover fire losses occurring on federally managed rangeland and are generally minimal compared to payments made for losses arising from drought.

county's eligible grazing period. County level drought conditions are classified weekly by the U.S. Drought Monitor which designates 5 levels of increasing drought severity ranging from 'D0: abnormally dry' to 'D4: exceptional drought.'

Livestock producers become eligible for one month of LFP payments when the U.S. drought monitor classifies at least some area of the county where they operate as experiencing 8 or more weeks of consecutive severe drought (D2: severe drought) during the county's eligible grazing period. Increasing drought severity increases the number of months of LFP payments a livestock producer is eligible to receive. For example, a livestock producer operating in a county that experiences 4 consecutive weeks of exceptional drought (D4) during the eligible grazing period is eligible for 5 months of LFP payments (see appendix ?? for more information on the LFP payment schedule). In 2022, per-animal LFP monthly payments range from \$122.95 per adult dairy cows and bulls to \$10.42 per reindeer (USDA-FSA, 2022).

To receive LFP payments an eligible livestock producer must submit an application to their local USDA-FSA office within 30 calendar days after the end of the calendar year in which the grazing loss occurred. Producers are also required to submit documentation demonstrating evidence of loss as well as proof that the affected grazing or pastureland is owned or leased. Contract producers are required to submit further documentation of their grower contract.

[Figure 3 about here.]

Figure 3 maps the distribution of total county-level LFP payments between 2008 and 2022. Counties with the largest aggregate LFP payments primarily concentrate in the western and central U.S. where drought conditions are generally more severe and common (Andreadis et al., 2005). Approximately 20% of counties in the continental U.S. received no LFP payments between 2008 and 2022. These counties are primarily located in the relatively more humid eastern U.S. and in urban counties (e.g., the Northeast and Southern California).

3 Research Design and Empirical Model

In order to estimate the impact of the LFP program on the outcome of interest, our empirical design exploits variation in county-level drought conditions timings. We leverage plausibly exogenous LFP design characteristics to assess the impact of the program within a quasi-experimental research design framework. Specifically, we use the 8 weeks of consecutive D2 drought LFP eligibility threshold to compare livestock sector outcomes in ‘treated’ (LFP eligible) counties to outcomes in nearby ‘control’ counties that also experienced some level of D2 drought during the 2014 to 2022 time period.

The standard method for estimating causal effects from panel data is the two-way linear fixed effects regression (TWFE) and takes the following form:

$$Y_{i,t} = \alpha_i + \gamma_t + \beta X_{i,t} + \theta_k Z_{i,t} + \varepsilon_{i,t}, \quad (1)$$

where $Y_{i,t}$ denotes the log transformed annual beef cattle herd size in county i and year t , and $x_{i,t}$ represents the LFP program indicator variable that equals 1 if county i in year t received LFP payments. α_i is the unobserved time-invariant county-specific effect and γ_t is the unobserved year-specific effect. $Z_{i,t}$ denotes a vector of time-varying covariates and $\varepsilon_{i,t}$ is the error term. However, using TWFE approach to estimate the impact of the LFP program on the outcome of interest faces three major empirical problems: the timing of treatment administration may differ across counties, each county may receive the treatment multiple times, and each county can go in and out of the treatment condition at different points in time.

Many recent studies have highlighted several important drawbacks of the TWFE regression for estimating causal effects (Sun and Abraham, 2021; Athey and Imbens, 2022; De Chaisemartin and d’Haultfoeuille, 2020; Goodman-Bacon, 2021). While many of these studies assumed staggered adoption, our data requires an approach that extends to a more general case, in which units can switch their treatment status multiple times

over time (Imai and Kim, 2021; Imai et al., 2021).

Figure 4 shows the treatment variation plot in which a red (blue) rectangle represents a treated (control) county-year observation. We observed that many counties did not receive the LFP payment from 2014 to 2022. Among those that did received the LFP payment, most have moved in and out of the treatment group through time which is a direct consequence of the LFP eligibility criteria based on annual drought conditions reported by the U.S. Drought Monitor.

[Figure 4 about here.]

To deal with these threats to identification, we use a new econometric approach, PanelMatch, that combines matching methods with a difference-in-difference estimator for panel data analysis, relaxing the linearity assumption (Imai et al., 2021). This technique compares counties which received the LFP payment in year t (treated units) with counties that have similar pre-treatment history but did not receive the LFP payment in the same year t (control units). Moreover, PanelMatch allows to estimate how treatment effects evolve over time and is more robust to model specification than TWFE. The proposed method involves the following steps: Firstly, we identify a set of control observations that share the same treatment history up to a pre-determined number of periods, for each treated observation. This set of matched control observations is referred to as a *matched set*. Subsequently, the matched set is refined by adjusting for observed confounding using standard matching and weighting techniques, to ensure that the treated and matched control observations have similar covariate values. Lastly, the Difference-in-Difference (DiD) estimator is applied to account for any underlying time trend.

Matched sets and causal quantity:

PanelMatch introduces two key parameters to identify the control units and to define the causal quantity. These key parameters, F and L , identify the temporal extent of the estimated causal impact and the number of periods of treatment history used to create

matched sets, respectively. We focus our analysis on the contemporaneous effect of the LFP program, i.e., we set the parameter F to 0. We opt to estimate contemporaneous treatment effects since counties treated in t may experience treatment reversal in $t + 1$ while others continue to be treated. As such, estimating the effect of treatment in t on outcomes in $t + 1$ depends on treatment status in $t + 1$.

In addition, the method also requires to select L which allows us to adjust for the treatment histories. We define $L = 2$ which indicates that the control observations share an identical treatment history up to 2 years. The selection of L is part of the identification assumption and thus, it is important to assess whether previous treatment status may act as a confounding variable that impacts both the current treatment and outcome (Imai and Kim, 2019). Given the values of F and L , the average treatment effect on the treated takes the following form:

$$\begin{aligned} \delta(F = 0, L = 2) = & E\{Y_{i,t}(X_{i,t} = 1, X_{i,t-1} = 0, \{X_{i,t-l}\}_{l=2}^L) - \\ & Y_{i,t}(X_{i,t} = 0, X_{i,t-1} = 0, \{X_{i,t-l}\}_{l=2}^L) \mid X_{i,t} = 1, X_{i,t-1} = 0\}, \end{aligned} \quad (2)$$

where counties that received the LFP payment in year t are the treated units ($X_{i,t} = 1$). Hence, $Y_{i,t}(X_{i,t} = 1, X_{i,t-1} = 0, \{X_{i,t-l}\}_{l=2}^L)$ is the potential outcome for counties that received the LFP payment and $Y_{i,t}(X_{i,t} = 0, X_{i,t-1} = 0, \{X_{i,t-l}\}_{l=2}^L)$ is the counterfactual potential outcome. Thus, $\delta(F = 0, L = 2)$ represents the contemporaneous causal effect of the LFP program assuming that the potential outcome depends on the treatment history up to four years back. Importantly, PanelMatch assumes no spillover effects. Thus, a county's potential outcomes are only affected by its own treatment history.

As the counterfactual outcome for treated counties cannot be observed, the potential outcome for counties that did not receive the LFP payment is used:

$$\delta(F = 0, L = 2) = E\{[Y_{i,t}(X_{i,t} = 1, X_{i,t-1} = 0, \{X_{i,t-l}\}_{l=2}^L) \mid X_{i,t} = 1, X_{i,t-1} = 0] - [Y_{i,t}(X_{i,t} = 0, X_{i,t-1} = 0, \{X_{i,t-l}\}_{l=2}^L) \mid X_{i,t} = 0, X_{i,t-1} = 0]\}. \quad (3)$$

PanelMatch relaxes the unconfoundedness assumption but, as TWFE, assumes a parallel trend in the outcome variable after conditioning on the treatment, outcome and covariate histories.

Once the value of L is determined, we construct the matched set of control units for each treated county. The counties included in the matched set and the treated county share exactly the same treatment history from time $t - L$ to $t - 1$. It is worth emphasizing that the matched sets only include observations from the same time period, which implies exact matching concerning the time period. Thus, the matched set is defined as:

$$M_{it} = \{i' : i' \neq i, X_{i',t} = 0, X_{i',t'} = X_{it'} \text{ for all } t' = t - 1, \dots, t - L\} \quad (4)$$

Refining the matched sets:

The matched sets defined in equation 4 only control for the treatment history. However, the parallel trend assumption implies to adjust for other confounders. Thus, matching techniques are implemented to account for additional time-varying covariates and refine the matched sets. The general idea is to select a subset of control counties within the initial matched set that are most similar to the treated county in terms of the observed covariates. Matching methods are intuitive tools to deal with selection into treatment, reduce model dependence and offer diagnostics for the assessment of the matches (Rubin, 2006; Ho et al., 2007). In addition, combining matching with fixed effects panel regression has become increasingly common to estimate the impact of conservation programs when randomization is not possible (Jones and Lewis, 2015; Ferraro and Miranda, 2017;

Rosenberg, 2020).

DiD estimator:

Assuming that parallel trends hold between treated counties and their matched comparison counties after conditioning on treatment history, lagged LFP payments, and covariate history, PanelMatch provides a nonparametric generalization of DiD estimator for the causal effect of the LFP on the livestock sector (equation 2). To do this, for each treated county the refined matched sets provides the control units to estimate the counterfactual outcome. We follow the method proposed by Imai et al. (2021) to compute the standard errors via a bootstrapping procedure with 2,000 iterations.

4 Data

To estimate the econometric model outlined in section 3, we integrate data on LFP program characteristics, LFP payments, drought conditions reported by the U.S. Drought Monitor, and livestock stocking rates. Joining these data allows sorting counties into treatment (LFP eligible) and control (LFP ineligible) groups to facilitate an assessment of the impact of LFP payments on subsequent county level stocking rates.

The process of generating the data used in this paper’s analysis begins with matching county-level eligible grazing periods to weekly drought severity data released by the U.S. Drought Monitor. USDA-FSA annually releases county-level data on LFP eligible grazing periods for 13 differing pasture types which, in some cases, have differing eligibility periods. We focus on three of the most common pasture types: native pasture, full season improved pasture, and warm season improved pasture. Together these pasture types account for more than 94% of all LFP payments distributed between 2019 and 2022.³ Native pasture and warm season improved pasture always have identical grazing periods for a given county while the LFP eligibility period for full season improved generally is longer, encapsulating some if not all of the eligibility period for native pasture and warm

³Data on LFP payments by pasture type are not available prior to 2019.

season improved. For example, the native pasture/warm season improved eligibility period for Florida's Orange County is March 15th to October 15th while the eligibility period for full season improved extends from December 1st to October 15th. It is relatively common for counties in temperate climates to have full season improved eligibility periods which begin before the calendar year.

Once each county's eligible grazing period is determined, we match those eligibility periods to weekly drought intensity data reported by the U.S. Drought Monitor. Specifically, we calculate for each county-year the number of consecutive weeks of D1, D2, D3, and D4 drought experienced within the county during the LFP eligibility period. We then use these data paired with county-level LFP payment data to determine treatment and control counties. We consider a treatment county to be those that experience at least 8 consecutive weeks of D2 drought during their eligible grazing period (the minimum criteria to receive one month of LFP payments) and received a non-zero quantity of LFP payments. We determine treatment status based on both eligibility and receipt of LFP payments as we are primarily interested in the the impact of LFP payments on livestock sector outcomes. Control group counties are those that experience 7 or fewer weeks of consecutive D2 drought during at least one county eligibility period between 2014 and 2022.

The key outcome variable for our analysis of LFP is log transformed county-level annual beef cattle herd size as reported by USDA's National Agricultural Statistics Service (NASS). Specifically, we join the county-level beef cattle herd size reported for the first of January of a given year to the treatment and control status of the county the previous year. For example, if a given county's reported beef cattle herd size in January 2021 is 2,000 head, then 2,000 head is used as the outcome variable for that county in 2020. This approach allows our analysis to capture changes in county herd size in response to LFP eligibility. LFP benefits are available to sheep, dairy, goat, and other livestock producers. We opt to focus exclusively on beef cattle based on data availability and the importance

of the beef cattle industry for the broader U.S. agricultural sector. Namely, county-level annual herd size estimates are only available for beef and dairy cattle and, as of 2016, the beef cattle industry comprised the largest share of cash receipts of all U.S. agricultural commodities (USDA-NASS, 2016). We focus specifically on the beef cattle industry, rather than looking at both the dairy and beef cattle industries, as herd liquidation in response to drought is most common among beef cattle producers (Leister et al., 2015).

[Table 1 about here.]

4.1 Covariates to Determine Matched Sets

As outlined in section 3, our empirical approach for estimating the impact of LFP involves created matched sets of counties based on previous treatment and control status. We leverage a suite of covariates to ensure that control group counties matched to a given treatment group county are similar in terms of their beef cattle production system to the treatment county. Specifically, we match control group counties to a treatment county based on the following covariates: the percent of county harvest hay acreage that is irrigated, the percent of county agricultural land that is pasture, the average county-level pasture rental rate, total average growing season precipitation, average growing season daily maximum temperature, percent of sandy soil, and percent of silt soil.

County-level annual LFP payment data were obtained from USDA-FSA. Data on percent of total county hay acreage that is irrigated and percent of total agricultural land in pasture were drawn from the 2017 Census of Agriculture as reported by USDA-NASS. The county average pasture rental rate is also from USDA-NASS and represents the rental averaging annual rates between 2014 and 2022. Average county growing season precipitation and average maximum temperature were obtained by aggregating PRISM 30-year normals data, which characterize the period between 1991 and 2020, to the county level (PRISM, 2023). Data on county-level soil characteristics, i.e., percent of sandy soil and percent of silt soil, were drawn from Yun and Gramig (2019). Table1 presents summary

statistics for the primary outcome variable of interest, log transformed cattle herd size, as well as the suite of covariates used to determine matching sets.

5 Results

Here we present results from the matching model outlined in section 3. Specifically, we use the econometric model to estimate the average treatment effect of the LFP on eligible counties that received LFP payments. We opt to estimate treatment effects among treated counties (i.e., average treatment effect on the treated) given that we were interested in how livestock sector outcomes differ in LFP eligible counties from LFP ineligible counties that also experienced some level of drought, rather than the aggregate impact of the LFP among both LFP eligible and ineligible counties.

Figure 5 presents point estimates and bootstrapped 95% confidence intervals for four differing model specifications. Specifically, we vary the suite of covariates used to refine and weight the matched sets pairing treatment and control counties. The covariate used to refine matched sets in each specification are as follows: 1) weeks of D2 drought in a given year's LFP eligibility period, 2) weeks of D2 drought and as county average temperature and precipitation, 3) weeks of D2 drought, county average temperature and precipitation, and county soil characteristics 4) weeks of D2 drought, county average temperature and precipitation, county soil characteristics, and county livestock sector variables (i.e., percent of hay irrigated, percent of agricultural land in pasture, and average pasture rental rate).

[Figure 5 about here.]

All model specification except the 4th, which includes the largest set of covariates for matched set refinement, yield statistically significant point estimates for treatment effects. These estimated treatment effects for the LFP range between 1% and 1.5% suggesting that the LFP increases county-level beef cattle herd sizes by a small but economically

significant margin compared to similar counties that also experienced drought conditions between 2014 and 2022. Overall our results demonstrate that the LFP does influence stocking and liquidation decisions among livestock producers, potentially mitigating some of the economic costs of drought borne by livestock producers.

6 Conclusion

This paper aims to characterize the effect of a agricultural risk management program tailored to aid livestock producers impacted by drought. Specifically, we explore how the USDA’s Livestock Forage Disaster Program, which provides payments to livestock producers located in counties where the severity of drought conditions exceeds predefined criteria, affects subsequent producer stocking and liquidation decisions.

This research contributes to the applied and agricultural economics literature by applying a novel methodology to evaluate the impact of a under-studied risk management program. Despite the significant government expenditures used to fund the LFP, to our knowledge no research has empirically modeled whether the program alters livestock producer decision-making or instead constitutes a simple income transfer. This distinction is important if the program aims to generate benefits outside of the livestock sector, namely by diminishing future consumer meat price increases created by herd liquidation in response to drought. If the program does not alter livestock producer decision making, then these program benefits likely do not accrue to the general public. Our results demonstrate that this is not the case. Rather, we find that LFP eligibility and payment does positively impact subsequent county-level herd sizes, suggesting that the program does mitigate some of the drought induced variation in cattle herd size and resultant future meat prices.

The methodology used to estimate the treatment effect of the LFP also constitutes a contribution to the broader literature. Specifically, we leverage a novel weighted match-

ing estimator to assess LFP treatment effects with panel data (Imai et al., 2021). Importantly, this estimator facilitates modeling treatment effects in contexts where units on observation can be treated in multiple, nonsequential time periods i.e., treatment reversal. This is important as most of the panel data treatment effect estimators used in the literature are not suitable for contexts where staggered treatment reversal is possible. However, treatment reversal is relevant to many arenas of agricultural economics as eligibility for many government programs focusing on conservation and technical/financial assistance vary across producers and geography and can change significantly with the passage of new legislation (i.e., Farm Bills).

This research is part of a broader literature exploring how agricultural producers respond and adapt to evolving climate conditions. This literature has raised important questions regarding how government subsidized risk management programs crowd-out or disincentivize producer adaptation, particularly in row and field crop production (Annan and Schlenker, 2015). These issues are also relevant to adaptation in the livestock sector. Additional research is needed to understand how programs like the LFP, designed to mitigate climate risk among producers, affects adaptation within the sector.

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Figures

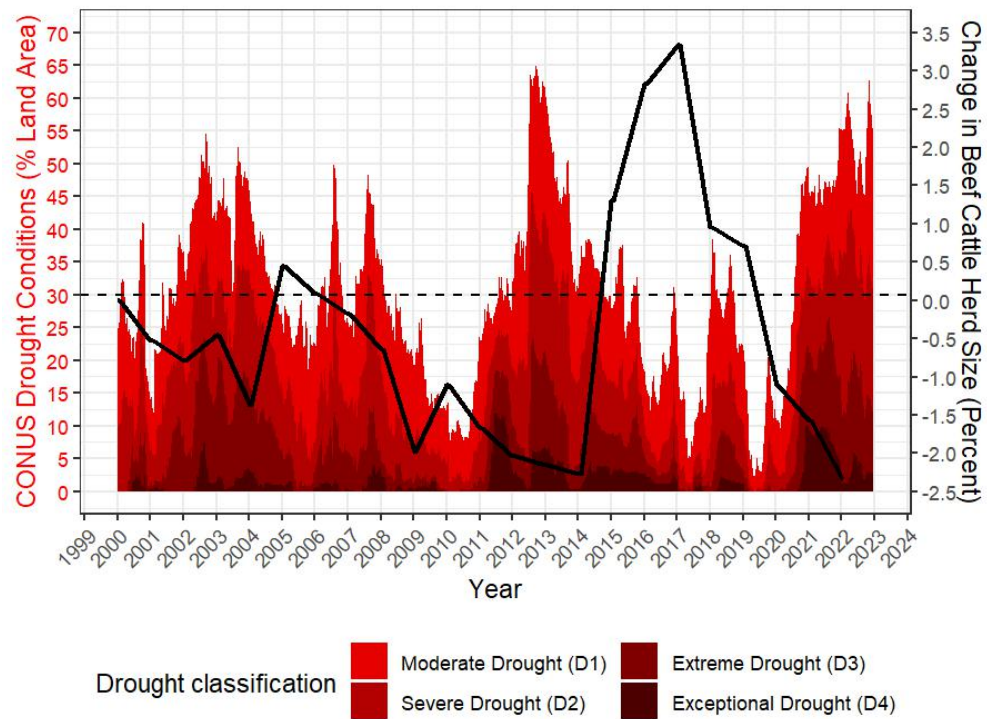


Figure 1: Drought Conditions and Changes in the U.S. Beef Cattle Herd Size, 2000-2022

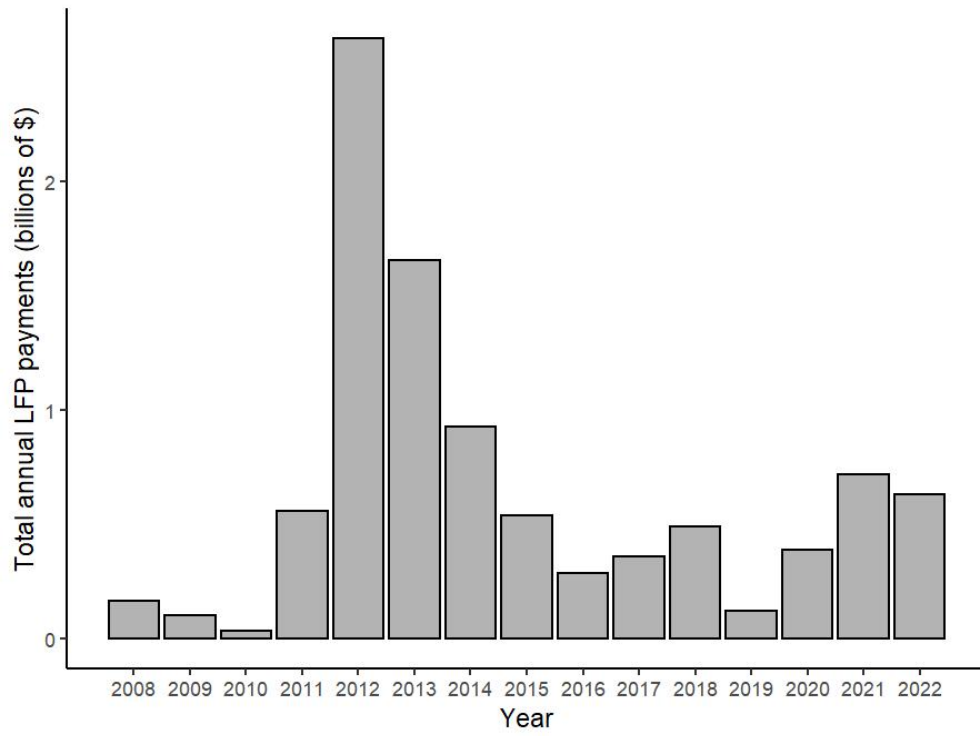


Figure 2: Aggregate Annual LFP Payments, 2008-2022

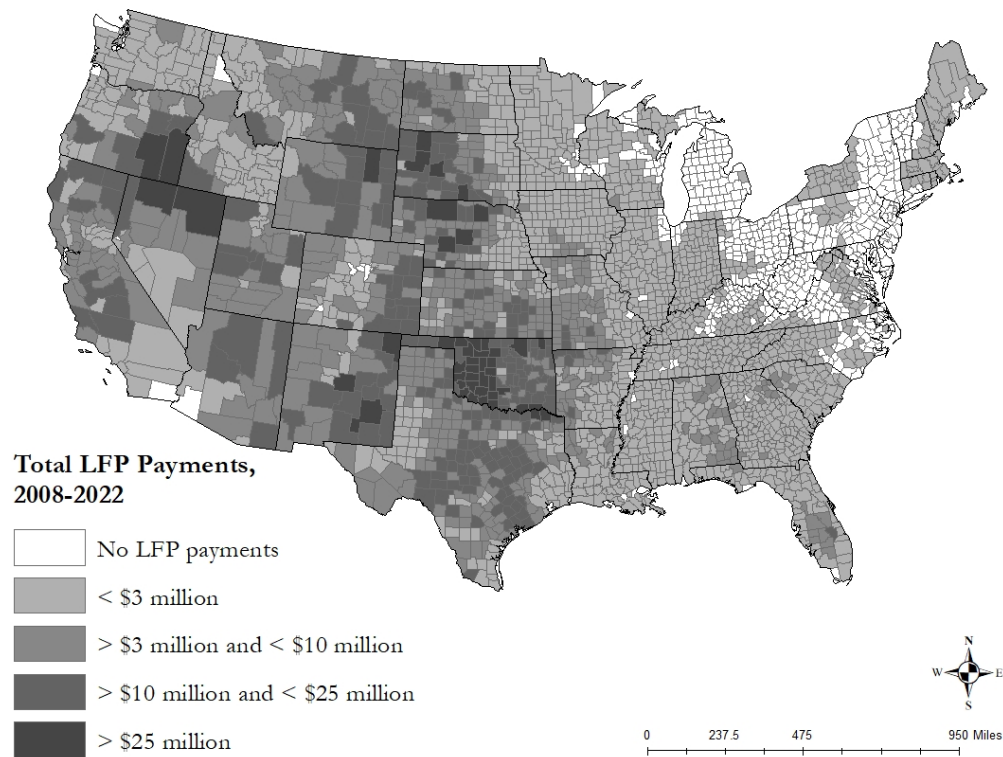


Figure 3: County-Level Aggregate LFP Payments, 2008-2022

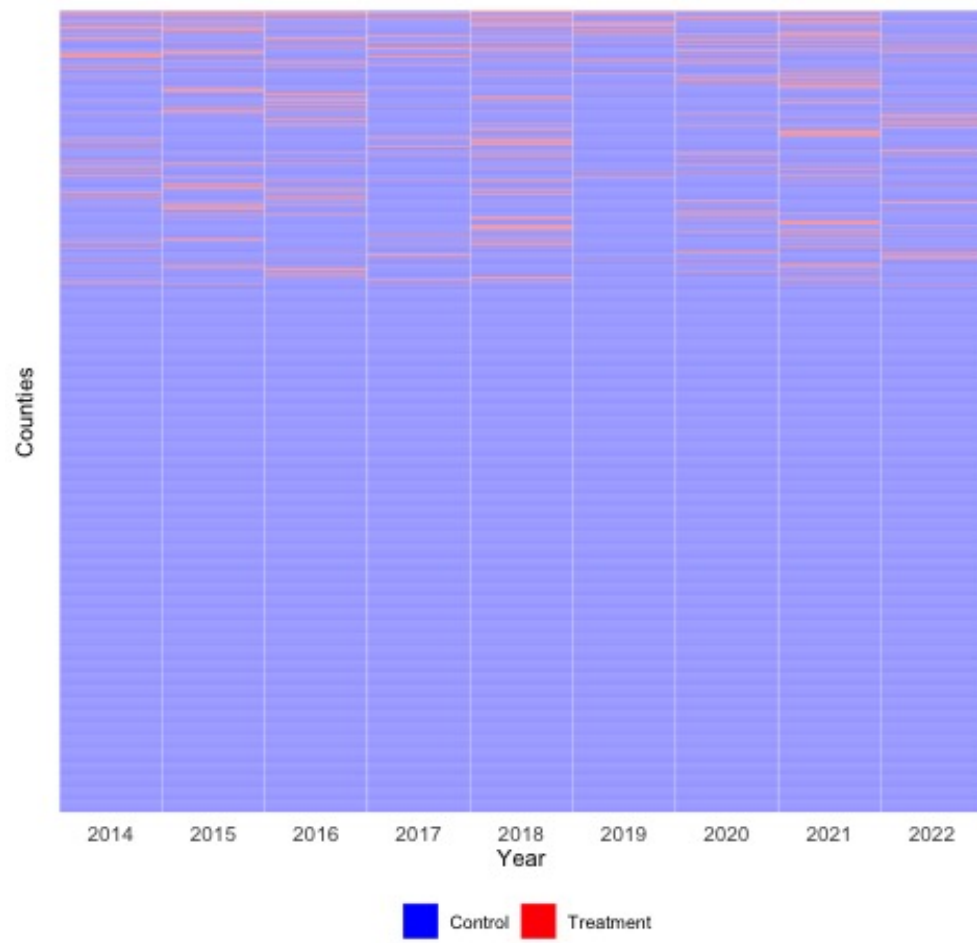


Figure 4: Distribution of Treatment across Space and Time

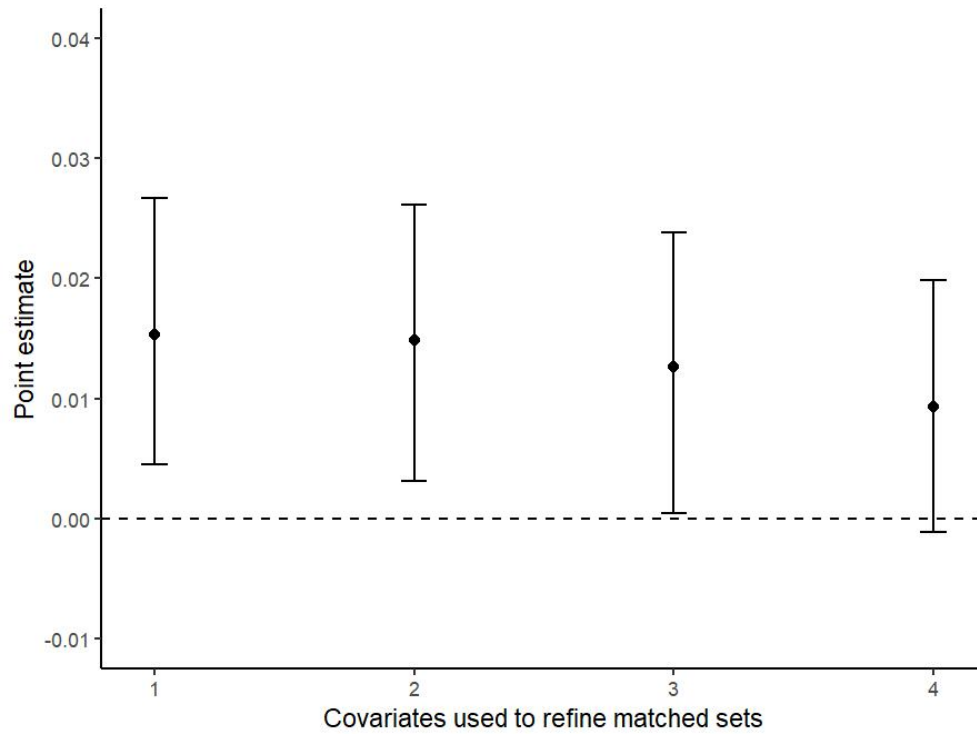


Figure 5: Estimated average treatment effects varying covariates used to refine matched sets

Notes: 95% confidence intervals are plotted for each point estimate.

Covariates used for refinement in differing specifications:

- 1) Weeks of D2 drought
- 2) Weeks of D2 drought and county average temperature/precipitation
- 3) Weeks of D2 drought, county average temperature/precipitation, and county soil characteristics
- 4) Weeks of D2 drought, county average temperature/precipitation, county soil characteristics, percent of hay irrigated, percent of ag land in pasture, and average pasture rental rate

Tables

Table 1: Summary Statistics for Outcome Variable and Matching Covariates

Statistic	N	Mean	St. Dev.	Min	Max
Log(Beef Cattle Herd Size)	7,990	9.2	1.0	4.6	11.9
Annual LFP Payments (dollars)	7,990	280,994.9	765,539.0	0	9,643,608
Percent of Hay Irrigated	7,990	19.4	30.3	0.0	100.0
Percent of Ag Land in Pasture	7,990	52.7	26.8	1.2	99.8
Average Pasture Rental Rate (dollars/acre)	7,990	18.8	13.5	0.8	89.8
Average Growing Season Precipitation (mm)	7,990	436.2	188.9	11.3	1,063.2
Average Growing Season Max Temperature (C)	7,990	26.3	3.8	17.1	35.7
Percent Clay Soil	7,990	28.1	9.2	3.9	64.2
Percent Sand Soil	7,990	35.9	18.2	5.5	93.8

Appendices

A Robustness Checks of Modeling Assumptions

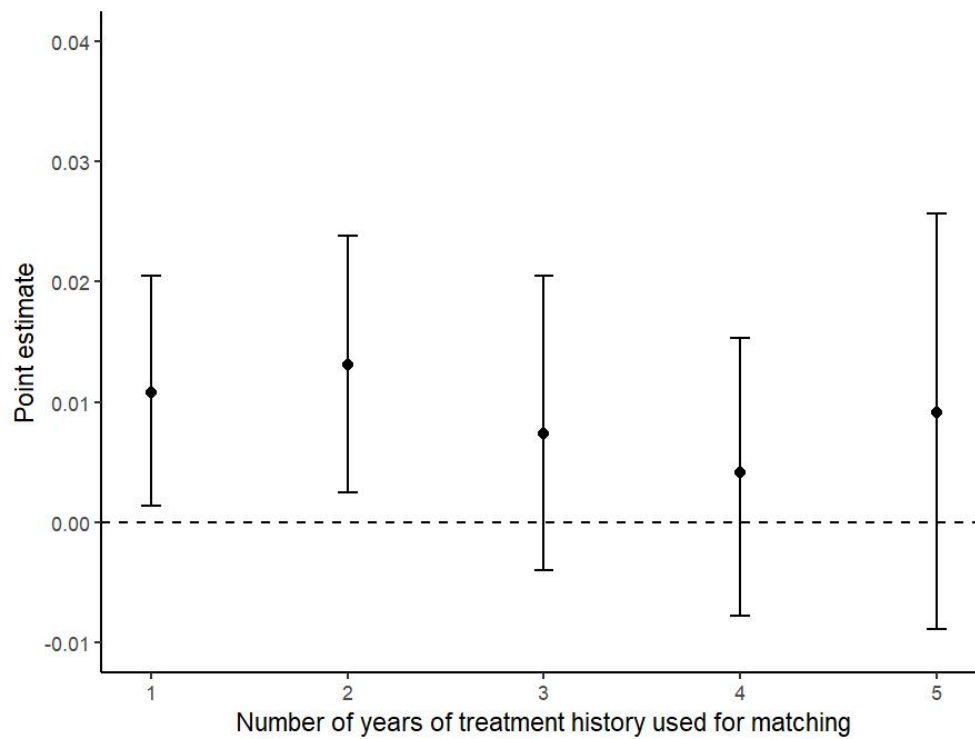


Figure A.1: Estimated average treatment effects varying number of periods of past treatment status used to create matched sets

Note: 95% confidence intervals are plotted for each point estimate.

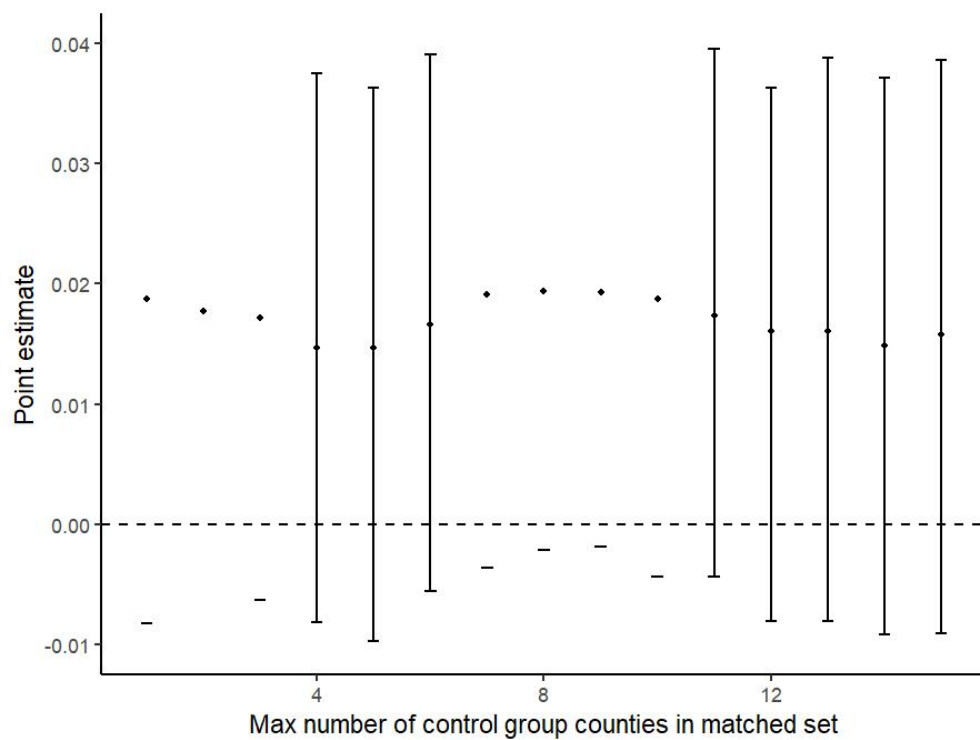


Figure A.2: Estimated average treatment effects varying maximum number of control counties allowed in each matched set

Note: 95% confidence intervals are plotted for each point estimate.