Further Supplemental Information

for

Does Receiving Government Assistance Shape Political Attitudes? Evidence from Agricultural Producers

Contents

A Further Description of Farm Programs

In this section we provide additional details on the programs featured in Figure 1 of the main text.

A.1 Features of Major USDA Farm Programs

Conservation Reserve Program (CRP)

The CRP was created as part of the 1985 farm bill amidst contentious congressional battles over agricultural target prices and production controls. The new program was nonetheless viewed as "generally noncontroversial and nonpartisan," in no small part because it managed to unite an ascendant environmentalist lobby with farmers who were happy to see 45 million acres of farmland removed from production during a period of low crop prices (Coppess 2018).

Since its inception, the CRP has taken the form of the government taking out long-term leases (currently 10–15 years) on private farmland, especially in environmentally sensitive areas. Farmers enrolled in the program agree to forgo planting most commodity crops, and are required to comply with basic conservation standards. Currently, the USDA also offers to pay up to 50% of the costs of planting cover crops on registered CRP acres (FSA 2019b).

Direct and Counter-Cyclical Program (DCP) and Average Crop Revenue Election (ACRE)

The Direct and Counter-Cyclical Program (DCP) was introduced in the 2002 farm bill (FSA 2003). As the name suggests, the DCP had two payment components—a "direct" payment based on the number of acres a farmer historically has planted (their "base acres"), and a potential "counter-cyclical" payment that was released if a national price index for enrolled crops fell below a certain target. The 2008 Farm Bill renewed the DCP and also introduced the optional Average Crop Revenue Election (ACRE) program. Farmers enrolling in ACRE gave up their standard counter-cyclical payments and took a 20% reduction in their direct payments, in exchange for a counter-cyclical payment that was triggered by state-level price declines and was based off of current planting acres (as opposed to base acres) (FSA 2009).

Agriculture Risk Coverage (ARC) and Price Loss Coverage (PLC) Programs

The 2014 farm bill replaced the DCP/ACRE programs with a pair of safety net programs that make payments when market conditions fall below certain thresholds. Starting in calendar year 2015, agricultural producers were allowed to enroll acreage into either the Agriculture Risk Coverage (ARC) program or the Price Loss Coverage (PLC) program, but not both. The program choice was locked in for the duration of the 2014 farm bill (that is, through 2018).

The Agricultural Risk Coverage (ARC) program is a revenue-based program, and provides payouts when county-level crop revenue of a commodity falls below a guaranteed level.[1] The Price Loss Coverage (PLC) program, on the other hand, has a price-based payment trigger. It makes payments when a target price exceeds the higher of the market year average price

[1]Farmers were also given the option of taking ARC payments based on fluctuations in individual farm revenue. However, this "individual" version of the ARC was far less popular than the "county-level" ARC, and constituted a negligible fraction of commodity payments between 2015 and 2019.

or the national average loan rate for the given commodity.

The 2018 farm bill reauthorized the ARC and PLC programs with a few tweaks to the payment formulas for each. Most importantly, farmers were given a chance to switch enrollment between the two programs, with the new decision locked in through 2022. While the ARC program was the choice of a large majority of farmers in 2014–2018, evolving market conditions led producers to enroll most acres in the PLC program for 2019–2022 (Coppess, Schnitkey, Krista, Nick, and Zulaf 2019).

Market Facilitation Program (MFP)

In summer 2018, trade conflict between the US and China quickly led to Chinese retaliatory tariffs being placed on US agriculture. The Trump administration responded by authorizing billions in direct payments to affected farmers via the Market Facilitation Program, with renewed tranches of payments issued in 2019 and 2020.

The MFP generally supported farmers who benefited from previous commodity programs. The 2018 edition of the MFP was paid out in three tranches in 2018 and 2019, with payments based on individual farmers' harvested production of each crop in 2018. The bulk of the payments were targeted at farmers growing corn, sorghum, soybeans, wheat, and cotton (CRS 2019), the first four of which are the main crops supported by the ARC/PLC programs. The 2019 edition of the MFP was paid out over three tranches in 2019 and 2020 for an expanded set of crops, with a payment formula centered around planted acres (CRS 2019).

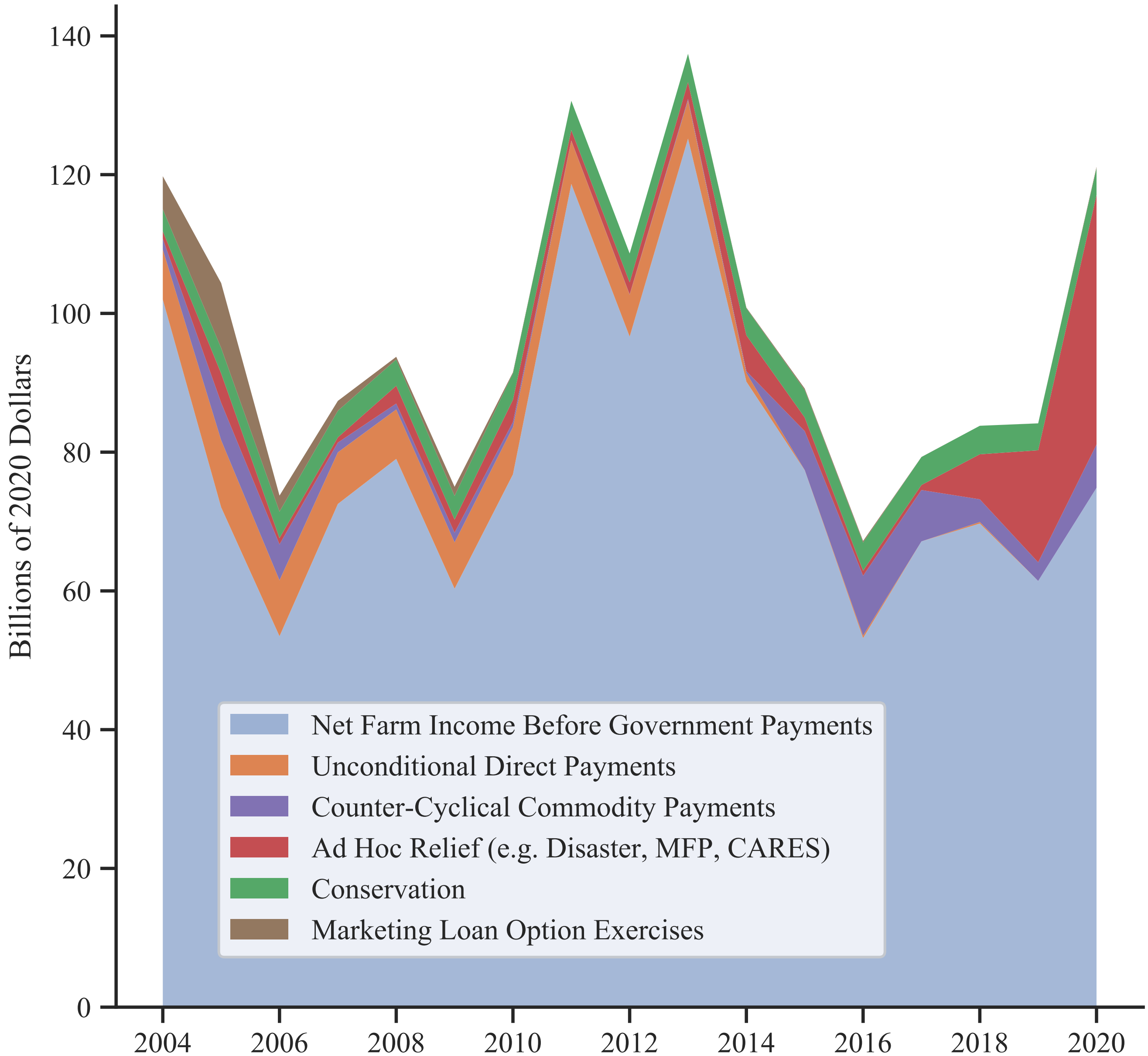
As depicted in Figure 1 of the main manuscript, the MFP was an outlier among USDA farm aid programs in terms of spending levels. However, it was also unprecedented in its legal authority. Whereas agricultural programs have historically been funded entirely through legislation, the MFP received no authorization from Congress. President Trump acted unilaterally via longstanding general authority under the Commodity Credit Corporation Charter Act of 1948 (Coppess, Schnitkey, Swanson, and Zulaf 2019).

A.2 Significance of Farm Programs for Farm Income

For the subset of US farmers that benefit from farm programs, direct government payments are consistently an important part of take-home pay. According to the USDA Economic Research Service (ERS), the total value of US agricultural production has exceeded $400 billion (in 2020 dollars) each year since 2011. However, farm inputs (e.g., livestock feed, fertilizer, seeds), machinery, and labor costs have been commensurately high, and annual real net farm income over the last decade has varied between $67 billion in 2016 and $137 billion in 2013. As depicted in Figure 1, direct government payments have constituted over 10% of net farm income each year since 2014, and have averaged 19% of total real net farm income during our primary sample years of 2015–2019.

A large majority of farm program spending across the last four farm bills has contributed directly to farmers' bottom lines. As of the 1996 farm bill, commodity payments are based on past farm-level production, and thus have been decoupled from planting decisions. As such, farmers who received DCP/ACRE and ARC/PLC payments did not face significant production restrictions for enrolling a particular crop in the programs. Likewise, ad hoc relief programs (such as natural disaster assistance, the MFP, and CARES Act payments) provided revenue at critical junctures without associated production costs. While conservation payments, such as CRP rental agreements, do require farmers to take land out of production, these leases by design have targeted marginally productive acreage and thus

Figure 1: Direct Government Payments as a Proportion of Net Farm Income



Notes: Aggregate payment and farm income totals come from USDA ERS Farm Income and Wealth Statistics. Market loan option exercises include Loan Deficiency Payments, Market Loan Gain payments, and Commodity Certificate Exchange payments.

have constituted modest revenue trade-offs for many participants.

A.3 Details on USDA Program Enrollment and Administration

In terms of internal policy design, the programs discussed above share several features in common with respect to enrollment and administration. Most USDA farm aid programs are administered at the local level through county-specific Farm Service Agency (FSA) offices. There are over 2,000 FSA county offices nationwide, covering nearly every rural county. FSA offices serve as ombuds to the bureaucracy, assisting producers with putting together their applications and receiving their benefits. The USDA encourages prospective farm program participants to register their farms in person at their local county office, where they obtain a unique farm number that facilitates access to USDA loans and farm aid programs.[2]

Individuals interested in leasing land through the CRP typically have had two main enrollment options. Most program acres have been enrolled through periodic "general sign-ups," during which landowners submit competitive bids for farmland they would like to enter (Stubbs 2014; Farm Service Agency 2021*a*). The USDA ranks bids according to an "Environmental Benefit Index" which incorporates the expected environmental benefits and financial cost of each offer, and then accepts bids according to the ranking until the current acreage enrollment cap is met (Stubbs 2014). A minority of CRP acres are leased through "continuous sign-up" initiatives, such as the Conservation Reserve Enhancement Program and the Farmable Wetland Program. Subprograms that enroll acreage through continuous

[2]For details, see `https://newfarmers.usda.gov/first-steps`. Most farm program participants are required to visit county FSA offices at least once per year to report updates to planted acreage (see `https://www.fsa.usda.gov/Assets/USDA-FSA-Public/usdafiles/FactSheets/2019/crop-acreage-reporting-19.pdf` for details on crop reporting requirements).

sign-ups are not restricted to the "general sign-up" periods, do not feature a competitive bidding process, and are targeted at specific areas of environmental concern (Stubbs 2014; 2019; Farm Service Agency 2021*b*). While the CRP is governed by the farm bill, most changes have been tweaks to the enrollment cap or the introduction of new "continuous sign-up" subprograms.

FSA offices serve similar functions in administering the ARC/PLC programs, but producers have had to make more decisions following the transition from the DCP/ACRE paradigm. To continue participating in commodity programs, farmers now had to decide whether to enroll in a counter-cyclical program with a commodity price trigger (the PLC), a counter-cyclical program based on county-level revenue (ARC-CO), or a counter-cyclical program based on individual farm revenue (ARC-individual). Producers were encouraged (but not required) to update their farms' historical payment yields and plantings at their local USDA office, and this new information was used to determine payments under the new counter-cyclical programs. Producers' reported yields and program choices were locked in until the next farm bill was passed in 2018. In 2019, farmers were given options to switch between the ARC and PLC programs, as well as update their PLC yields.

The MFP had a similar application process, although it changed slightly over its first and second iterations. Producers were able to leverage already-collected information (e.g., crop portfolios and yields) in putting together their applications. Given the addition of this new program in 2018, producers had even more contact with the FSA in their role as ombuds. A reporter at *Successful Farming* noted that "[t]ypical Iowa farmers will make five to six trips...to their county's Farm Service Agency office this year" (McGinnis 2019).

In addition to the program features and benefit variation we focus on in this study, it is also useful to consider how participation in USDA farm aid programs involves administrative burdens for participants. As Herd and Moynihan (2018) explain, many government programs involve learning costs and compliance costs (especially when program administrators are charged with determining and verifying who is eligible for benefits), and that is certainly the case for all three of the programs we study. The ARC/PLC, CRP, and MFP all require extensive paperwork, documentation, regular interactions with and visits to the local FSA county office, and often complex enrollment decisions. For example, the ARC and PLC require that producers refile their program contract every year, even if no changes to the individual's farming operation were made. Likewise, the 2018 MFP issued payments according to certified harvested production, a design detail that necessitated extra documentation and delayed payments, frustrating farmers who were most in need of relief at the outset of the trade war (Rappeport 2018). While the CRP was the most popular of the three programs according to our survey, this did not preclude survey respondents from expressing frustration with its administration. One survey respondent commented:

> The reason I am only somewhat supportive [of the CRP and ARC programs] is that while they do provide some support, the bureaucracy that administers it is needlessly large and slow with many levels of employees who's existence is solely due to the need to push paperwork back and forth. They make decisions that affect my land and livelihood without an agricultural background. These decisions can have ramifications lasting decades...I've been nationally recognized for my conservation work and am sought after as a speaker to advocate for conservation practices, but I'm only luke warm on CRP and other programs because of the bureaucracy.

Other respondents complained that the program administration is understaffed and overloaded with work ("Seems like nothing is being done and the processes are slowing to a crawl. I have applied for CRP cost share last Nov '19 and not seen a penny [yet]...FSA is overloaded with work and seems to not get the people needed to do the jobs."). One farmer in Idaho noted that "[t]he CRP program works, but the paperwork is a nightmare."

In these ways, the administrative burdens associated with these three programs are not all that different from those explored in-depth by Herd and Moynihan (2018), such as enrolling in Medicare or accessing health insurance through the ACA exchanges. Also similar are some of the up-front problems involved in rolling out new programs, which can cause significant burdens for individuals trying to access benefits. Just like healthcare.gov had significant problems at the outset—problems that were ultimately smoothed out—the MFP was initially slow in delivering payments to farmers (Rappeport 2018). By 2019 (our survey was conducted in 2020), however, this, too, was resolved, as the MFP switched over to planted acres and therefore required less documentation. In these ways, therefore, the learning and compliance costs of USDA programs are comparable to those of other social programs that have been examined in the literature.

Notably, however, there are also features of USDA programs that help to lessen the administrative burden for participants. First, USDA program beneficiaries have the assistance of local ombuds whose job it is to help agricultural producers learn about, sign up for, and navigate different USDA programs. Thus, similar to how ACA navigators helped people to enroll in insurance on the exchanges, and just as tax preparers can sometimes help individuals access the EITC, these USDA ombuds help to lessen learning and compliance costs for farmers and ranchers. Herd and Moynihan (2018) also suggest that learning costs can be lessened when the eligible individuals have strong social networks and group memberships that share information. That is likely the case for agricultural producers, especially since they are eligible for these benefits as businesses and likely benefit from formal and informal professional networks. Also, in general, once individuals receive benefits from one program, they might be more likely to learn about and enroll in other programs, and this is likely the case for USDA program recipients: the local FSA office has their documentation and a unique recipient ID on file. Moreover, as they make regular trips to the local office to satisfy program reporting requirements, it probably becomes easier for them to learn about and enroll (and re-enroll) in other USDA programs. For example, for the MFP, farmers could submit the same documentation they would use when submitting a crop insurance claim, and the system was actually a simpler version of the one many producers used for the Loan Deficiency Payment program between 1996 and 2006 (Johnson 2018; Graff 2018).

Thus, the administration of the programs we examine has features in common with that of other programs studied in the literature on administrative burdens. However, the learning and compliance costs of these three programs do not differ substantially: while they each have their own eligibility and enrollment criteria, and while there were some initial glitches with the MFP, on the whole, the learning and compliance costs are very similar across the board.

Moreover, on another type of cost discussed by Herd and Moynihan (2018)—psychological costs—there also are not substantial differences between these three programs. The Herd and Moynihan (2018) discussion of SNAP is illustrative of what psychological costs can look like: individuals enrolling in SNAP have to answer a large number of questions about them and their households, many of which are intrusive and personal, and then actually using the benefits at the grocery store can be stigmatizing. These psychological costs can dampen recipients' support for the programs and weaken the connection between receiving benefits and supporting the program (Soss 1999). While we argue that the ARC/PLC programs are perceived by some farmers as arbitrary and capricious, it is not because of how those programs are administered, or because of negative, stigmatizing interactions with local FSA offices. Instead, we argue it is because of the actual policy design of ARC/PLC and its predecessor programs: the long history of policy changes and the political contentiousness of the policy serves to weaken the link between receiving benefits and support for the program. We do not think the three programs we examine differ substantially from one another in terms of any psychological costs of applying for and qualifying for benefits. That said, further qualitative study of individuals' experiences with their local FSA offices and the administration of these programs would be a fruitful area for future research.

B Additional Survey Details, Ethical Considerations, and Question Wording

The survey for this study was approved as "exempt" by the Institutional Review Boards (IRBs) of the researchers' home institutions. All respondents are volunteers. The information screen we provided at the beginning of the survey explained clearly that participation in the survey was voluntary and that answers would be kept confidential and anonymous. Respondents were not compensated monetarily; we explained to respondents that by participating in the survey, they would contribute to scientific knowledge. The survey also provided an opportunity for respondents to share their views on agricultural issues facing the country. We also purposely took great care in designing the study to ensure that there was no deception.

In an effort to make sure the survey was accessible by less-abled people, we had a phone help line and provided them with an option to conduct the survey by mail if they wished. We also gave them detailed contact information for the principal investigators as well as the IRB in case they had questions or concerns about the survey. One of the project's principal investigators responded to those requests personally.

As we explain in the main paper, the sample for the study is highly targeted and is not meant to be nationally representative. Our focus is on rural Americans—an understudied and important political constituency, and one whose neighborhoods have been ravaged by crises ranging from the opioid epidemic to economic decline to catastrophic damage from climate change. Additionally, it is important to understand attitudes toward government among this population given the geographic malapportionment of US political institutions.

Table 1 lists the survey items discussed in our analyses in the order they were presented to respondents in the survey. Note that the ARC/PLC and CRP treatment groups viewed an informational treatment screen between items "vote2016" and "gov_helped," whereas respondents in the control group proceeded from one question screen to the next.

The following 14 variables constituted the pro-government index: gov_helped, gov_opps, gov_trust, gov_waste, fair_share, deficit, gov_society, gov_disasters, gov_specinterests, gov_distress, gov_environ, gov_medical, gov_retire, gov_eat.

Table 1: **Questions and Choice Text for Survey Items**

Survey Item	Question Text	Choice Text
crop_acres	Thinking about the last 5 years, roughly how many acres of crops or hay have you grown per year, on average? Please enter 0 if you haven't cultivated crops or hay in the last 5 years.	[Respondents entered a positive integer]
livestock_acres	Thinking about the last 5 years, roughly how many acres have you raised livestock/poultry on per year, on average? Please enter 0 if you haven't raised any livestock/poultry in the last 5 years.	[Respondents entered a positive integer]
pid3	Generally speaking, do you think of yourself as a . . .	"Democrat", "Republican", "Independent", "Other party (Please specify):"
pid6	[If pid3 = "Democrat"] Would you call yourself a strong Democrat or a not very strong Democrat?	"Strong Democrat", "Not very strong Democrat"
pid6	[If pid3 = "Republican"] Do you consider yourself a strong Republican or a not very strong Republican?	"Strong Republican", "Not very strong Republican"
pid6	[If pid3 is neither "Democrat" nor "Republican"] Do you think of yourself as closer to the Democratic Party or the Republican Party?	"Democratic Party", "Republican Party"
ideology	We hear a lot of talk these days about liberals and conservatives. Here is a seven-point scale on which the political views that people might hold are arranged from extremely liberal to extremely conservative. Where would you place yourself on this scale?	"Extremely liberal", "Liberal", "Slightly liberal", "Moderate, middle of the road", "Slightly conservative", "Conservative", "Extremely conservative"
vote2016	Whom did you vote for in the 2016 presidential election?	"Donald Trump", "Hillary Clinton", "Someone else", "Did not vote", "Decline to state"
gov_helped	Government programs have helped me in times of need.	"Strongly agree", "Somewhat agree", "Somewhat disagree", "Strongly disagree"
gov_opps	Government has given me opportunities to improve my standard of living.	"Strongly agree", "Somewhat agree", "Somewhat disagree", "Strongly disagree"

gov_trust	How often can you trust the government to do what is right?	“Always”, “Most of the time”, “About half the time”, “Some of the time”, “Never”
gov_waste	Do you think that government wastes a lot of the money we pay in taxes, wastes some of it, or doesn’t waste very much of it?	“Wastes a lot”, “Wastes some”, “Doesn’t waste very much”
fair_share	When it comes to paying federal income taxes, do you feel you are asked to pay your fair share, more than your fair share, or less than your fair share?	“Fair share”, “More than fair share”, “Less than fair share”
deficit	What do you think is the best way to deal with the federal budget deficit?	“Cut government spending and raise taxes”, “Cut government spending but do not raise taxes”, “Do not cut government spending but raise taxes”, “Do not cut government spending and do not raise taxes”
gov_society	Government should support investments and activities that are important to society but that individuals and businesses might not provide on their own, such as scientific research and national defense.	“Strongly agree”, “Somewhat agree”, “Somewhat disagree”, “Strongly disagree”
gov_disasters	Government should step in to provide relief to individuals and businesses after natural disasters like hurricanes, floods, and earthquakes.	“Strongly agree”, “Somewhat agree”, “Somewhat disagree”, “Strongly disagree”
gov_specinterests	When government supports particular investments and economic activities, special interests usually benefit at the expense of society as a whole.	“Strongly agree”, “Somewhat agree”, “Somewhat disagree”, “Strongly disagree”
gov_distress	Government should step in and support individual industries in times of economic distress.	“Strongly agree”, “Somewhat agree”, “Somewhat disagree”, “Strongly disagree”
gov_environ	Government should be active in efforts to conserve the natural environment and protect wildlife populations.	“Strongly agree”, “Somewhat agree”, “Somewhat disagree”, “Strongly disagree”

gov_medical	Government should ensure that every citizen receives adequate medical care.	“Strongly agree”, “Somewhat agree”, “Somewhat disagree”, “Strongly disagree”
gov_retire	Government should ensure that every citizen has adequate income in retirement.	“Strongly agree”, “Somewhat agree”, “Somewhat disagree”, “Strongly disagree”
gov_eat	Government should guarantee every citizen enough to eat and a place to sleep.	“Strongly agree”, “Somewhat agree”, “Somewhat disagree”, “Strongly disagree”
identity_farmer	People often describe themselves in various ways, for example by their nationality, their religion, or their occupation. How much do you think of yourself as a “farmer”?	“A great deal”, “A lot”, “A moderate amount”, “A little”, “Not at all”
subsidies	Do you think agricultural subsidies paid to farmers should be increased, decreased, or kept the same?	“Increased”, “Decreased”, “Kept the same”
crp_support	Do you support or oppose the USDA’s Conservation Reserve Program (CRP), which provides financial and technical assistance to farmers to protect natural resources?	“Strongly support”, “Somewhat support”, “Somewhat oppose”, “Strongly oppose”
arc_support	Do you support or oppose the USDA’s Agricultural Risk Coverage (ARC) and Price Loss Coverage (PLC) programs, which provide income support payments when crop revenues and prices drop below certain levels?	“Strongly support”, “Somewhat support”, “Somewhat oppose”, “Strongly oppose”
mfp_support	Do you support or oppose the USDA’s Market Facilitation Program (MFP), which provides assistance to farmers with commodities impacted by foreign tariffs?	“Strongly support”, “Somewhat support”, “Somewhat oppose”, “Strongly oppose”
trump_approve	Do you approve or disapprove of the way Donald Trump is handling his job as President?	“Strongly approve”, “Somewhat approve”, “Somewhat disapprove”, “Strongly disapprove”
military	Have you ever served or are you currently serving in the U.S. military, the National Guard, or military reserves?	“Yes”, “No”
gender	Are you male or female?	“Male”, “Female”
age	In what year were you born?	[Respondents selected their birth year]

education	What is the last grade of school you completed?	“Less than high school”, “High school graduate”, “Technical/trade school”, “Some college”, “College graduate”, “Some graduate school”, “Graduate degree”
hispanic	Are you of Hispanic or Latino origin? - Selected Choice	“No”, “Yes, Mexican, Mexican American, Chicano”, “Yes, Puerto Rican”, “Yes, Cuban”, “Yes, another Hispanic or Latino origin (please specify):”
race	Which of the following best describes your race (mark all that apply)?	“White”, “Black or African American”, “Asian”, “American Indian or Alaska Native”, “Native Hawaiian or Other Pacific Islander”, “Some other race (please specify):”

C Survey Invitation

Below, we produce a copy of the the survey invitation that we mailed out to each of the nearly 44,000 members of our sampling frame. We contracted with a mailing firm to send out these invitations at the end of May 2020. Note that the mailing firm populated the fields `fullname`, `address_info`, `address`, `city`, `st`, `zip`, and `greeting` from a spreadsheet created using the most recent mailing information available from our FOIA data production. We formally requested that respondents fill out our Qualtrics questionnaire by July 15, 2020, but we ultimately utilized all responses submitted through the end of July 2020 in our analyses.

Your Invitation
Stanford Research Study

fullname
address_info
address
city, st zip

Stanford
University

May 23, 2020

greeting,

I am writing to ask for your help in understanding the views of farmers and ranchers on issues facing our country. Because your input as an agricultural producer is very important, I invite you to participate in a special online survey conducted through the Stanford University Graduate School of Business.

You were selected from a publicly available database of agricultural producers maintained by the U.S. Department of Agriculture. The online survey takes about 20 minutes to complete. Your answers are completely confidential. None of your information from the survey will ever be shared with political organizations or the public.

To ensure that only agricultural producers who have been invited can participate in the survey, we have provided a unique access code. To begin the survey:

- Enter the following URL into any web browser: tinyurl.com/AgOpinions

- Enter the following “Access Code” in the place provided: access_code

If you have trouble accessing the survey, please email me at neilm@stanford.edu or call me at (408) 772-7969.

I hope that you enjoy completing the questionnaire, and I look forward to receiving your responses by July 15, 2020.

Sincerely,

Neil Malhotra
Professor and Principal Investigator
Stanford University

P.S. Your response is very important to me. Thank you again for participating!

Research by Stanford University Graduate School of Business
655 Knight Way, Stanford, CA 94305

Figure 2: Survey Invitation Letter

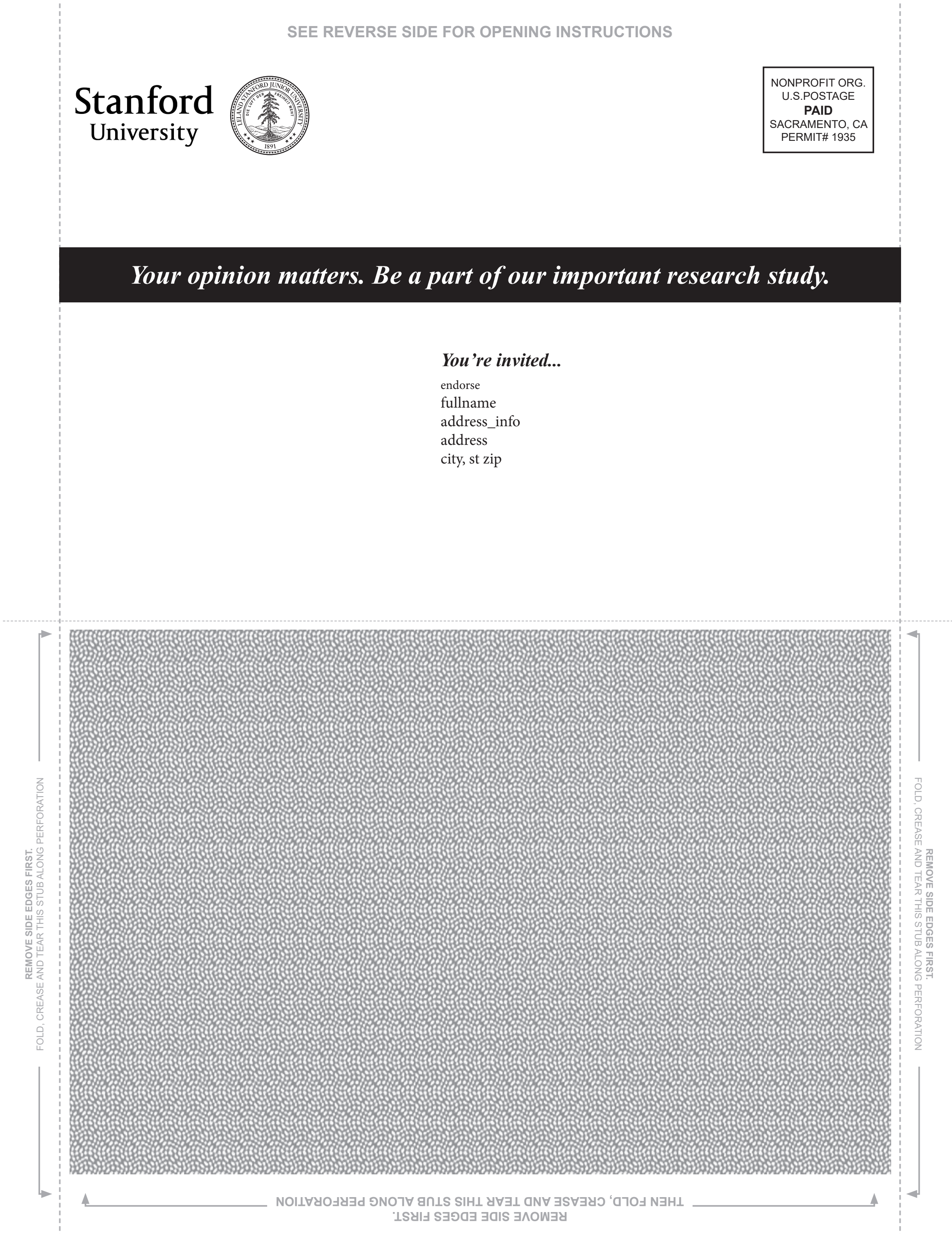


Figure 3: Survey Invitation Envelope

D Validation of Farmer Identity Question

We asked respondents, "People often describe themselves in various ways, for example by their nationality, their religion, or their occupation. How much do you think of yourself as a 'farmer'?" The distribution of responses was: 35.4% ("a great deal"), 23.4% ("a lot"), 25.1% ("a moderate amount"), 13.8% ("a little"), 2.4% ("not at all."). As shown in Figure 4, responses to this question are positively associated with farm size. Further, as shown in Table 2, responses to this question are positively associated with program support, even when controlling for participation and producer demographics. The results are weaker for CRP, which is to be expected given that it compensates producers to *not* engage in farming. This suggests that this survey item is a valid method of assessing survey respondents' commitment to agriculture as a way of life.

Figure 4: Distribution of Farm Size by Strength of Farmer Identity

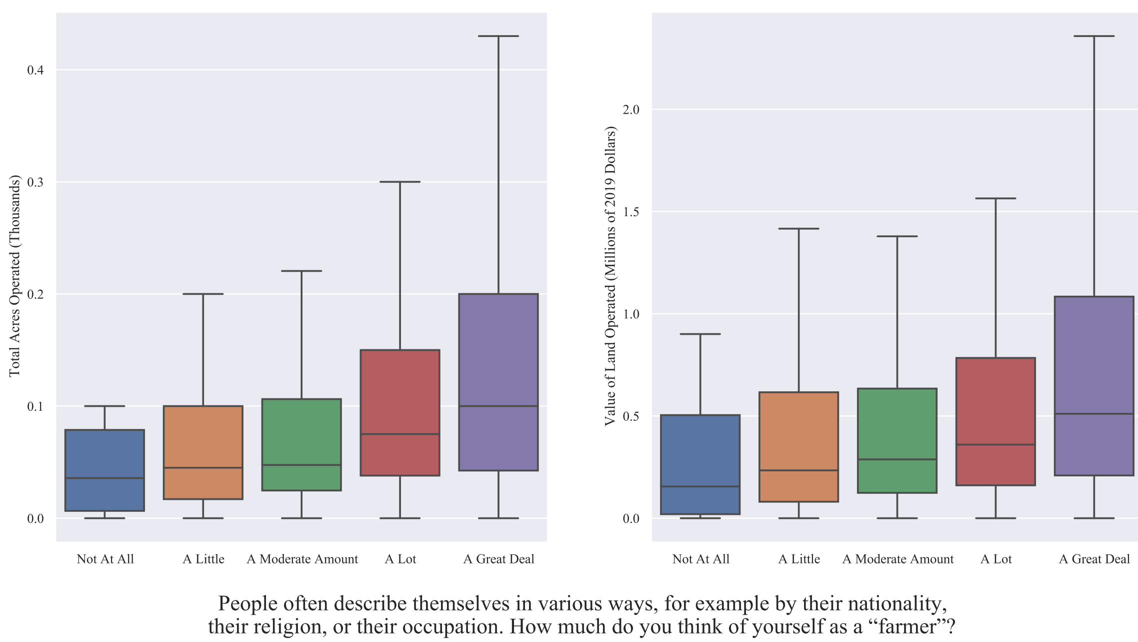


Table 2: Farmer Identity is Positively Associated with Agricultural Program Support

	(1)	(2)	(3)	(4)	(5)	(6)
Farmer Identity	0.186***	0.155***	0.171***	0.178***	0.035	0.056**
	(0.030)	(0.033)	(0.029)	(0.032)	(0.026)	(0.027)
MFP Receipt (binary)	——	0.060**	——	——	——	——
		(0.025)				
ARC Receipt (quintile)	——	——	——	-0.001	——	——
				(0.006)		
CRP Receipt (quintile)	——	——	——	——	——	0.016***
						(0.005)
Conservative	——	0.033*	——	-0.035**	——	-0.108***
		(0.019)		(0.018)		(0.014)
Veteran	——	-0.001	——	-0.010	——	0.001
		(0.025)		(0.022)		(0.019)
Female	——	0.080***	——	0.062**	——	0.002
		(0.025)		(0.026)		(0.022)
Age	——	0.177***	——	0.259***	——	0.171***
		(0.060)		(0.062)		(0.051)
Education	——	-0.119***	——	-0.053	——	-0.006
		(0.035)		(0.033)		(0.029)
Total Acres Farmed	——	0.001	——	0.051	——	-0.109***
		(0.042)		(0.033)		(0.041)
Farm Value	——	-0.007	——	-0.016**	——	0.009*
		(0.008)		(0.007)		(0.005)
Constant	0.576***	0.504***	0.600***	0.517***	0.803***	0.737***
	(0.023)	(0.058)	(0.022)	(0.055)	(0.020)	(0.045)
Observations	1,060	1,035	1,064	1,038	1,065	1,040
R-squared	0.035	0.067	0.032	0.072	0.002	0.094

Note: Robust standard errors in parentheses. Dependent variable for columns (1)-(2) is support for the MFP. Dependent variable for columns (3)-(4) is support for the ARC/PLC. Dependent variable for columns (5)-(6) is support for the CRP. *** p<0.01, ** p<0.05, * p<0.1 (two-tailed)

E Linking Payments to the L2 Voter/Commercial Files

E.1 Data and Pre-Processing

To examine the demographics and political affiliations of the population of USDA farm program recipients (and our sampling frame in particular), we merged the full set of available USDA payment records for 2004–2020 with voter and consumer files obtained from the commercial vendor L2. For each of the 50 states plus DC, L2 maintains voter files with essential data preprocessing (e.g., purging duplicates and linking voter profiles over time) and a number of useful added fields. Most importantly, these files include a party affiliation field that is modeled using party registration records and primary election participation. Additionally, L2 merges in external data sources to determine the race, ethnicity, education, and occupation of each individual in its voter files. While these voter files cover an extensive portion of the US adult population, we nonetheless augment these state-by-state datasets with L2's national commercial file, which features a similar set of demographic fields for voters and non-voters alike.

Linking farm payment records to L2 consolidated voter/consumer profiles is inherently difficult due to the lack of standardized and highly informative fields in the USDA payment files. In particular, recipient names are not broken into constituent parts (i.e., first name, middle name, last name, suffix) and in many cases refer to a business entity rather than an individual (e.g., "CHET MARTIN FARMS LLC", "LA 31 DAIRY FARM INC"). Additionally, the current FSA record system does not provide unique recipient identifiers, and records lack useful identifying characteristics—such as age and gender—that would help narrow down potential comparisons.

To surmount these difficulties and obtain a merge with both high precision and recall, we created a highly customized record-linkage algorithm that leverages extensive pre-processing and auxiliary data to squeeze as much matching-relevant information as possible from the USDA program data. We start by using text analysis to parse each recipient name into constituent components: first name, first middle name, second middle name (rarely populated), last name, and suffix.[3] We standardize the resulting name fields by uppercasing all letters and stripping out whitespace and punctuation. We standardize suffixes by converting generations to integers, so that (for instance) "SR" and "I" map to the same value. We then merge in nicknames (and formal versions of nicknames) using the proprietary pdNicknames database. We also assign each farm recipient profile a gender based on first name if the SSA name popularity rank for a given gender is 20 times greater than that of the other gender.

Address pre-processing similarly centered on extensive text analysis to extract street and PO Box numbers. In addition, we geocoded addresses in the USDA payment data.[4] As L2 provides geographic coordinates for each address in the voter and commercial files, we

[3]We do this by categorizing each recipient name into one of 92 distinct regular expressions based on the structure and organization of its name components. When a recipient name indicates a couple (e.g., "JEFF AND MARIE MARSHALL FAMILY CORPORATION") we split the profile in two and separately consider comparisons with L2. Additionally, in cases in which we cannot extract a likely human name from the recipient name box, we are usually able to extract a name from the first or second address boxes (e.g., "GOLDEN AMBER GRAINS" has second address field "% TONY LINNEBUR").

[4]In the case of PO Box mailing addresses or addresses that otherwise are not amenable to geocoding, we use representative latitude/longitude coordinates for the provided ZIP code.

are therefore able to calculate straight-line distances for every pair of potential matches we evaluate.

Finally, we merge in auxiliary information from additional FOIA requests to mitigate problems associated with a lack of a unique identifier in our 2004-2020 transaction-level data. For the purposes of our probabilistic record-linkage algorithm, we consider an individual "profile" in the FSA data to be unique combination of name and address. In principle, this can introduce measurement error, since some recipients report different addresses or names across years. However, we obtained FSA recipient files for 2004–2012 and 2014–2017 that link unique recipient IDs to each name and address reported when registering for payments. We merge in these unique identifiers to our continuous 2004–2020 transaction-level data. Despite requiring an exact match on name, as well as an exact match on address or ZIP code, this procedure allows us to assign a unique identifier to the vast majority of transactions between 2004 and 2020. This improves the accuracy of our record-linkage algorithm, as it allows us to match all of the name-address combinations belonging to a unique FSA identifier to an L2 profile so long as we can match *any* of the name-address combinations to that L2 profile.

E.2 Probabilistic Record Linkage Model Specification

After the pre-processing stage, our record-linkage procedure centers around estimating the canonical record-linkage model of Fellegi and Sunter (1969). We direct readers to Enamorado, Fifield, and Imai (2019) for a full theoretical treatment of this model, and instead provide a brief summary of the model's structure within our setting. In the notation of Enamorado, Fifield, and Imai (2019), consider datasets $\mathcal{F}$ (farm subsidy recipients) and $\mathcal{V}$

(voters). Each recipient $i \in \mathcal{F}$ can be compared to a voter $j \in \mathcal{V}$ along seven dimensions:

$$K = \{\texttt{first}, \texttt{middle}, \texttt{last}, \texttt{suffix}, \texttt{location}, \texttt{occupation}, \texttt{age}\}.$$

For a comparison between profiles $i \in \mathcal{F}$ and $j \in \mathcal{V}$, we define an agreement vector $\gamma_{ij} \equiv (\gamma_{\texttt{first}}, \gamma_{\texttt{middle}}, \gamma_{\texttt{last}}, \gamma_{\texttt{suffix}}, \gamma_{\texttt{location}}, \gamma_{\texttt{occupation}}, \gamma_{\texttt{age}})$ such that each coordinate $k \in K$ reflects a discrete-valued similarity along the specified dimension. For example, $\gamma_{\texttt{last}}(i, j)$ takes on one of three values (0, 1, or 2) to indicate the string-distance similarity between the last names of i and j. In particular, $\gamma_{\texttt{last}}(i, j) = 2$ if there is an exact match on last name, whereas $\gamma_{\texttt{last}}(i, j) = 0$ indicates that the two surnames are quite dissimilar. The full definitions of the agreement measures $\gamma_k(\cdot, \cdot)$ are given in Table 3; note in particular that $\gamma_{\texttt{occupation}}$ and $\gamma_{\texttt{age}}$ rely only on the characteristics of the given L2 profile.

Having defined the agreement vector, we can write down our record linkage model as follows. Let M_{ij} be a latent mixing variable that indicates whether $i \in \mathcal{F}$ and $j \in \mathcal{V}$ are actually a match. We assume that

$$M_{ij} \overset{\text{i.i.d.}}{\sim} \text{Bernoulli}\left(\lambda\right),$$

where $\lambda \in (0, 1)$ denotes the (unknown) probability of a match across all comparisons under consideration. Additionally, for $m \in \{0, 1\}$ and $k \in K$,

$$\gamma_k\left(i, j\right) \mid M_{ij} = m \overset{\text{indep}}{\sim} \text{Discrete}\left(\pi_{k,m}\right),$$

where $\pi_{k,m}$ is a vector containing the probabilities of realizing each agreement level in di-

Table 3: Description of Match Agreement Measures

Dimension	Level	Description
`first`	4	Exact match on first name (and names are more than initials)
	3	First name of i is a nickname for first name of j
	2	First name of i starts with / ends with first name of j, OR there is a Jaro-Winkler string similarity of at least 0.9
	1	Profile i provides only a first initial, and it matches first initial of j
	0	None of the above criteria are satisfied
`middle`	4	Exact match on both middle names (and names are more than initials)
	3	Either middle name of profile i is an exact match with either middle name of profile j, OR there is a Jaro-Winkler string similarity between first middle names of at least 0.9
	2	Profile i provides only a middle init, and it matches either middle init of j
	1	Jaro-Winkler string similarity between first middle names of at least 0.85
	0	None of the above criteria are satisfied
`last`	2	Exact match on last name
	1	Jaro-Winkler string similarity between last names of at least 0.94
	0	None of the above criteria are satisfied
`suffix`	2	Profiles i and j both have suffix field populated, and there's a match
	1	Profile i has first-gen suffix ("Sr." or "I"), while profile j has no suffix
	0	Profile i has suffix field populated, and it conflicts with j
`location`	5	Recipient mailing street number and ZIP match exactly with L2 street number and ZIP code (mailing, voter file residence, or commercial file residence)
	4	Recipient PO box number and ZIP match exactly with L2 PO box and ZIP
	3	Haversine distance between profiles less than 1 mile
	2	Haversine distance between profiles less than 10 miles
	1	Haversine distance between profiles less than 50 miles
	0	None of the above criteria are satisfied
`occupation`	1	Voter file occupation is "Skilled Trades-Farmer" OR commercial file occupation is "Farmer/Dairyman" OR commercial file occupation group is "Farmer"
	0	None of the above criteria are satisfied
`age`	5	L2 profile age > 70
	4	L2 profile age $\in (60,70]$
	3	L2 profile age $\in (50,60]$
	2	L2 profile age $\in (40,50]$
	1	L2 profile age $\in (30,40]$
	0	L2 profile age ≤ 30

Note: The Fellegi and Sunter (1969) model employs a missing at random (MAR) assumption, and by construction a missing value in one dimension has no bearing on the inferred match probability for a given comparison.

mension k given that the comparison is actually a match ($m = 1$) or not ($m = 0$). In words, $\pi_{\texttt{last},1}$ is a triple containing the conditional probabilities that a comparison of records yields a match on last name of similarity level 0, 1, or 2 given that the two records in question are actually a match. Likewise, $\pi_{\texttt{last},0}$ is the triple of probabilities that a surname match level is obtained conditional on a pair of records actually *not* being a match.

Given there are a total of $5+5+3+3+6+2+6 = 30$ distinct agreement levels across the seven match dimensions, we have 61 parameters to estimate: the overall match probability (λ), 30 conditional-on-match agreement level probabilities ($\pi_{k,1}$), and 30 conditional-on-nonmatch agreement level probabilities ($\pi_{k,0}$). As noted in Enamorado, Fifield, and Imai (2019), with a couple of technical assumptions,[5] we can write down a likelihood function for this data-generating process and readily estimate these 61 parameters using the Expectation-Maximization (EM) algorithm.

E.3 Record Linkage Implementation

Large-scale record linkage nearly always necessitates the use of a blocking technique, in which the researcher places restrictions on which comparisons are to be evaluated. We

[5]These assumptions are not innocuous. In particular, we must assume conditional independence among linkage variables given the match status. In practice, problems associated with violations of this assumption are similar to multicollinearity issues in linear regression modeling. If two match categories measure essentially the same information, parameter estimates can become highly unstable. To mitigate this issue in our setting, we chose our set of seven match dimensions to be maximally disconnected. For example, instead of separately evaluating similarity of street name and ZIP code, we bundled all information relating to location into a single match dimension.

consider comparisons of unique name-address combinations found in the payment records (N_F = 4,801,431) with unique L2 voter/consumer profiles (N_V = 313,614,991), and so without any blocking rules, we'd need to make $N_F \times N_V \approx 1.5$ quadrillion comparisons in each iteration of the EM algorithm.[6]

This would be computationally infeasible, and so we estimate the Fellegi-Sunter parameters separately for each state (and DC), and within each state we only consider comparisons such that the following conditions are jointly satisfied:

1. First four letters of last name match,[7]
2. First initials match, OR recipient first initial is missing, OR one profile's first name is a nickname for the other,
3. Suffix fields match, OR either profile has a missing suffix, and
4. Match on gender OR gender field is missing for either OR exact match on first name.

While these four conditions are quite permissive, they rule out many highly implausible comparisons, and—in conjunction with blocking on state—they reduce the total number of comparisons to a more tractable 2.5 billion.

[6]We use the PySpark package `splink` to execute our blocking strategy, estimate model parameters via the EM algorithm, adjust for surname frequency, and produce Figures 5 and 6. Documentation is available at https://github.com/moj-analytical-services/splink

[7]We also allowed, as an alternative, for an exact match between recipient surname and an alternative surname found in the L2 commercial file. This seemed to cover some of the instances in which recipient surnames changed because of marriage.

Estimating the model parameters allowed us to compute a match probability for each comparison, as well as a match probability adjusted for the relative frequency of each profile's surname (see Enamorado, Fifield, and Imai (2019) for details). After manually reviewing several hundred comparisons, we settled on a decision rule that (with a couple of caveats[8]) accepts matches if either match probability exceeds 95%.

Finally, after deciding which direct comparisons were appropriate matches, we leveraged FSA datasets from 2004-2012 and 2014–2017 that link individual FSA IDs to the FSA IDs of businesses that are partly or wholly owned by the individual in question. In each case in which we were highly confident in a match between an L2 ID and a FSA recipient ID for an individual, we also linked the L2 ID in question to any business(es) associated the individual's FSA recipient ID.

Table 4 depicts the fraction of distinct USDA recipient profiles successfully matched to one or more L2 profiles via our probabilistic record-linkage algorithm. Among the 43,331 sampling frame members with mailing addresses in the 50 states or DC, 93% were successfully matched to one or more L2 ID. In particular, 85% were matched to L2's national voter file, which means that we observe L2's party affiliation measure for over 4 out of 5 sampling frame members. The second half of Table 4 depicts the rate at which L2's demographic fields are populated for successfully matched USDA program recipients. In particular, we obtain the ethnicity, gender, education, and age of the vast majority of our sampling frame members.

[8]We also accepted the best available comparison if it met a series of other criteria determined through manual review of a sample of comparisons. Details are available upon request.

Table 4: **Match Rates Among USDA Recipients**

	Sampling Frame $N = 43{,}843$	Recipients (2015–2019) $N = 1{,}520{,}891$	Recipients (2004–2020) $N = 3{,}346{,}034$
% of Recipients Linked to...			
Any L2 Profile	93%	85%	71%
Exactly One Profile	77%	76%	66%
Multiple L2 Profiles	16%	9%	5%
An L2 Voter Profile	85%	73%	58%
An L2 Consumer Profile	87%	77%	64%
Directly to an L2 ID	78%	76%	66%
Indirectly to an L2 ID	20%	11%	6%
% of Matched Recipients with...			
Populated Ethnicity / Race	93%	94%	94%
Populated Gender	100%	100%	100%
Populated Education	94%	89%	88%
Populated Age	99%	98%	98%

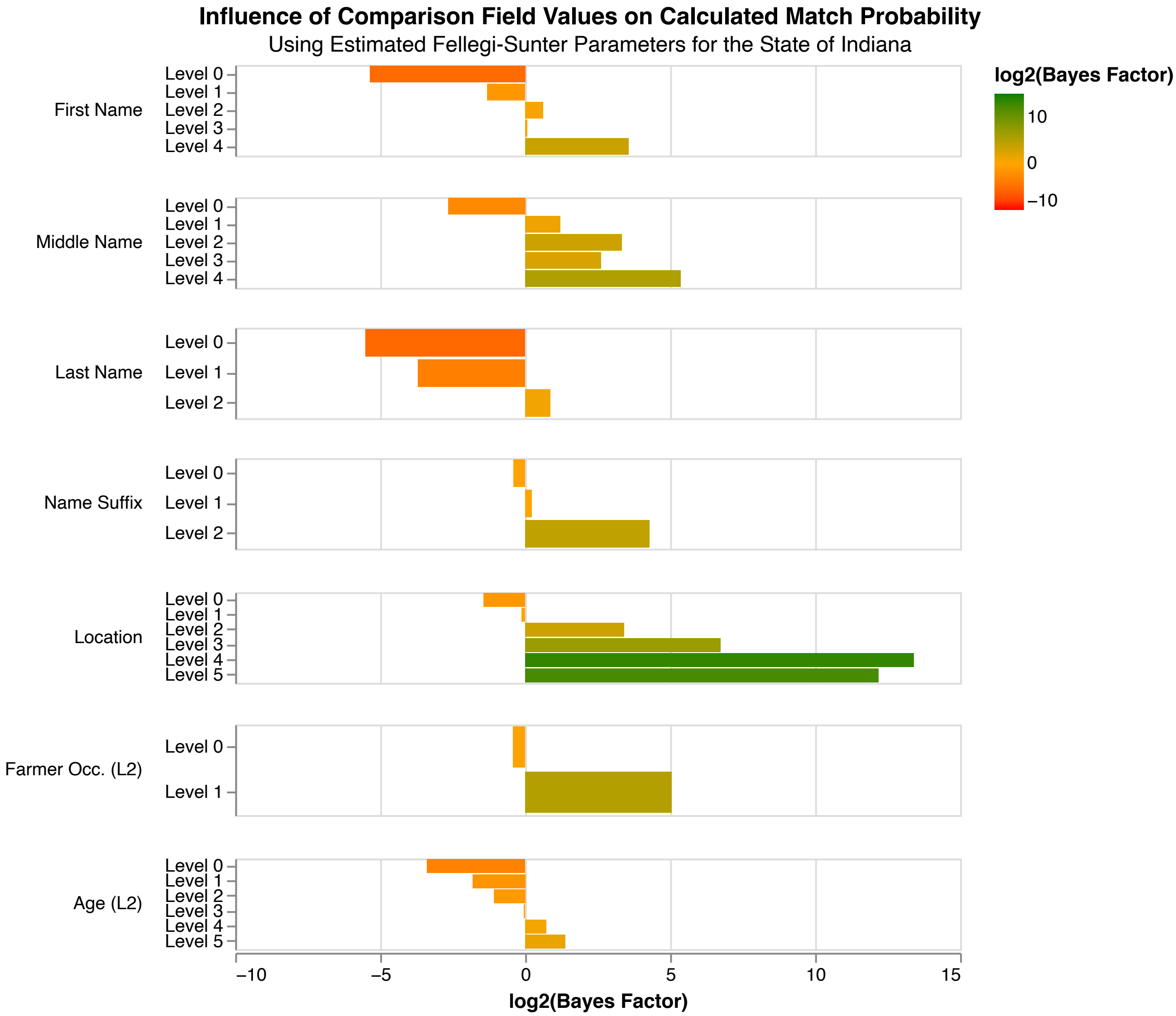
Notes: Sampling frame size of 43,843 differs slightly from N stated in main manuscript because the record-linkage algorithm only considered recipients with addresses within the 50 US states and DC. Matching to an L2 voter profile is not exclusive of matching to an L2 consumer profile, since L2 has already linked many individuals between these two datasets. As such, a producer may be matched to "exactly one profile" even if she is matched to both a voter profile and and a consumer profile. A USDA business / organization recipient is said to be "indirectly" linked to an L2 profile if it is first linked to an individual USDA recipient profile via the USDA business party share files. Direct / indirect matches are not mutually exclusive because of the possibility of USDA profiles matching to multiple L2 profiles.

E.4 An Example Record Linkage Comparison

We conclude our discussion of this method with an example match result. Sen. Mike Braun (R-IN) is one of multiple members of the Senate Agricultural Committee who has personally received substantial payments from multiple USDA farm programs.

Figure 5 depicts the record linkage model parameters that were estimated for Indiana. To show the impact of each dimension on the match probability, we can compute a Bayes factor for the alternative hypothesis that the comparison is a match. For a given match dimension $k \in K$ and agreement level a, the Bayes factor is simply the ratio of estimated conditional-on-match and conditional-on-nonmatch probabilities:

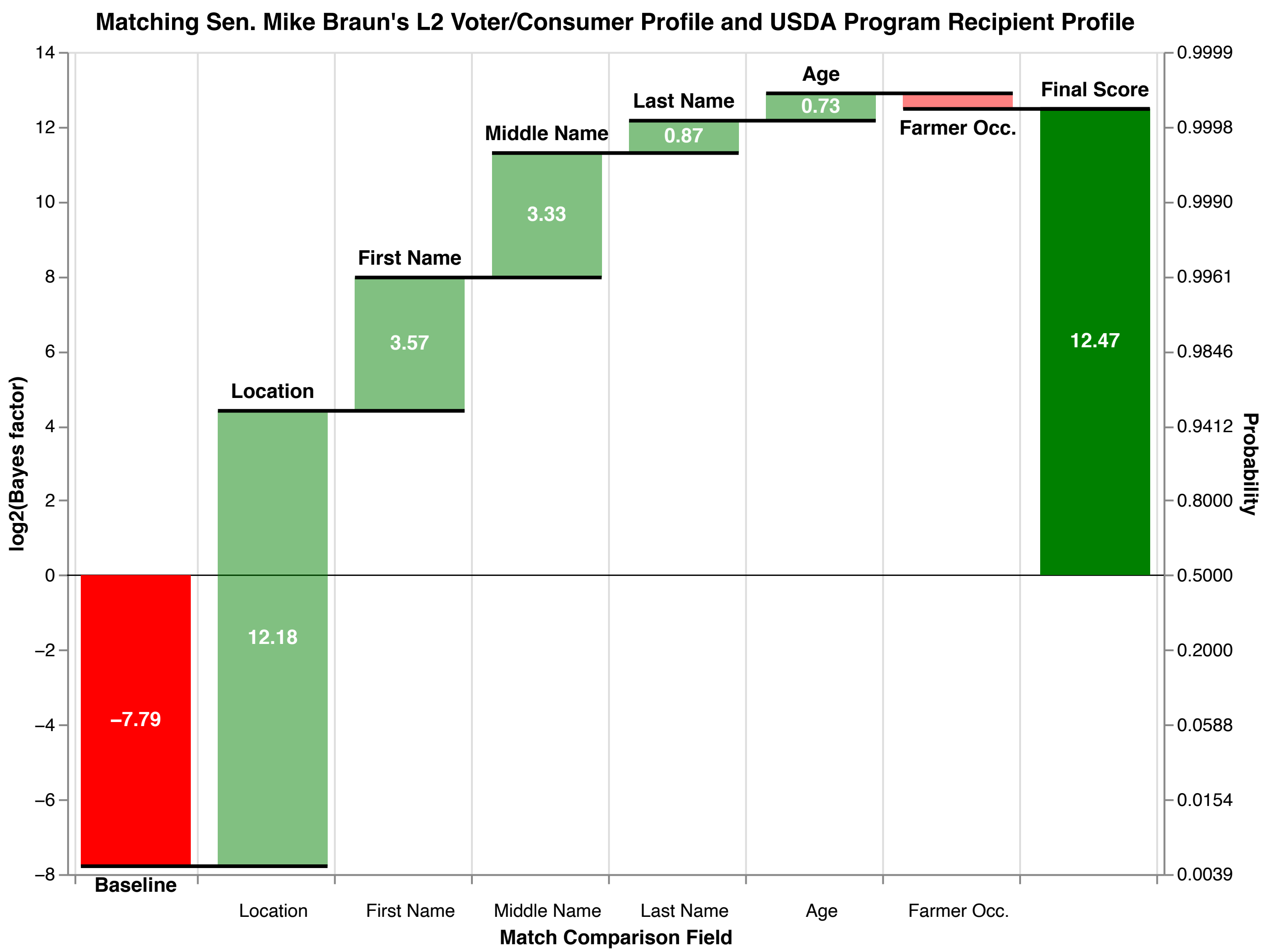
Figure 5: Overview of Estimated Record-Linkage Model Parameters



$$B_k(a) = \frac{\pi_{k,1}(a)}{\pi_{k,0}(a)} = \frac{\Pr(\gamma_k = a \mid M = 1)}{\Pr(\gamma_k = a \mid M = 0)}.$$

Figure 5 demonstrates that, given our blocking strategy, exact matches on address or PO box are by far the strongest indicator that a comparison is a valid match.

Figure 6: An Example Record-Linkage Result



Our payment data show that "MICHAEL K BRAUN" of Jasper, Indiana has received payments from commodity, conservation, and disaster programs as recently as 2008 under the distinct USDA recipient ID A02852792. Our blocking strategy yields 90 candidate comparisons from the consolidated L2 Indiana voter and commercial files. Of these 90 distinct Indiana residents, 25 are named "Michael Braun" or "Mike Braun," and in particular there are two distinct individuals named "Michael Braun" in Jasper, neither of whom resides at the USDA recipient's mailing address. Nonetheless, as shown in Figure 6, the algorithm finds it very easy to link recipient ID A02852792 to L2 ID LALIN702723, a "Michael K Braun" with the exact same mailing address.

Were our algorithm to stop here, however, we would actually miss all of the Senator's program receipts since 2008. Braun's annual financial disclosures show that he holds a 50% stake in Maple Land, LLC. By linking Braun's personal recipient ID (A02852792) to his associated business entity ID (A11599702), we find that the Senator has benefited from farm programs in each year between 2008–2020 via "MAPLE LAND CO LLC."

F Analysis of Non-Response

In this section we assess the potential for non-response bias given the response rate was 2.4%. To do so, we collect as much demographic data as possible on the sampling frame of 43,941 producers. USDA payment files provide limited information on these individuals: transaction amounts, names, and addresses. To collect more data, we merge USDA payment recipient data with a 208 million person voter file and a 240 million person consumer file constructed by L2 (see Appendix A above for record linkage details). The consolidated L2 voter / consumer file not only has voting histories and demographic characteristics of Americans, but also is merged with datasets from commercial vendors to obtain information on individuals who are not registered voters.

Having merged nearly the universe of 2004–2020 USDA payment records with L2 voter and consumer profiles, we obtain demographic information for 40,976 of the 43,941 producers in our sampling frame. From the payment information alone, we can compare members of the sampling frame with the 1,072 respondents based on rates of urban/rural residence (using mailing address counties). However, the USDA-L2 merge allows us to additionally mitigate potential differential non-response in terms of gender, age, education, and ethnicity.

Table 2 in the main text compares average L2 sampling frame demographics with self-reported demographics from the 1,072 individuals who completed our survey. While nearly an identical fraction of individuals in both groups are identified as white and not Hispanic, it appears that individuals with higher levels of education were more likely to respond (as is common in survey research). Additionally, the respondent sample appears to skew somewhat more male and college-educated.

To gauge the effect of such differential response on our main estimates, we construct post-stratification weights using entropy balancing procedures of Hainmueller (2012), which bring the first moments of the respondent sample demographics in line with those of the sampling frame. After applying weights, the respondent sample matches the sampling frame perfectly in terms of average age, educational attainment (% not completed high school, % high school, % associate's degree or some college, % undergraduate degree, % graduate degree), gender composition, and geography (% living in a non-metropolitan rural county, non-metropolitan urban county, metropolitan county with population under 1 million, metropolitan county with a population over 1 million).

We use these weights to gauge the extent to which any potential bias in non-response affects the inferences reported in the paper. Specifically, we replicate all regression analyses with post-stratification weights, and compare each weighted coefficient estimate to its unweighted analogy in Figures 7-10 (below). This procedure, in particular, weights upwards less-educated and female individuals since they make up a smaller portion of the sample than they would if education and gender did not predict survey response. This estimation procedure is less statistically efficient and more noisy because the weights themselves introduce statistical error and reduce the effective sample size.

Nonetheless, as shown in Figures 7-10, the point estimates are extremely similar when comparing the weighted and non-weighted analyses. This suggests that survey non-response is not affecting the main inferences made in the paper. Although only a small subset of the invited producers completed the survey, those who did reply likely did not exhibit different relationships between the key independent and dependent variables of interest than those who did not.

Figure 7: Reproduction of Table 3 Estimates with Poststratification Weights

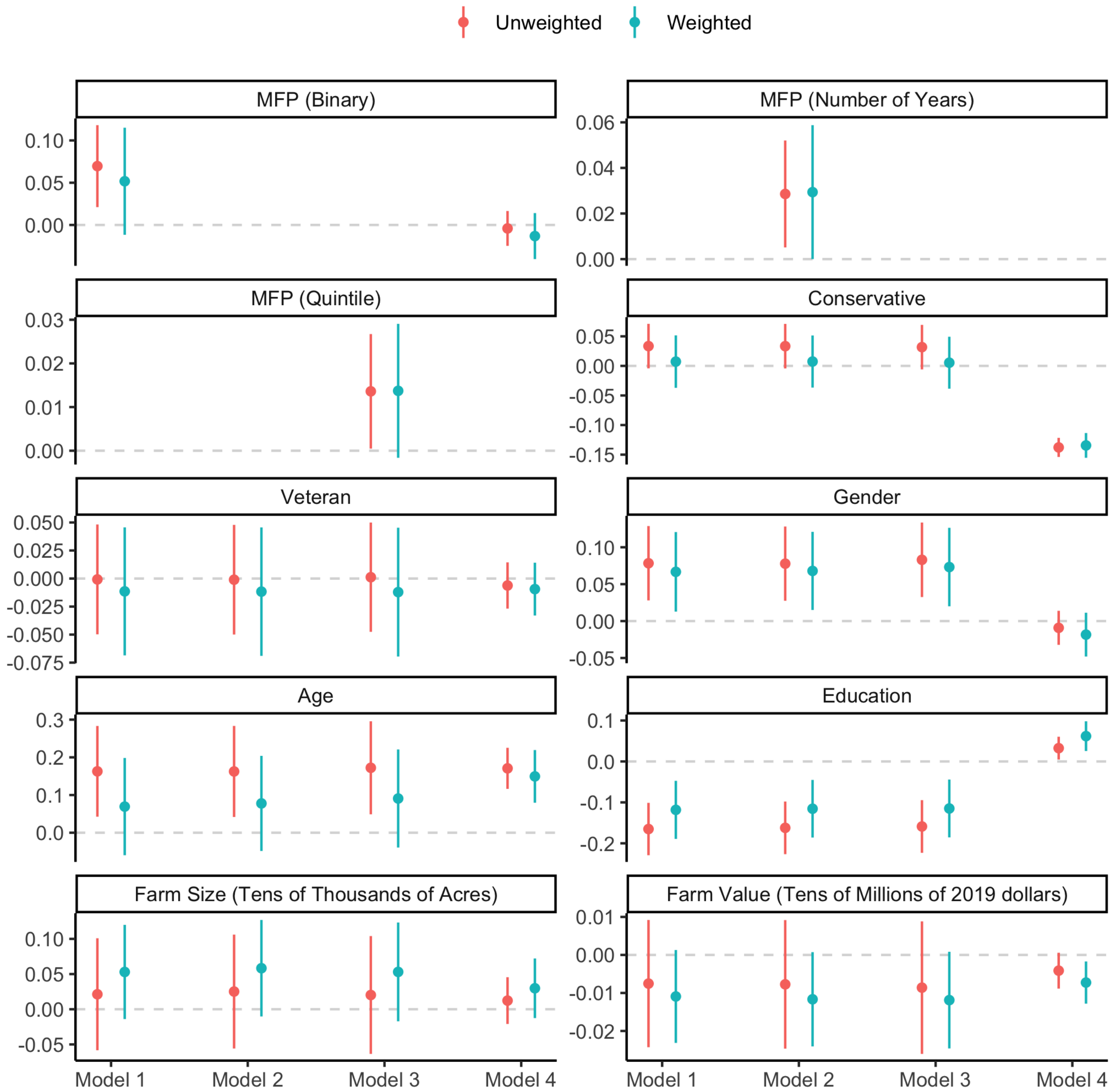


Figure 8: Reproduction of Table 4 Estimates with Poststratification Weights

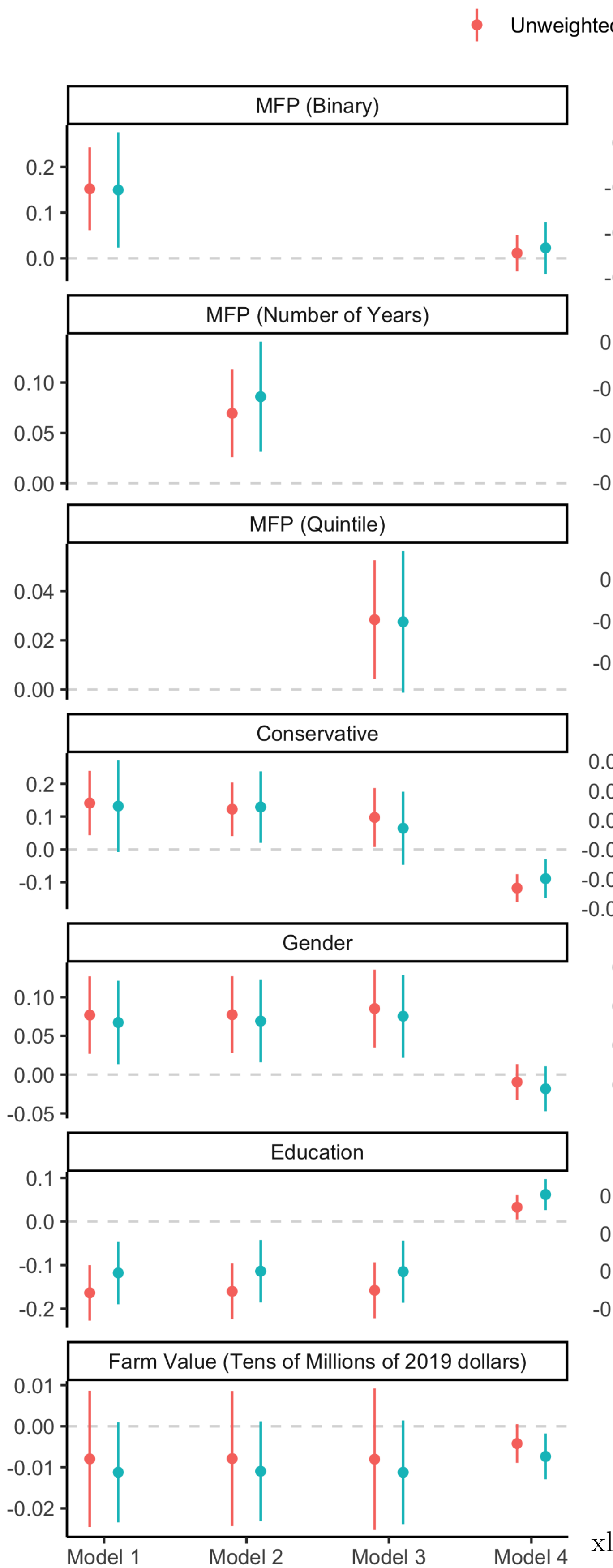


Figure 9: Reproduction of Table 5 Estimates with Poststratification Weights

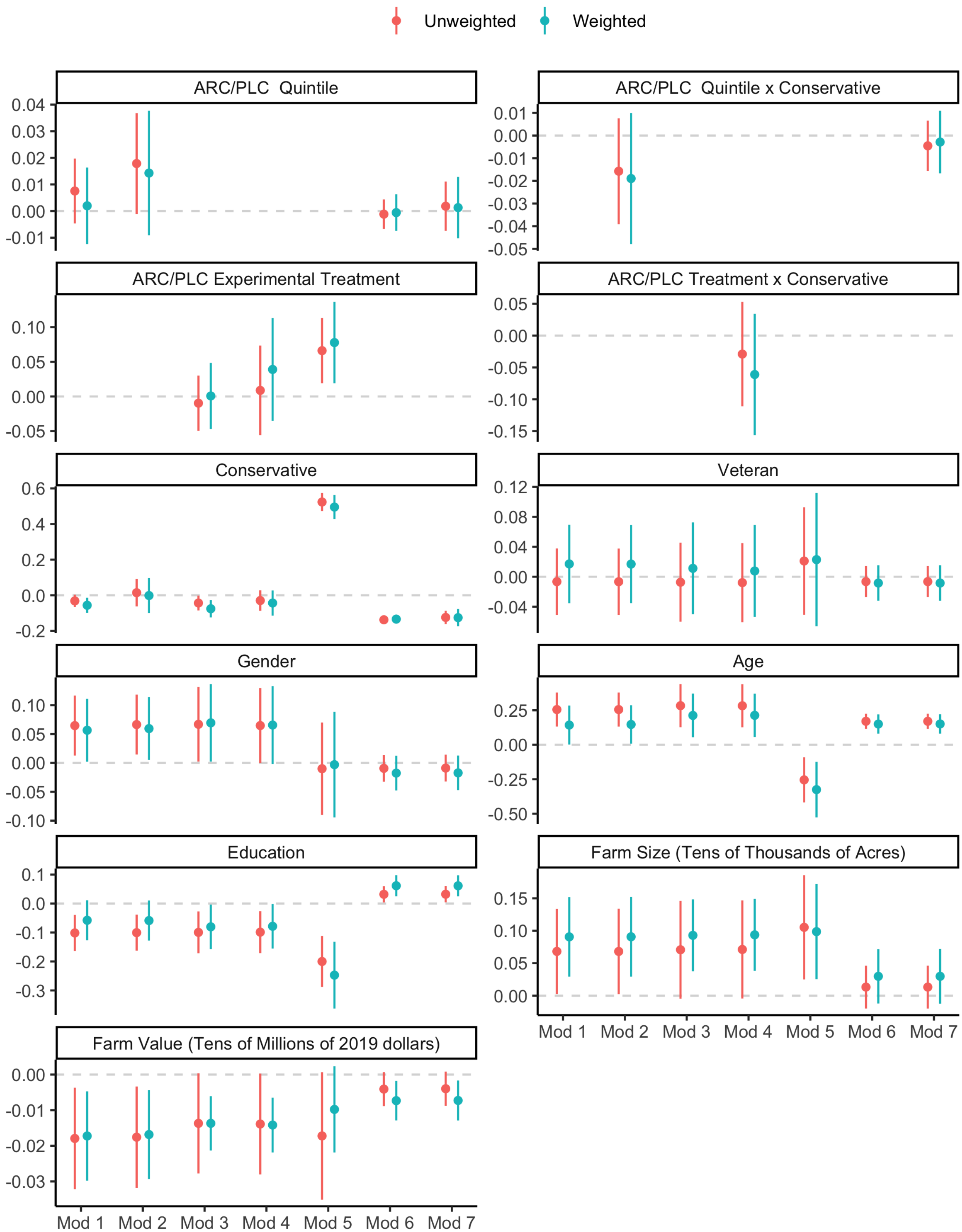
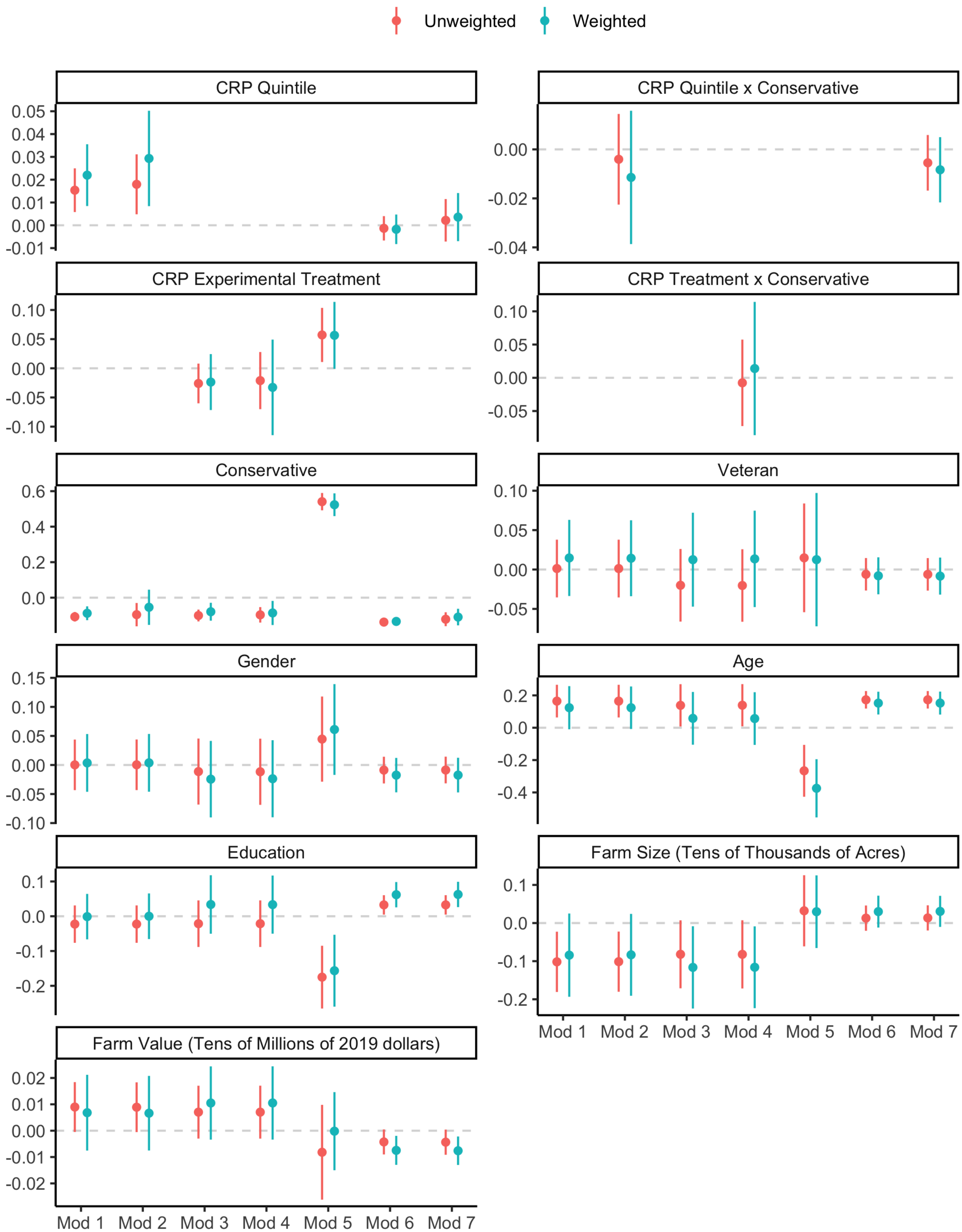


Figure 10: Reproduction of Table 6 Estimates with Poststratification Weights



G Attrition

As shown in Table 5, there was no significant relationship between treatment assignment and non-response for the six main outcome variables presented in the main text.

Table 5: Attrition

	ARC/PLC Group $N = 414$	Control Group $N = 410$	CRP Group $N = 429$	One-Way ANOVA P-Value
Completed Survey	86.2%	87.8%	82.8%	.10
Answered MFP Support	86.0%	87.8%	83.0%	.13
Answered ARC/PLC Support	87.0%	87.6%	83.5%	.18
Answered CRP Support	87.2%	87.8%	83.2%	.11
Answered Trump Approval	86.5%	88.1%	83.2%	.12
Government Positivity Index	90.8%	91.0%	88.6%	.43

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