Selected Presentation at the 2020 Agricultural & Applied Economics Association Annual Meeting, Kansas City, Missouri, July 26-28

Understanding the U.S. Publics' Voting on Animal Welfare and Genetically Modified Organism Labeling Ballot Initiatives

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ABSTRACT

In recent years, 11 ballot initiatives concerning animal welfare (AW) regulations and genetically modified organism (GMO) labeling standards have come before voters in eight states. The outcomes of these votes can have significant impact on agricultural producers and markets in the form of vote-buy gaps and unfunded mandates. In this paper, we analyze demographic and voting data from these 11 recent initiatives and create a prediction function for future legislation. We find that important indicators of the success of both an AW and a GMO initiative include socio-economic indicators, political party, and education level, though there is a statistically significant difference in education level and poverty rate between likelihood of AW and GMO initiative support. Predictions for all 50 states indicate that, excluding Alaska and Florida, every state would vote to pass an AW initiative today, though only Hawaii, Massachusetts, New Jersey, New York, Rhode Island, and Vermont are predicted to pass a GMO labeling initiative today. These results suggest that Public Law 114-216, otherwise known as the law which designed the National Bioengineered Food Disclosure Standard (NBFDS), would not have passed in almost all states if put before voters, but that a national AW law would pass. We anticipate that these results will allow both producers and industry representatives alike to better predict and prepare for initiatives that may impact their markets.

HIGHLIGHTS

- Ballot initiatives require mandatory changes in on farm production practices
- Given vote-buy gaps, initiatives result in unfunded mandates for producers
- There is positive support for initiatives to change livestock production practices
- There exists little support for mandatory GMO labeling laws
- Socio-economic factors, political party, and education level predict voting outcome

KEYWORDS

Animal welfare, ballot referendum, demographics, genetically modified organisms, voting, willingness to vote

1. Introduction

There are two main ways for citizens to create change in markets: using the traditional market and voting. The first is the traditional market mechanism most think about where prices and quantities change due to shifts in demand from changing consumer preferences, disposable income, and prices of substitutes or complements. Here, an individual either consumes or abstains from consuming a product, and this in aggregation gradually leads to changes in the market. The second way, and the motivation for this paper, are market interventions on behalf of the government or some other outside party. Citizens vote or support a cause or group, and through this lobbying, are able to enact changes in market structure through laws and regulations without consuming the product.

The market interactions focused on in our analysis are state-wide ballot initiatives; these allow for different sets of preferences to be realized without traditional market participation. An individual's consumption choices reflect the preferences they impose on themselves, while voting reflects the preferences a person wants to impose on everyone else. Through voting on or lobbying for topics related to agricultural production, such as banning certain animal confinement systems due to animal welfare (AW) concerns and genetically modified organism (GMO) labeling, non-market participants, such as vegetarians, vegans, or others with dietary restrictions or preferences are able to influence the markets (Norwood & Lusk 2011). However, unlike traditional market forces of supply and demand, changes are mandatory. Legislation that controls what items are available imposes choice set changes on everyone in the market, while choosing to purchase a given item does not exclude others from purchasing a different item. Therefore, supply side changes must be made to continue participating in the market and every consumer's choice set is reduced on the demand side.

Market interventions can create market inefficiencies in the form of vote-buy gaps and unfunded mandates (Sumner et al. 2008). The vote-buy gap is a behavioral phenomenon in which there is a difference in consumption patterns and consumer opinion (Lusk, Tonsor, and Norwood 2018). The existence of vote-buy gaps poses significant economic issues for farmers. When initiatives are passed, farmers are often required to change production practices. Changes in one state can have a ripple effect, and uneven regulation across states in the absence of a national standard can put the more heavily regulated producers at a disadvantage, as previous studies have found that the majority of increased production costs incurred due to these regulations is borne by producers and not passed on to consumers (Sumner 2008). While the ballot initiatives in question are only state-wide and not national initiatives, these initiatives can significantly impact the intrastate and interstate agricultural economy (Sumner 2008). One reason for the creation of the 2016 National Bioengineered Food Disclosure Standard (NBFDS) was to address concerns about uneven legislation across states and the corresponding market effects.

These initiatives usually result in unfunded mandates – statutes that require state and local governments to achieve specific actions but provide no monetary funds to do so (Lusk, Tonsor, and Norwood 2018). These unfunded mandates are further compounded by vote-buy gaps since some consumers would be unwilling to pay price premiums for the new products produced under the new guidelines, and in the absence of the previous non-compliant choices, may choose not to purchase at all. Another issue is that most of the state-specific agricultural legislations included in our analysis are vague and open to multiple interpretations, offering little guidance to farmers facing difficult production changes. As such, some initiatives have led to significant market inefficiencies and major agricultural industry disruptions (Mullally & Lusk 2018; Malone & Lusk 2016; Lusk 2010). Due to the passage of some of these state level initiatives and the corresponding change in agricultural markets, farm managers can no longer ignore the emerging discussion regarding changing farm production practices.

In this research, we construct a series of econometric models to determine how demographic characteristics impact state-level voting outcomes on farm animal welfare (AW) and genetically modified organism (GMO) labeling initiatives. Using the results from this analysis, we then simulate the effects of introducing hypothetical AW and GMO regulations in all 50 states. For AW initiatives, the predictions generated from our regression allows individual farmers and the affected industry as a whole to better anticipate and prepare for market distortions, which may help lessen the financial impact of new regulations. For GMO initiatives, we aim to contrast predicted individual state support with the national mandatory GMO labeling law passed in 2016 to determine if a national vote would have resulted in the same outcome. We add to the existing literature by developing this generalized model, determining if there are differences in the effects of demographic variables on the success of AW and GMO ballot initiatives. We chose to analyze majority-vote ballot initiatives and not state government legislative actions so that voter opinions are realized more accurately. Table 1 lists the 11 ballot initiatives which will be the focus of this article – spanning eight states and 16 years.

Table 1: Ballot Initiatives of Interest

State	Year	Topic	Initiative Name	Ballot Initiative Description
Arizona	2006	AW	Proposition 204	Ban on Cruel and Inhumane Confinement of Animals
California	2008	AW	Proposition 2	Standards for Confining Farm Animals
California	2012	GMO	Proposition 37	Mandatory Labeling of Genetically Engineered Food Initiative

California	2018	AW	Proposition 12	Farm Animal Confinement Initiative
Colorado	2014	GMO	Proposition 105	Mandatory Labeling of GMOs Initiative
Florida	2002	AW	Amendment 10	Animal Cruelty Amendment
Massachusetts	2016	AW	Question 3	Minimum Size Requirements for Farm Animal Containment
Ohio	2009	AW	Amendment 2	Livestock Care Standards Amendment
Oregon	2002	GMO	Measure 27	Labeling of Genetically Engineered Foods Act
Oregon	2014	GMO	Measure 92	Mandatory Labeling of GMOs Initiative
Washington	2013	GMO	Initiative 522	Mandatory Labeling of Genetically Engineered Food Measure

The prevalence of AW initiatives has increased in the past two decades. In the past, "people [did] not know much about the way farm animals are raised," (Norwood & Lusk 2011) however, the public is privy to the details of animal agricultural practices due to the efforts of animal rights groups like The Humane Society of The United States (HSUS) and People for the Ethical Treatment of Animals (PETA). Studies show that the more informed people are on how animals are raised, the more important the animal welfare debate becomes to them (Norwood & Lusk 2011). This greater personal significance often paves the way for the passage of ballot initiatives that abolish specific agricultural practices and considerably impact farm managers. Each year, 50-60 new bills come before the United States Congress regarding animal welfare, largely due to the powerful force of grassroots organizing from HSUS and PETA (Norwood & Lusk 2011).

The debate over the safety of GMOs and how to incorporate them into the food supply has also grown in the last few decades. Prior research has looked at consumer attitudes and response to GMO labeling policies (Lee & Yoo 2011), an initial step in GMO labeling legislation. The frequency of GMO ballot initiatives increased up until 2016. Five states previously voted on proposed GMO labeling ballot initiatives and over 20 states proposed legislation. While several states passed these laws, only Vermont's went into effect. The potential for a patchwork of state level laws and the need for a compromise between forces pressing for a much stricter labeling law versus forces that opposed mandatory labeling laws altogether (Bovay & Alston 2018) led to the NBFDS in 2016, as part of Public Law 114-216. The NBFDS requires the U.S. Department of Agriculture to establish a national disclosure standard for GE foods and precludes states from setting their own standards for mandatory genetically engineered (GE) or GMO labels. The effects of this law have prompted additional studies on willingness to pay (WTP) for non-GMO foods (McFadden & Lusk 2018).

Previous studies have analyzed the consumption side of market changes for animal welfare (Bir et al. 2020; Ortega & Wolf 2018; Wolf & Tonsor 2017; Norwood & Lusk 2011b; Lagerkvist & Hess 2011; Carlsson et al. 2007a; Carlsson et al. 2007b) and GMO labeling (Kaneko & Chern 2005; Lee & Yoo 2011; McFadden & Lusk 2018) utilizing survey data. The majority of these studies do not isolate many demographic variables in their final models or discuss demographics as part of their results, though a few do include either age, gender, education, income, or a combination of these. In particular, Ortega & Wolf (2018) find age and income to be a significant determinant in egg, ground pork, and pork chop purchasing behavior, while information such as weekly consumption was not. In contrast, our study models the demographic trends on the voting side of the vote-buy gap phenomenon rather than consumer WTP.

Relatively few studies connect citizens' voting behavior to WTP. Waterfield et al. (2020) examine the relationship between WTP a price premium for products that avoid utilizing a controversial technology, in this case GMOs, and willingness to vote (WTV) in favor of imposing regulations or bans on these technologies. This analysis is done using a WTP survey and explaining consumer choices with utility maximization framework, while considering individuals' income and perceived risks. They find that low-income voters in particular display the widest difference between reported support for GMO regulations and private WTP; in effect, low income individuals bear the majority of the burden of regulation costs relative to other socio-economic groups. However, due to the existence of vote-buy gaps, using purchasing behavior to predict voting outcomes results in poor predictions. Indeed, Hamilton et al. (2003) found consumption behavior to be a poor predictor of political behavior. Our study differs from previous work in that we look at the voting side of consumer behavior, not the WTP side. By building our predictor model, we first contribute to the literature by helping to bridge the gap between political action and economic action. We utilize voting data from 11 recent ballot initiatives for AW and GMO regulations to determine what subset of voters are likely to support these regulations; our findings can be used alongside others' WTP studies to help pinpoint potential vote-buy gaps.

The three previous works most similar to ours are those by Videras (2006), Smithson et al. (2014), and Bovay & Alston (2016). Using county-level voting and demographic data, Videras (2006) found that religion, political preferences, and socio-economic factors were important determinants of support for Florida's 2002 ballot initiative, which limited farming practices deemed cruel to pigs. Smithson et al. (2014) took a similar approach as Videras (2006), using demographic and voting data from California's 2008 ban on gestation crates and battery cages. Contrary to Videras (2006), Smithson et al. (2014) found that political preference was an important indicator of support for the initiative, while religion and socio-economic variables were less so. Bovay & Alston (2016) utilized precinct-level voting and demographic data from California's 2012 proposed GMO labelling law, Proposition 37. They found that education, race, political party, and other socio-economic factors such as number of dependents and share of residents living in a food desert to be statistically significant indicators for predicting support for Proposition 37. Extrapolating from California's 2012 data as well as data from Oregon, Colorado, and

Washington, Bovay & Alston (2016) predict that only three states (Hawaii, Rhode Island, and Vermont) would have passed Proposition 37 if it had been on the 2012 ballot.

While two of these studies only used one AW initiative from one state and time period to make their predictive models and one used four states' GMO labeling voting data, our model contributes to the literature by using data from 11 initiatives, multiple states, and a span of 16 years to create a better predictive model. These increased observations allow for more variation in the data, which generates a model more robust to the differences across data points. Furthermore, our model accounts for differences in demographic independent variables between GMO and AW and includes fixed effects across initiatives, which again produces a model that better fits the data. Finally, our work improves upon the results produced by Videras (2006), Smithson et al. (2014), and Bovay & Alston (2016) by generating updated voting outcome predictions for both AW and GMO ballot initiatives for all 50 states; Videras (2006) predicted AW outcomes for only Florida, Smithson et al (2014) predicted only AW outcomes for the 50 states, and Bovay & Alston predicted only GMO labelling outcomes for all 50 states. Since these initiatives have already proven to result in market inefficiencies and disruption (Mullally & Lusk 2018; Malone & Lusk 2016), there is a need to analyze the potential for future AW regulations' success in the voting booths. Additionally, it is useful to evaluate state-specific support for the NBFDS in order to achieve a sense of how appropriate this standard was for the affected markets nationally.

The remainder of this paper proceeds as follows. First, we give underlying microeconomic theory and describe the method for modelling individuals' utility in a voting and consumption dependent framework. Then we present our initial hypotheses for independent demographic variables and their relation to support of AW and GMO ballot initiatives. Next, we describe our data collection methods and give the descriptive statistics for each initiative used in our model. Afterwards, we discuss our process for selecting the optimal model and present our model for discussion, analyzing the outcomes of our initial hypotheses. Finally, we give our predictions for voting outcomes for initiatives to change production practices in animal agriculture and mandatory labeling of GMO food products in all 50 states, compare these predictions to actual outcomes or enacted legislation, and discuss policy implications.

1. Microeconomic Theory

For our behavioral model, we assume that citizens are utility-maximizers; in particular, their utility will increase with both their purchasing and voting behavior. In our model, citizens maximize their utility with respect to their basket of goods, their vote, and their personal moral convictions.

$$max_{V,X}[U(V,X)]$$

$$V = V(M), \qquad X = X(M), \quad X * P \leq W$$

Equation (1)

Where X is the vector of goods, P is the vector of prices, W is an individual's wealth, V is the vector of votes an individual casts, M is a vector of moral, religious, ethical concerns, and scientific knowledge that the citizen considers when making decisions. M is important to include, as an individual's morals, religious beliefs, ethical concerns, and scientific knowledge impact the way they view issues and whether or not they will vote in support of a piece of legislation. A person's morals and religious beliefs consist of their personal convictions relating to the rightness or wrongness of an action; whether some proposed change will better align with their preferred world view. An individual's ethical concerns and scientific knowledge consist of their logical approach to the issue at hand. The relative strength or weight of these characteristics for each individual will determine how much utility they obtain from purchasing certain goods or voting in support of or against a piece of legislation.

We will use the framework put forth by McFadden (1974) to display the assumed structure of citizens' utility. This construction details how to include both tangible and intangible characteristics of goods, commonly referred to as credence attributes, in the consumer demand equation. We describe utility in this way since consumers obtain utility from both consuming the good itself, in this case consuming a good and casting a vote, as well as from personal, moral, or ethical satisfaction. These characteristics that generate personal satisfaction from consumption of a product generally show up as labels and verified certifications on a physical product. Our assumed general utility function consists of a matrix of goods consumed and their respective marginal utilities ($V'\gamma$) the vector of votes the consumer may or may not cast and their marginal utilities ($V'\gamma$).

$$U(V, X) \ = X'\beta + V'\gamma$$

Equation (2)

Furthermore, we assume that consumers act rationally; both their purchasing and voting behavior reflects their goal of utility maximization taking all information and beliefs into account. This assumption that agents seek to maximize their expected utility subject to the choice sets they are presented with is the key idea of random utility theory. In this paper, we will only estimate the voting portion of this utility function, unlike previous literature that has looked mainly at the monetary and consumption decisions (Waterfield, et al. 2020; Norwood et al. 2019).

2. Hypotheses

Past studies in areas including animal science, political science, and religion have shown common links between demographic characteristics and support for animal welfare and GMO issues. Using these conclusions, we can predict the covariates impact on voting outcomes. The debate about moral concerns for animals, commonly known as "social contracts" between the natural world and humans has persevered for many years (Larrère and Larrère 2000; Te Velde et al. 2002; Rollin 2004), and these moral concerns have manifested in the form of specialty food items with various GMO and animal welfare-related certifications. We therefore anticipate a link between these moral ideas and the success of legal actions in imposing these concerns in agricultural markets. As demographic characteristics could have divergent impacts on AW and GMO voting outcomes, we will discuss hypotheses for each type of legislation separately. We will test all of these variables to see which are the strongest predictors. Our hypothesized strong predictor variables include political, religious, and racial indicators, as we believe these are groups that people more commonly self-identify with when it comes to social opinions.

3.1 Farm Animal Welfare

Our hypotheses for the impact of demographic variables on AW legislation are based on previous literature concerning demographics and support for animal rights. As people with low income levels focus mainly on obtaining the basic necessities for survival, they are unable to prioritize AW in the same way as individuals with more disposable income. Thus, we hypothesize higher income should be linked with higher support for AW, similar to the results reported in Smithson et al. (2014). We expect that higher levels of education will link to lower support for AW, as more educated individuals are more likely to view animal and human similarities and differences more scientifically (Jerolmack 2003). Political ideologies do appear to impact support for AW. Membership in the Democratic party has been linked to higher concern for animal welfare in a wide variety of past studies and contexts, see for example McKendree et al. (2014), Deemer and Lobao (2011), Czech and Borkhataria (2001), Miele et al. (1993), and Heleski et al. (2006). Furthermore, from past studies and voter data, we know that liberals are more supportive of animal welfare measures, in general, than conservatives, so we anticipate the higher the percent of registered Democrats, the more votes in favor of AW legislation (Smithson et al. 2014).

Previous research also suggests that religion plays a large role in an individual's view of the natural world and thus impacts views on animals and animal welfare (Videras 2006). For instance, Catholics tend to be more supportive of animal welfare issues than Protestants and Evangelicals (Smithson et al. 2014; Oldmixon 2017). One argument supporting this is that the influence of Judeo-Christianity has led to the current level of disregard for environmental issues and disregard for animal welfare in society, due to the biblical presumption of man's granted dominance of the Earth by God (Singer 2001). Overall, non-religious, non-Christians, and Catholics are most in favor of AW; therefore, we expect an increase in the number of Catholics per 1,000 people to have a positive impact on votes in favor of AW, while the impact of other religions should be negative (Cornish 2016; Jerolmack 2003; Flynn 2001). Studies have shown that non-white Americans tend to view AW more positively, so we predict that effects of higher percentages of these groups will also be positive (Jerolmack 2003; Franklin et al. 2001; Nibert 1994; Peek et al. 1996; Uyeki & Holland 2000). Lastly, higher percentages of males have been found to correlate with less support for AW, while younger age groups tend to have a positive view of AW (McKendree et al. 2014; Cornish 2016; Jerolmack 2003). Thus, we should see that a higher male to female ratio as well as median age should have a negative impact on votes in support of AW.

3.2 Labeling of Genetically Modified Organisms

We expect high incomes will have a positive impact on votes in favor of GMO labeling regulations since individuals with higher incomes can afford these specialty products. However, we believe that higher levels of education will have a negative impact on votes in favor of GMO regulations as more educated individuals tend to view GMOs as "safe" versus "unsafe" (Pew Research 2015). Differences in cultural worldviews are related to citizens' preferences for increased or mandatory labeling of GMOs (Kemper et al. 2018). In 2011, a Vatican panel voiced strong support for GMOs in the fight against world hunger, so we anticipate that a higher number of Catholics in a population will have a positive impact on votes in favor of GMO legislation; on the other hand, religious studies researchers have found that Mainline Protestants and Evangelical Protestants are wary of the morality of GMOs and therefore would not support them (Meldolesi 2011; Pew Research 2015b; Omobowale et al. 2009). Past studies have shown that non-white Americans are more likely to view GMOs negatively than white Americans (Pew Research 2015a & 2016). In accordance with these studies, we hypothesize that higher percentages of non-white citizens will have negative impacts on votes in favor of GMO regulations. Unlike in the case of AW, past studies have not found differences between political ideologies in relation to views on GMOs, so we do not predict that the percent of registered Democrats will have a significant impact on GMO legislation support (Pew Research 2015a & 2016). Finally, we predict that a lower median age (Pew Research 2015a) and a higher number of males (Bovay & Alston 2016, Pew Research 2015a) will positively impact votes in favor of GMO regulations.

3. Data & Methodology

4.1 Data Collection

Descriptive statistics from our data, given both as unweighted and weighted by counties within each state, are summarized in Table 2. Counties with less than 2,000 people were dropped, then each county within a state was given a weight corresponding to the fraction of its population relative to the overall state population, minus any dropped counties. Weighting is important when evaluating demographic makeup, as weighting the data by county ensures more realistic and accurate predictions. In the US, state-level elections are determined by a majority vote; therefore, relative populations should be considered when collecting the data. The weighting procedure used in our study should be intuitive: if County A has two times the population of County B, then the demographic percentages and voting outcomes from County A will be given two times the importance of those from County B in the state-wide calculations.

Our study analyzes 11 different AW and GMO food labeling ballot initiatives in Arizona (AZ), California (CA), Colorado (CO), Florida (FL), Massachusetts (MA), Ohio (OH), Oregon (OR), and Washington (WA). There were a total of five GMO initiatives and six AW initiatives included in our data set; for each we collected county-level demographic and voting data. We collected data on median household income, median value of owner-occupied housing, and the percent of people in poverty as proxies for income levels. We used the number of males per 100 females as our gender variable and the percent of persons of 25+ years of age with a bachelor's degree as our education variable. Race, median age, population density, and the percent of registered voters identifying as Democrat were included directly. Data on the numbers of Mainline Protestants, Evangelical Protestants, and Catholics was also collected to determine religious patterns. To account for consumer familiarity with farming practices, we use the variable farm density, which is the number of people per farm. Finally, we include final percentage vote in favor of ballot initiative so that the log-odds of success can be calculated.

The majority of county level demographic data was downloaded from the United States Census website (census.gov). Data was used from the Census year closest to the year the state level ballot initiative was on the ballot. Data on the county level voting results of the state ballot initiatives of interest and the election results of the democratic candidate in the presidential election closest to the year of the ballot initiative were both retrieved from the respective state's Secretary of State election records. All religion data, adherents of Mainline Protestant, Evangelical Protestant, and Catholic, was retrieved from the Association of Religious Data Archives. Data collection methods and sources are detailed more explicitly in Appendix A.

Table 2: Descriptive statistics for each initiative (unweighted/weighted)

Variable	Arizona 2006 (AW)	California 2008 (AW)	California 2012 (GMO)	California 2018 (AW)	Colorado 2014 (GMO)	Florida 2002 (AW)
Males per 100 females	100.30 / 100.38	103.94 / 100.23	103.13 / 98.91	103.13 / 98.91	108.70 / 101.66	106.96 / 96.46
Percent of persons 25+ with bachelor's degree	17.73 / 25.74	24.33 / 29.33	24.33 / 29.28	24.33 / 29.28	27.66 / 35.47	16.73 / 22.42
Percent registered Democrat	43.64 / 43.54	53.18 / 60.57	51.51 / 59.90	50.02 / 61.33	42.27 / 49.43	43.24 / 48.60
Household income ($1,000)	38.71 / 47.81	54.45 / 61.59	52.69/ 59.04	64.21 / 73.45	52.60 / 62.75	37.20 / 40.48
Median home value ($1,000)	155.63 / 218.69	407.60 / 498.47	407.60 / 497.60	407.60 / 497.60	214.55 / 242.01	172.94 / 220.69
Percent white	52.84 / 57.87	57.09 / 40.12	57.09 / 40.15	57.09 / 40.15	76.16 / 70.01	75.00 / 65.52
Percent black	1.83 / 4.06	3.27 / 6.17	3.27 / 6.16	3.27 / 6.16	1.54 / 4.02	13.93 / 14.55
Percent Hispanic	29.72 / 29.65	28.47 / 37.59	28.47 / 37.61	28.47 / 37.61	19.02 / 20.65	8.53 / 16.75
Poverty rate	18.75 / 14.22	14.16 / 13.31	17.18 / 16.97	14.37 / 13.36	14.60 / 12.18	17.85 / 15.61
Evangelical Protestants per 1,000 people	94.42 / 94.44	77.94 / 73.20	88.82 / 94.02	88.82 / 94.02	135.49 / 107.84	217.79 / 139.60

Mainline Protestants per 1,000 people	30.47 / 43.36	35.92 / 34.44	23.40 / 23.64	23.40 / 23.64	61.69 / 44.35	61.30 / 58.82
Catholics per 1,000 people	231.34 / 188.72	225.98 / 295.56	234.20 / 274.70	234.20 / 274.70	187.65 / 155.50	94.00 / 163.08
Population density	52.05 / 276.54	658.72 / 1745.48	663.25 / 1739.02	663.25 / 1739.02	148.19 / 771.62	287.43 / 840.77
Farm density	419.48 / 1594.93	2914.04 / 5759.58	2915.67 / 5682.53	2915.67 / 5682.53	552.91 / 3387.99	575.19 / 1452.98
Median age	38.65 / 36.16	38.50 / 35.20	38.50 / 35.19	38.50 / 35.19	41.23 / 36.28	39.62 / 39.07

Table notes: See Appendix A for further detail on each state and each data category.

Variable	**Massachusetts 2016 (AW)**	**Ohio 2009 (AW)**	**Oregon 2002 (GMO)**	**Oregon 2014 (GMO)**	**Washington 2013 (GMO)**
Males per 100 females	94.25 / 93.67	97.98 / 95.43	99.55 / 98.39	100.29 / 98.03	100.42 / 99.30
Percent of persons 25+ with bachelor's degree	36.11 / 37.72	16.96 / 23.69	21.45 / 28.27	21.45 / 28.37	23.09 / 30.47
Percent registered Democrat	60.00 / 59.24	43.73 / 51.23	40.04 / 50.73	42.69 / 58.84	45.61 / 55.43
Household income ($1,000)	70.21 / 75.90	44.67 / 46.30	38.94 / 44.50	45.94 / 52.20	49.23 / 59.62
Median home value ($1,000)	395.69 / 359.05	121.56 / 136.01	196.01 / 247.77	196.01 / 248.69	209.79 / 284.83
Percent white	80.44 / 76.12	91.25 / 81.04	86.56 / 83.48	82.79 / 78.45	78.47 / 72.53
Percent black	5.54 / 6.65	4.08 / 12.29	0.55 / 1.63	0.69 / 1.81	1.24 / 3.57
Percent Hispanic	7.93 / 9.58	2.23 / 3.09	7.70 / 8.06	10.58 / 11.74	12.73 / 11.24

Poverty rate	10.23 / 10.49	14.58 / 15.16	15.32 / 13.79	17.59 / 16.44	16.26 / 14.13
Evangelical Protestants per 1,000 people	29.91 / 34.34	141.72 / 129.19	118.18 / 113.58	109.16 / 116.67	114.99 / 122.04
Mainline Protestants per 1,000 people	59.39 / 47.09	121.69 / 99.98	53.44 / 51.85	41.77 / 36.62	50.65 / 45.85
Catholics per 1,000 people	387.27 / 449.05	127.14 / 173.82	88.60 / 101.63	89.19 / 104.25	113.72 / 116.63
Population density	1568.29 / 2423.21	291.43 / 1034.69	97.88 / 438.11	110.64 / 498.91	130.93 / 472.37
Farm density	8140.14 / 12545.99	313.06 / 1861.15	93.85 / 321.44	101.39 / 351.09	136.70 / 494.07
Median age	40.71 / 39.10	39.72 / 38.78	39.01 / 36.39	42.66 / 38.65	40.90 / 37.36

Table notes: See Appendix A for further detail on each state and each data category.

4. 4.2 Methods for Analysis

Ordinary least squares regression (OLS) with continuous and weighted county level demographic data was used to predict voting outcomes. Weighting the data by county ensures more realistic and accurate predictions, as state-level elections are determined by a majority vote; therefore, relative populations should be considered when analyzing the data. Other possible regression models could be used, including logit and Tobit models, though there is no reason why either would be superior to OLS. All three require simulation or numerical techniques at some stage of the process, and our choice is merely our preference.

We began by estimating the basic OLS model, without dummy variables, interaction terms, or fixed effects. Following the framework of Videras (2006) and Smithson et al. (2014), we design our regression equation to be estimated as in Equation (3) below, where the log of the odds of success of a vote on an initiative is determined by a vector of explanatory demographic variables:

$$\ln\left(\frac{V_i}{1-V_i}\right) = (W' \times \beta_i) + \varepsilon_i$$

Equation (3)

where V_i is the predicted "yes" portion of the vote; W is the matrix of demographic variables, β_i is the vector of demographic variable coefficients, and ε_i is the random error term. With this model we estimated individual initiative specific models (11 individual models), models pooled by topic (1 pooled AW model, 1 pooled GMO model), and a model with all initiatives pooled together. Utilizing a Likelihood Ratio Test, we determined that the fully pooled model gave the best fit for our data. In addition to the better fit, in order to improve predictive power and to develop a more generalizable model, we chose to estimate the full pooled model over the individual unpooled state or partially pooled topic specific models to maximize degrees of freedom and variability in the data. Thus, we expanded equation (3) to include initiative-specific interaction terms, and dummy indicators for fixed state effects:

$$\ln\left(\frac{V_i}{1-V_i}\right) = (W' \times \beta_i) + (GMO \times W' \times \delta_i) + (D' \times \theta_i) + \varepsilon_i$$

Equation (4)

Here, GMO is a dummy variable for GMO topic initiatives to create GMO-specific demographic interaction terms. β_i is the vector of demographic variable coefficients for our baseline topic (AW). δ_i is the vector of interaction term coefficients, which describe the distinctive effect of these demographic variables on the log odds ratio for the GMO initiatives compared to AW initiatives. θ_i is the vector of initiative-specific dummy variable coefficients. We include the initiative-specific dummy variables in our model as we are aggregating cross-sectional data from eleven different initiatives, rather than just a single initiative as seen in previous works. These dummy variables are included to account for any unobserved inter-initiative differences. For the initiative-specific dummy variables, both Ohio 2009 and Washington 2013 are not displayed in the model to avoid perfect collinearity among a given topic.

We use the Schwarz's Bayesian Criterion (SBC) to select the best model from the pooled data. We began by estimating the full model including all the initiative-specific dummy variables and topic interaction terms for each explanatory variable and compared this model to the full model without interaction terms. The SBC values for the model with topic variable interaction terms showed a better fit to the data than the model without interaction terms; therefore, we proceeded in testing for variable significance within the interaction term model. We tested the significance of variables and their topic variable interaction terms pairwise in several groups using Wald tests. These groups broke the variables into race, religion, economic, and general demographic categories. Variables were removed in groups so long as SBC values continued to improve. We give the pooled 11-initiative model in the body of this paper for discussion and reference, while topic-specific and individual initiative models are in Appendix B. Our final best fit model included median household income, median home value, poverty rate, percent of individuals 25+ years old with a bachelor's degree, percent of registered Democrats, as well as the GMO interaction terms and the initiative-specific dummy variables.

5. Results & Discussion

The regression results for our pooled 11-initiative model are given in Table 3. Our model shows that certain demographic indicators are strong predictors of the success of an initiative and impacts differ across topics.

Table 3: Pooled 11 Initiative Model

VARIABLES	
Household income (in $1000)	-0.012*
	(0.006)
Median home value (in $1000)	0.003***
	(0.0001)
Poverty rate	-0.044**
	(0.021)
Percent of persons 25+ with bachelor's degree	-0.022***
	(0.007)
Percent registered Democrats	0.016***
	(0.004)
GMO	-2.282***
	(0.571)
GMO * household income (in $1000)	2.91e-6
	(0.008)
GMO * Median home value (in $1000)	-0.001
	(0.001)
GMO * poverty rate	0.055**
	(0.023)
GMO * Percent of persons 25+ with bachelor's degree	0.035***

	(0.008)
GMO * percent registered Democrats	-0.004
	(0.006)
Arizona 2006	-0.151
	(0.098)
California 2008	-0.914***
	(0.253)
California 2012	-0.481***
	(0.111)
California 2018	-0.801***
	(0.219)
Colorado 2014	-0.493***
	(0.053)
Florida 2002	-0.944**
	(0.381)
Massachusetts 2016	0.263***
	(0.084)
Oregon 2002	-0.821***
	(0.082)
Oregon 2014	0.018
	(0.090)
Constant	1.106**
	(0.472)
Observations	532
R-squared	0.7175
SBC	657.3605

Table notes: **Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1**

Table 4: Estimated Percent Change in V_i Given a 10% Change in Independent Variables

Demographic Variables	**Effect of Increase**	**Effect of Decrease**
GMO Variables		
Household Income in $1,000	-4.40%	4.49%
Median Home Value in $1,000	4.10%	-4.03%
Poverty Rate	1.10%	-1.10%
Percent of persons 25+ with a bachelor's degree	2.54%	-2.51%
Percent Registered Democrat	4.24%	-4.16%
AW Variables		
Household Income in $1,000	-2.92%	2.89%
Median Home Value in $1,000	3.55%	-3.60%
Poverty Rate	-2.64%	2.61%

Percent of Persons 25+ with a bachelor's degree	-2.75%	2.72%
Percent Registered Democrat	3.75%	-3.80%

Table notes: All variables included in the model were increased or decreased by 10%, all else held equal, and the predicted percent change of votes in favor of a given ban are reported

5.1 Animal Welfare Results

In this section, we will interpret the signs and effects of the coefficients associated with AW initiatives obtained from our regression. As the coefficient values in our model are not directly interpretable, we use 10% changes and interpretations similar to those used in Videras (2006) to analyze our estimates; these are given in Table 4. We note that for the baseline AW coefficients, those on median household income, median home value, poverty rate, percent registered Democrats, and percent of people 25+ with a bachelor's degree are all statistically significant, as well as the constant term (Table 3). Our model supports the hypotheses that education will have a negative impact on AW voting outcomes while higher percentages of democrats will have a positive impact. The effect of a 10% increase or decrease in education, all else held equal, corresponds respectively to a 2.75% and 2.72% expected percent change in votes in favor of an AW ballot initiative (Table 4). A 10% increase in the percent of registered Democrats results in a predicted 3.75% percent increase in votes in favor, while a 10% decrease results in a predicted 3.80% decrease in votes in favor (Table 4). The three income variables included in our model do not give a clear support nor denial of our original hypothesis that higher income levels will correspond with increased support for AW legislation; while the positive coefficient of median home value and the negative coefficient on poverty rate support our hypothesis, the negative value on median household income does not (Table 3). While we had predicted that race, religion, gender, and age would be important indicators for success of AW legislation, our tests for significance and best model fit excluded these variables from the final regression. Finally, all of the individual AW-specific dummy variables except for Arizona 2006 had strongly significant fixed effects (Table 3).

In comparison to the previous work done by Videras (2006) and Smithson et al. (2014), both of which only analyzed AW initiatives, our results differ considerably. Our study utilized more AW initiatives and included GMO initiatives to build our model. Additionally, both Videras (2006) and Smithson et al. (2014) selected final models that both included different explanatory variables than ours does, as well as more variables. In particular, Videras (2006) included vote in the 1996 presidential election, gender, residents in rural areas, and religion variables as statistically significant predictors, yet found the non-interacted income variable to be insignificant. These results differ from ours in several ways. First, we find the effect of political affiliation to be much stronger in our study relative to Videras (2006). Additionally, we found socio-economic indicators, in this case median income, median home value, and poverty rate, to have noticeable effects on support for AW initiatives, unlike Videras (2006). Further contrasting Videras (2006), we find that religion, gender, and rural resident populations are not relevant for predicting AW initiative support.

On the other hand, Smithson et al. (2014) included a rural population variable, median home value, the number of Mainline Protestants per 1,000 people, and the percent of black citizens as statistically significant variables, while other income, religion, race, political, and education variables were insignificant. We find that median home value is a stronger indicator of support for an AW initiative than Smithson's results. Furthermore, we did not find rural populations, religion, or race to be needed for our predictions. We suspect the differences between our model and these previous models are due mainly to the fact that these models used only a single initiative, while we used eleven initiatives spanning two topics to create a more robust prediction. This increase in data, wider geographic area, and longer time span strengthen our model.

4.2 Labeling of Genetically Modified Organism Results

Given the interaction terms in the model, the impact of the demographic variable on the GMO label voting outcomes is the sum of the base animal welfare coefficient value plus the GMO interaction term. Poverty rate and percent of people 25+ with a bachelor's degree are the two significant deviations from the AW baseline; the other variables are not statistically different form the AW baseline (Table 3). However, note that in Table 4, we include the non-significant GMO interaction terms on median household income, median home value, and percent registered Democrats to estimate the percentage changes for votes in favor. A 10% increase in the poverty rate corresponds to a predicted 1.10% increase in votes in favor of GMO legislation, while a 10% decrease results in a predicted 1.10% decrease in votes in favor of GMO legislation (Table 4). Changes in education have almost twice the predicted effect as poverty rate: a 10% increase in education leads to a predicted 2.54% increase in votes in favor of GMO regulations and a 10% decrease corresponds with a 2.51% decrease in votes in favor (Table 4). Additionally, the GMO constant term is negative and significant, indicating less support overall for GMO legislation relative to AW legislation; this is not surprising given that none of the GMO initiatives passed (Table 3).

Since the baseline AW coefficients can be thought of as the GMO coefficients for median household income, median home value, and percent registered Democrats, we will use those for evaluating our original hypotheses. The coefficients on the interaction term between both GMO and education and GMO and poverty were statistically significant, meaning we will treat both education's and poverty rate's effect on votes in favor of GMO regulations as different than that of AW (Table 3). None of our original hypotheses for the relationship between demographics and support for GMO legislation were supported by the coefficients reported by our model; that is, higher income levels and higher numbers of registered Democrats have not been found to correspond with increased support for GMO legislation. Likewise, our original hypothesis that increased education would correspond to lower levels of support for GMO legislation is not supported by the regression coefficients. Furthermore, our predictions that race, religion, gender, and age would be important indicators of GMO support were shown to be false, as again, these variables were not ultimately significant enough to be included in our model. Like our study, Bovay & Alston (2016) also found that their original hypotheses for links between demographics and GMO labeling preferences were incorrect. All of the individual GMO-specific dummy variables, except for Oregon 2014, had strongly significant fixed effects; we assume that the majority of the effects for Oregon 2014 were captured by the previous Oregon 2002 dummy variable (Table 3). As there is no other research of this kind relating to GMO initiatives, we cannot compare our results to previous studies.

There is a simple explanation for why our original hypotheses about demographics for both AW and GMO initiatives were not supported. Previous research has tried to determine which individuals are more likely to support higher levels of AW or are less concerned about the growing prevalence of GMOs in our food supply. When making our predictions about the signs and significance of the coefficients on each demographic variable, we considered only this previous research on support for AW or GMO causes. However, support for AW or GMOs is not necessarily the same thing as considering who would support additional AW regulations or who would vote for rules controlling GMO use and labeling. Potentially, an individual who supports GMOs would be less likely to want or need labels, so they may actually prefer fewer labels or restrictions on their use in agriculture and therefore would vote against any initiatives of this nature. On the other hand, individuals who are against the wide use of GMOs in our food supply would have incentive to vote for the ballot initiatives regulating GMO labeling practices. A logical question then forms: Does the type of label matter in these outcomes? Crespi and Marette (2003) find that the market distortion associated with "Does Contain" and "Does Not Contain" GMO labels differs depending on the population of consumers. In particular, the label "Does Contain" should be used if there are significant numbers of consumers with a strong reluctance for consuming GMO goods relative to the number of indifferent consumers, while the label "Does Not Contain" should be used otherwise. To the best of our knowledge at the time of this paper, there has not been research published investigating how this difference impacts consumer preferences or producer decisions empirically in the United States. However, this difference could significantly impact realized market distortions due to voting outcomes. As such, our flipped results make sense even though they initially appear conflicting.

5. Policy Implications

The first goal of this paper is to use our model to predict future AW policies like Propositions 2 and 12 in California and their effects; see Sumner (2008) or Malone & Lusk (2016) for details about Propositions 2 and 12 and their impacts on agricultural industries. The types of legislation like both Propositions 2 and 12 are commonly unfunded mandates and have the potential to create vote-buy gaps. Unfunded mandates and vote-buy gaps have impacts on the financial stability of farmers and can disrupt market structures, making it difficult for farmers to adapt to new regulations. Due to these concerns for farmer and agricultural industry welfare, it is important to develop a method to predict future ballot initiatives that may result in unfunded mandates and vote-buy gaps.

Using our model, we input the most recent data possible from all 50 states to test the odds of success for future hypothetical AW initiatives and to test how well the 2016 national GMO labeling law adheres to individual state support. As our model uses more data than previous works and includes AW and GMO labeling initiatives, we expect that our results are more reliable than past studies. One must consider the that there has been changes in both political makeup, socio-economic status, and demographics in the United States in the past six years since Smithson et al. (2014) published their 50 state predictions. Our model accurately predicted the actual vote percentages from the 11 original initiatives used. Furthermore, with the additional years since similar predictions were last computed by Smithson et al. (2014) who only predicted AW outcomes, and Bovay & Alston (2016) who only predicted GMO labeling outcomes, the debates around AW and GMOs have continued. As such, it is possible that voters are more aware about AW and GMO concerns than they were even six years ago.

Table 5: State predictions generated by our model using most recent weighted data available

State	AW	GMO	State	AW	GMO
Alaska °	46%	26%	Montana	**61%**	42%
Alabama	**56%**	38%	Nebraska	**57%**	36%
Arizona (61.9%)* † °	**59%**	44%	Nevada	**73%**	46%
Arkansas	**57%**	37%	New Hampshire °	**69%**	44%
California (62.5% / 48.2%)* †	**63%**	47%	New Jersey °	**74%**	**50%**
Colorado (32.9%) †	**63%**	34%	New Mexico	**61%**	45%
Connecticut °	**71%**	49%	New York °	**74%**	**55%**
Delaware	**71%**	46%	North Carolina	**60%**	43%
Florida (51.3%)* † °	44%	47%	North Dakota	**58%**	36%

Georgia	**58%**	42%	*Ohio (63.4%*)* † °	**63%**	41%
Hawaii °	**84%**	**59%**	Oklahoma	**52%**	34%
Idaho	**58%**	38%	*Oregon (49.6%)* † °	**68%**	49%
Illinois °	**67%**	46%	Pennsylvania	**65%**	42%
Indiana † °	**61%**	38%	Rhode Island † °	**73%**	**52%**
Iowa °	**64%**	39%	South Carolina †	**59%**	41%
Kansas	**56%**	37%	South Dakota	**58%**	37%
Kentucky	**56%**	38%	Tennessee °	**57%**	39%
Louisiana	**57%**	39%	Texas	**55%**	39%
Maine † °	**69%**	45%	Utah	**55%**	36%
Maryland	**72%**	49%	Virginia	**66%**	45%
Massachusetts (74.8%)* † °	**77%**	**54%**	Vermont	**70%**	**50%**
Michigan † °	**64%**	44%	*Washington (47.9%)*	**70%**	48%
Minnesota °	**65%**	43%	West Virginia †	**57%**	36%
Mississippi °	**55%**	40%	Wisconsin	**66%**	42%
Missouri °	**61%**	40%	Wyoming °	**59%**	33%

Table notes: Initiatives that specifically ban further AW or GMO legislation are not included in the table. Where actual weighted vote percentages are given in parentheses, * indicates AW, and italics indicates the states used to calibrate the model. States with an (†) next to them have passed AW legislation and states with a (°) next to them have passed GMO legislation in line with those used to calibrate the model. Predicted percentages that indicate a "pass" of an initiative are bolded. States shaded in grey allow ballot initiative referenda.

In Table 5, the states whose data were used to estimate the model are given in italics and actual vote percentages are given in parentheses for comparison. An (*) indicates the topic of the original 11 initiatives as AW. A bold-font percentage indicates that AW or GMO legislation is predicted to pass. States shaded in grey allow ballot initiatives, the same process used for the 11 initiatives in our model; other states use a variety of different processes for ratifying legislation. Though some states do not allow ballot initiatives, our results are still useful in predicting the likely viewpoints of state officials and legislature members that have the power to enact AW or GMO legislation. The (†) and (°) symbols indicate states that have already passed AW or GMO initiatives, respectively.

Our predictions given in Table 5 show that, excluding Alaska and Florida, every state would vote to pass an AW initiative today, though only Hawaii, Massachusetts, New Jersey, New York, Rhode Island, and Vermont are predicted to pass a GMO labeling initiative today. The implications of these potential votes are far-reaching for multiple segments of the economy. Like Videras (2006) discussed, accurate predictions for votes on initiatives and any resulting unfunded mandates or vote-buy gaps will allow industries in affected states to best devise a course of action, be it advertising campaigns, lobbying, or proactively helping their producers to adjust to new regulations.

Interestingly, in the case of Florida's Amendment 10, the Animal Cruelty Amendment circa 2002 versus present-day, our model predicts a flip-flop in voter support for AW. Why might this be? The most recent data available shows a large increase in Florida's weighted average household income, poverty rate, education level and percent of registered Democrats, but a decrease in median home value. Since the coefficients for household income, poverty rate, and education are all negative, they push the predicted votes in support down, while the number of Democrats pushes predicted votes up. The positive coefficient for median household value also pushes the present-day predicted votes in support down due to the decrease in home value. Overall, there is a stronger downward force than upward, and so according to our model, present day Florida is not predicted to pass an AW initiative with its current demographic makeup.

A second goal of this paper was to determine if the NBFDS of 2016 reflects the opinions of individual states overall. From our table above, it is clear to see that the standard is not in line with a predicted majority vote, and therefore is suboptimal. This is not surprising, given previous works analyzing both this standard and mandatory labeling requirements in general. Bovay and Alston (2016) found that few states would have passed a GMO labelling law similar to California's Proposition 37, and Bovay and Alston (2018) found that the NBFDS is worse for consumers and producers than the absence of any mandatory labeling laws. Studies outside of the United States offer insights into market outcomes generated by labeling regulations. In Canada and France, one study found that imposing mandatory labeling policies did not improve consumers' right to choose, nor did they result in significant utilization of these labels (Grue`re 2006). In effect, government action and spending to implement these policies cost taxpayers more than it benefited them. Furthermore, mandatory labeling is only an optimal choice when many people strongly prefer the labelled product (Zilberman et al. 2018). As such, the passing of the 2016 NBFDS does not appear to have been in the best interests of consumers or producers and did not align with what citizens wanted.

However, the fierce interstate competition created by patchwork bans and regulations, like those used in this paper, can result in conflicting welfare effects. In the U.S., the agricultural sector enjoys the benefits of industrialization and a competitive market, both of which drive production up, increase innovation, and ultimately produce the best product. Additionally, these regulations generate more intrastate competition, which has a positive impact on total factor productivity (TFP) (Gong 2018). To this end, ballot initiatives may not be detrimental. On the other hand, national level bans or regulations can have protectionist outcomes in international trade and decrease consumer choice sets (Punt & Wessler 2016; Ghozzi et al. 2018). Fulton and Giannakas (2004) describe more theoretical implications for welfare in markets where non-GMO and GMO segregation costs are high, such as when labeling is required. In particular, consumers and producers are expected to see a reduction in welfare overall due to these segregation costs and the potential for increased consumer aversion. These market-wide impacts are important for affected industry leaders to consider.

6. Conclusion

Citizens can participate in agricultural markets through traditional market forces (supply and demand) or voting. Impacting a market through voting behavior is primarily how people who usually do not interact in the market in the traditional sense, such as vegans and vegetarians in meat markets, can express their preferences and create changes in multiple markets. Voting outcomes impact the choice set of every agent in a market, unlike purchasing. Choosing to purchase a given item does not exclude others from purchasing a different item, while legislation that controls what items are available imposes choice set changes on everyone in the market. The changes focused on in this paper were AW and GMO ballot initiatives, which have become more common in recent years. These initiatives are frequently in the form of unfunded mandates and have the potential to create vote-buy gaps. The market inefficiencies caused by these initiatives and the resulting vote-buy gaps are concerning for both agricultural producers and industries. As such, there is need for accurate methods to predict where ballot initiatives may be passed so that industries can better prepare for possible market effects.

The purpose of this study was to create a generalizable predictor function for the outcomes of ballot initiatives. Our work assumes citizens maximize utility subject to their voting behavior, consumption patterns, and personal morals or ethics. We used county-level voting and demographic data from 11 AW and GMO initiatives spanning 16 years and eight states to generate our model. Our final model included median home value, median household income, poverty rate, education, percent of registered Democrats, the GMO topic-specific dummy variable, interactions between the topic dummy and the aforementioned demographic variables, and all of the initiative-specific fixed effects. We found that the strongest indicators for the success of an AW ballot initiative were lower levels of education and higher percentages of Democrats, while the socio-economic variables offered mixed results. For GMO labeling initiatives, the socio-economic variables were again conflicting, though higher levels of education and percentages of Democrats were positive indicators of success. Overall, the likelihood of success for a GMO labeling initiative was significantly less than for the success of an AW initiative; this is seen in the strongly significant and negative GMO dummy variable. The discrepancies in our original hypotheses versus our results for GMO initiatives are most likely due to the fact that supporting the use or development of GMOs, as previous research has studied, is not the same as supporting GMO labeling initiatives. Individuals that support the use of GMOs in the food supply probably would see no reason to label products that contain them.

Using the most recent data available for all 50 states, we find that all states except Alaska and Florida would pass AW ballot initiatives today, yet only Hawaii, Massachusetts, New Jersey, New York, Rhode Island, and Vermont would pass GMO labeling ballot initiatives today. Our prediction for Florida flipped relative to the actual vote outcome, likely due to demographic changes such as socio-economic indicators and political affiliation since Amendment 10, Animal Cruelty Amendment passed in 2002. We also find that the 2016 NBFDS does not align with predicted individual state support; this standard would not have passed if put to a national majority vote and therefore does not accurately represent the preferences of Americans.

Producers and industry leaders can use our results to predict and prepare for future AW ballot initiatives; however, when applying our results, it should be kept in mind that the data used in this paper is from only 11 initiatives and our model is relatively simple. As such, future work in this area would benefit from more initiatives' data or data from other states. Along these lines, future studies could compare our results to other types of ballot initiatives, such as right to farm initiatives, to determine any trends. Finally, others should conduct a more detailed analysis of

GMO labeling and AW voting data and control for the difference between supporting a cause and supporting initiatives or regulations about that cause.

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Appendix A: Data Collection Methods

Data Collection Procedures

For all data retrieved from the Counties Data File Download website (https://www.census.gov/support/USACdataDownloads.html), all reference codes are found in the file, Mastdata.xls, found under "Reference Information Files." The most recent Counties Data Files are from the 2010 US Census.

Votes for State Initiative

Arizona 2006, Proposition 204: Votes on Proposition 204 came from the Arizona's Secretary of State Records for the 2006 General Election (https://apps.azsos.gov/election/2006/General/ElectionInformation.htm). The file "Official Election Results (PDF)" was downloaded on February 8, 2019. Data regarding the voting outcome of Proposition 204, by county, is found on page 15 of the document.

California 2008, Proposition 2: Votes on Proposition 2 came from the California's Statement of Vote from the 2008 General Election (https://www.sos.ca.gov/elections/prior-elections/statewide-election-results/presidential-general-election-november-4-2008/statement-vote/). The file "Complete Statement of Vote (PDF)" was downloaded on January 11, 2019. Data regarding the voting outcome of Proposition 2, by county, is found on page 57 of the document.

California 2012, Proposition 37: Votes on Proposition 37 came from the California's Statement of Vote from the November 6, 2012 General Election (https://www.sos.ca.gov/elections/prior-elections/statewide-election-results/general-election-november-6-2012/statement-vote/). The file "Complete Statement of Vote (PDF)" was downloaded on February 10, 2019. Data regarding the voting outcome of Proposition 37, by county, is found on page 67 of the document.

California 2018, Proposition 12: Votes on Proposition 12 came from the California's Statement of Vote from the November 6, 2018 General Election (https://www.sos.ca.gov/elections/prior-elections/statewide-election-results/general-election-november-6-2018/statement-vote/). The file "Complete Statement of Vote (PDF)" was downloaded on February 10, 2019. Data regarding the voting outcome of Proposition 12, by county, is found on page 98 of the document.

Colorado 2014, Proposition 105: Votes on Proposition 105 came from Colorado's 2014 Abstract of Votes cast from the November 4, 2014 General Election (https://www.sos.state.co.us/pubs/elections/Results/Archives.html). The file "State election results, 2013-2014 (PDF)" was downloaded on February 15, 2019. Data regarding the voting outcome of Proposition 105, by county, is found on page 148 of the document.

Florida 2002, Amendment 3: Votes on Amendment 10 came from Florida's Department of State 2002 General Elections results (https://results.elections.myflorida.com/downloadresults.asp?ElectionDate=11/5/2002&DATAMODE=).

Massachusetts 2016, Question 3: Votes on Question 3 came from Massachusetts's Secretary of the Commonwealth 2016 General Elections results (http://electionstats.state.ma.us/ballot_questions/view/2741/).

Ohio 2009, Issue 2: Votes on Issue 2 came from the Ohio's Statement of Vote from the November 3, 2009 General Election (https://www.sos.state.oh.us/elections/election-results-and-data/2009-election-results/state-issue-2-november-3-2009/). The file "State Issue 2 Official Results: November 3, 2009" was downloaded on February 10, 2019.

Oregon 2002, Measure 27: Votes on Question 3 came from the Oregon's Secretary of State results from the 2002 General Election (https://sos.oregon.gov/elections/Pages/electionhistory.aspx).

Oregon 2014, Measure 92: Votes on Measure 92 came from the Oregon's Secretary of State results from the 2014 Election Results and Statistics **(**https://sos.oregon.gov/elections/Pages/electionhistory.aspx).

Washington 2013, Initiative 522: Votes on Initiative 522 came from the Washington's Secretary of State results from the "2013 Elections" general results **(**https://www.sos.wa.gov/elections/research/).

Median Household Income

Data regarding median household income is found on the "Small Area Income and Poverty Estimates (SAIPE) Program" page on the US Census Bureau website (https://www.census.gov/programs-surveys/saipe.html). The file "US and All State and Counties" was downloaded on February 8, 2019. In the file, "Median Household Income" data is found in column W.

Median Value of Owner-Occupied Housing

Housing value data is found on the USA Counties Data File Download website (https://www.census.gov/support/USACdataDownloads.html). File HSG03.xls was downloaded on April 7, 2019.

Percent of People all Ages in Poverty

Data regarding poverty is found on the "Small Area Income and Poverty Estimates (SAIPE) Program" page on the US Census Bureau website (https://www.census.gov/programs-surveys/saipe.html). The file "US and All State and Counties" was downloaded on February 8, 2019. In the file, "Poverty Percent All Ages" data is found in column H.

Males per 100 females

Gender data is found on the USA Counties Data File Download website (https://www.census.gov/support/USACdataDownloads.html). File SEX01.xls was downloaded on January 18, 2019.

Persons 25+ years of age with a Bachelor's degree or higher

Education data is found on the USA Counties Data File Download website (https://www.census.gov/support/USACdataDownloads.html). File EDU02.xls was downloaded on January 18, 2019.

Votes for Democratic Presidential Candidate

Arizona 2006, Proposition 204: Votes for the Democratic ticket, Kerry-Edwards, in the 2004 Presidential election came from the Arizona's Secretary of State Records for the 2004 General Election (https://apps.azsos.gov/election/2004/Info/ElectionInformation.htm). On the website, click "General Election Information (November 2, 2004). The file "Official Election Canvass of Results PDF" was downloaded on April 14, 2019.

California 2008, Proposition 2: Votes for the Democratic ticket, Obama-Biden, in the 2008 Presidential election came from the California's Statement of Vote Records for the 2008 General Election (https://www.sos.ca.gov/elections/prior-elections/statewide-election-results/presidential-general-election-november-4-2008/statement-vote/). The file "Complete Statement of Vote (PDF)" was downloaded on January 11, 2019. Data regarding the voting outcome for President, by county, is found on page 17 of the document.

California 2012, Proposition 37: Votes for the Democratic ticket, Obama-Biden, in the 2012 Presidential election came from the California's Statement of Vote Records for the November 6, 2012 General Election (https://www.sos.ca.gov/elections/prior-elections/statewide-election-results/general-election-november-6-2012/statement-vote/). The file "Complete Statement of Vote (PDF)" was downloaded on February 10, 2019. Data regarding the voting outcome for President, by county, is found on page 18 of the document.

California 2018, Proposition 12: Votes for the Democratic ticket, Clinton-Kaine, in the 2016 Presidential election came from the California's Statement of Vote Records for the 2016 General Election (https://elections.cdn.sos.ca.gov/sov/2016-general/sov/2016-complete-sov.pdf). The file "Complete Statement of Vote (PDF)" was downloaded on January 11, 2019. Data regarding the voting outcome for President, by county, is found on page 17 of the document.

Colorado 2014, Proposition 105: Votes for the Democratic Ticket, Obama-Biden, in the 2012 Presidential election came from Colorado's 2012 Abstract of Votes on the November 6, 2012 General Election (https://www.sos.state.co.us/pubs/elections/Results/Archives.html). The file "State Election results, 2012 (PDF)" was downloaded on February 15, 2019. Data regarding the voting outcome for President, by county, is found on page 17 of the document.

Florida 2002, Amendment 3: Votes for the Democratic Ticket, Clinton-Gore, in the 1996 Presidential election came from Florida's Department of State records for the November 5, 1996 Abstract of Votes on the November 6, 2012 General Election https://results.elections.myflorida.com/Index.asp?ElectionDate=11/5/1996&DATAMODE=). The file "Download Results" was downloaded on February 15, 2019.

> *Note: The 1996 Presidential election was used opposed to the 2000 Presidential election due to the controversial results in Florida in 2000.

Massachusetts 2016, Question 3: Votes for the Democratic ticket, Clinton-Kaine, in the 2016 Presidential election came from the Massachusetts Secretary of the Commonwealth results for the 2016 General Election (https://elections.cdn.sos.ca.gov/sov/2016-general/sov/2016-complete-sov.pdf).

Ohio 2009, Issue 2: Votes for the Democratic ticket, Obama-Biden, in the 2008 Presidential election came from the Ohio's Secretary of State results for the November 4, 2008 General Election (https://www.sos.state.oh.us/elections/election-results-and-data/2008-election-results/).

Oregon 2002, Measure 27: Votes for the Democratic ticket, Kerry-Edwards, in the 2004 Presidential election came from the Oregon's Secretary of State Records for the 2004 General Election (https://sos.oregon.gov/elections/Pages/electionhistory.aspx). On the website, click "General Election Information (November 2, 2004). The file "Official Election Canvass of Results PDF" was downloaded on April 14, 2019.

Oregon 2014, Measure 92: Votes for the Democratic ticket, Obama-Biden, in the 2008 Presidential election came from the Oregon's Secretary of State Records for the 2008 General Election (https://sos.oregon.gov/elections/Pages/electionhistory.aspx). On the website under "Oregon Statewide Election Results", click "2008".

Washington 2013, Initiative 522: Votes for the Democratic ticket, Obama-Biden, in the 2012 Presidential election came from the Washington's Secretary of State results for the 2008 General Election (https://www.sos.wa.gov/elections/research/).

Mainline Protestant Adherents (per 1000 population)

Religious data came from the Association of Religious Data Archives (http://www.thearda.com/QL2010/). Collect data from the "Percent" column. In our work, we multiplied the percent values by ten in order to report the value as Adherents per 1000 population.

Evangelical Protestant Adherents (per 1000 population)

Religious data came from the Association of Religious Data Archives (http://www.thearda.com/QL2010/). Collect data from the "Percent" column. In our work, we multiplied the percent values by ten in order to record report the value as Adherents per 1000 population.

Catholic Adherents (per 1000 population)

Religious data came from the Association of Religious Data Archives (http://www.thearda.com/QL2010/). Collect data from the "Percent" column. In our work, we multiplied the percent values by ten in order to record report the value as Adherents per 1000 population.

White

Race data is found on the USA Counties Data File Download website (https://www.census.gov/support/USACdataDownloads.html). File POP01.xls was downloaded on January 18, 2019.

Black

Race data is found on the USA Counties Data File Download website (https://www.census.gov/support/USACdataDownloads.html). File POP01.xls was downloaded on January 18, 2019.

Hispanic

Race data is found on the USA Counties Data File Download website (https://www.census.gov/support/USACdataDownloads.html). File POP02.xls was downloaded on January 18, 2019.

Median Age

Age data is found on the USA Counties Data File Download website (https://www.census.gov/support/USACdataDownloads.html). File AGE01.xls was downloaded on January 18, 2019.

Population Density

Population data is found on the USA Counties Data File Download website (https://www.census.gov/support/USACdataDownloads.html). File POP01.xls was downloaded on January 18, 2019.

Farms per County

Agricultural data is found on the USA Counties Data File Download website (https://www.census.gov/support/USACdataDownloads.html). File AGN01.xls was downloaded on January 25, 2019.

Population by County

Population data is found on the USA Counties Data File Download website (https://www.census.gov/support/USACdataDownloads.html). File PST01.xls was downloaded on January 25, 2019.

Appendix B: Additional Models

Table B.1.: AW Initiative-Specific Models

VARIABLES	California 2008	Florida 2002	Ohio 2009	California 2018
Household income (in $1000)		-0.211	0.032**	-0.013***
		(0.144)	*(0.012)*	*(0.003)*
Median home value (in $1000)	4.534e-4	0.012**	-0.004	6.084e-4
	(4.147e-4)	*(0.006)*	*(0.003)*	*(4.038e-4)*
Poverty rate	-0.010	-0.216	0.017	-0.037***
	(0.010)	*(0.153)*	*(0.019)*	*(0.009)*
Percent of persons 25+ with bachelor's degree	0.012*		-0.033***	0.019***
	(0.006)		*(0.010)*	*(0.006)*
Percent registered Democrats	0.007**		-0.013***	0.013***
	(0.003)		*(0.004)*	*(0.002)*
Mainline Protestants (per 1000 people)	-0.002**		0.002***	
	(0.001)		*(6.914e-4)*	
Evangelical Protestants (per 1000 people)	-0.003*		6.229e-4	
	(0.001)		*(5.269e-4)*	
Catholics (per 1000 people)	2.030e-4		7.937e-4**	
	(4.694e-4)		*(3.777e-4)*	
Percent white	0.013***			-0.007**
	(0.004)			*(0.003)*
Percent black	0.042***			0.015
	(0.010)			*(0.010)*
Percent Hispanic	0.013**			0.006*
	(0.006)			*(0.003)*
Number of males per 100 females				-0.003*
				(0.002)
Population density			1.415e-4	
			(9.86e-5)	
Farm density			1.06e-5	

			(1.55e-5)	
Median age				0.021***
				(0.008)
Constant	-1.38**	9.012	0.265	-0.154
	(0.520)	*(6.791)*	*(0.720)*	*(0.486)*
Observations	57	67	88	58
R-squared	0.8567	0.2906	0.7108	0.9569
SBC	**-53.55504**	**213.1468**	**-19.93727**	**-88.53886**

Table notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table B.2.: GMO Initiative-Specific Models

VARIABLES	***Washington 2013***	***Oregon 2014***	***Oregon 2002***	***Colorado 2014***	***California 2012***
Household income (in $1000)	-0.023**	0.011	-0.031*	-0.004	-0.018***
	(0.009)	*(0.015)*	*(0.016)*	*(0.002)*	*(0.003)*
Median home value (in $1000)	0.003***	0.002***	0.002***	0.003***	0.002***
	(8.265e-4)	*(6.905e-4)*	*(7.012e-4)*	*(6.612e-4)*	*(3.463e-4)*
Poverty rate	-0.043*	0.031	-0.005	0.016	-0.002
	(0.023)	*(0.022)*	*(0.031)*	*(0.010)*	*(0.009)*
Percent of persons 25+ with bachelor's degree	-0.002	-0.002	0.002	-0.003	0.012**
	(0.004)	*(0.0078)*	*(0.005)*	*(0.004)*	*(0.006)*
Percent registered Democrats	0.023***	0.017***	0.019***	0.015***	0.016***
	(0.006)	*(0.003)*	*(0.004)*	*(0.002)*	*(0.001)*
Mainline Protestants (per 1000 people)			-0.006***	-0.004***	-0.004
			(0.002)	*(0.001)*	*(0.002)*
Evangelical Protestants (per 1000 people)			-0.004***	5.00e-4	1.410e-4
			(8.997e-4)	*(4.40e-4)*	*(0.001)*
Catholics (per 1000 people)			-1.022e-4	8.205e-4***	-6.993e-4***
			(9.649e-4)	*(2.386e-4)*	*(2.374e-4)*
Percent white	-0.027*	0.021**	0.009	-0.036*	
	(0.013)	*(0.010)*	*(0.011)*	*(0.019)*	
Percent black	-0.063***	0.657***	0.299**	-0.048**	
	(0.019)	*(0.095)*	*(0.114)*	*(0.024)*	
Percent Hispanic	-0.033**	0.026**	0.006	-0.048**	
	(0.012)	(0.011)	(0.014)	(0.020)	
Number of males per 100 females		-0.038***			0.011***
		(0.009)			*(0.003)*
Population density		-0.003***	7.428e-4	-9.65e-5	-5.63e-5***
		(4.232e-4)	*(4.801e-4)*	*(1.700e-4)*	*(1.530e-5)*
Farm density		0.001	-0.002**	1.230e-5	6.990e-6***
		(6.821e-4)	*(0.001)*	*(2.39e-5)*	*(2.07e-6)*
Median age		0.0149			0.003
		(0.010)			*(0.007)*
Constant	2.494	-1.715	-1.184	1.551	-1.950***
	2.004	*(1.810)*	*(1.803)*	*(1.969)*	*(0.694)*
Observations	39	36	36	63	58

R-squared	0.9702	0.9682	0.9586	0.9281	0.9353
SBC	*-57.35804*	*-47.01249*	*-41.09901*	*-49.97681*	*-82.68977*

Table notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1

Table B.3.: AW and GMO Initiatives Grouped Models

VARIABLES	Animal Welfare Model	GMO Model
Household income (in $1000)	-0.012*	-0.002
	(0.006)	*(0.003)*
Median home value (in $1000)	0.003***	0.002***
	(9.517e-4)	*(4.489e-4)*
Poverty rate	-0.044**	0.036***
	(0.021)	*(0.009)*
Percent of persons 25+ with bachelor's degree	-0.022***	0.005
	(0.007)	*(0.003)*
Percent registered Democrats	0.016***	0.014***
	(0.004)	*(0.004)*
Mainline Protestants (per 1000 people)		-0.003***
		(0.001)
Evangelical Protestants (per 1000 people)		-1.720e-4
		(4.799e-4)
Catholics (per 1000 people)		3.095e-4
		(3.023e-4)
Percent white		0.016***
		(0.004)
Percent black		0.034***
		(0.012)
Percent Hispanic		0.003
		(0.004)
California 2012		-0.407***
		(0.119)
Colorado 2014		-0.427***
		(0.062)
Oregon 2002		-0.730***
		(0.063)
Oregon 2014		-0.038
		(0.065)
Arizona 2006	-0.414***	
	(0.110)	
California 2008	-1.176***	
	(0.248)	
California 2018	-1.064***	
	(0.203)	
Florida 2002	-1.207***	
	(0.408)	
Ohio 2009	-.263***	
	(0.084)	
Constant	1.369***	-3.247***
	(0.517)	*(0.570)*

Observations	300	232
R-squared	0.4090	0.9033
SBC	**509.3051**	**-96.01747**

Table notes: Standard errors in parentheses, *** p<0.01, ** p<0.05, * p<0.1