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RESEARCH ARTICLE

Mitigating Structural Inequities in U.S. Agricultural Risk Management

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Abstract
The USDA has implemented policies to address inequities for socially disadvantaged farmers and ranchers. This research examines agricultural risk inequities and the impact of 2018 Farm Bill programs on crop insurance use among minority and veteran farmers. Results indicate that minority and veteran farmers are disproportionately located in regions of the U.S. with higher risks of drought and excess precipitation. Yet, these producer groups had lower use of crop insurance prior to the implementation of the 2018 Farm Bill. However, the incentive programs created under the 2018 Farm Bill have increased use of federal crop insurance among these vulnerable populations.

Keywords: Agricultural risk; crop insurance; premium subsidies; socially disadvantaged farmers; 2018 farm bill

JEL classifications: Q18; J15

1. Introduction

The economic geography of modern agriculture in the United States resides on a foundation of racial disparity (Collins et al., 2024; Fagundes et al., 2020; Muhammad et al., 2024; White, 2011). Homestead laws and other historic policies created geographic concentrations of minority producers in areas less amenable to farming (Dismukes et al., 1997; Horst and Marion, 2019; Muhammad et al., 2024).[1] Homesteads still required capital for beginning farmers, and over half of the homesteads failed due to weather and market difficulties (Muhammad et al., 2024). Moreover, actual and *de facto* discrimination both result in unequal access to government farm support (Graddy-Lovelace, 2017; Murphy, 2023).[2] Recently, the USDA has implemented several policies aimed at mitigating these structural inequities (Giri et al., 2024; Rosch, 2021). Structural inequalities for the purposes of this paper are widespread historical, social, political, and economic factors that shape society, including property rights and access to resources (Farmer, 2004; Fiske et al., 2022).

[1]For example, native populations were forcibly moved from their lands to "reservation" areas. Additionally, slaves, indentured servants, and recent immigrants were often ineligible for Homestead programs. Further, land distribution programs for minority producers, including post-Civil War land redistribution to former Black slaves, led to smaller farm sizes for minority producers (Dismukes et al., 1997).

[2]Lawsuits such as *Pigford v. Glickman* for Black producers and *Keepseagle v. Vilsack* for Native American producers have highlighted discriminatory practices, particularly in USDA agricultural lending.

Crop insurance is just one option for whole-farm risk management, alongside crop diversification, new technologies, vertical integration or contracting, and off-farm employment. However, increased availability and affordability of crop insurance has made it an increasingly attractive option and one lenders see favorably. This research seeks to map inequities in the domain of agricultural weather risk and investigate whether recent policy efforts have improved the use of modern risk management tools among socially disadvantaged farmers.[3] Our objectives are twofold:

1. First, we assess the presence and extent of structural inequities in U.S. agricultural risk management, evaluated both in terms of the magnitude of agricultural risk factors socially disadvantaged farmers face and their ability to manage these risks via use of affordable federal crop insurance.
2. Second, we investigate whether incentive programs adopted under the Agriculture Improvement Act of 2018 (i.e., the 2018 Farm Bill) have increased use of federal crop insurance among socially disadvantaged farm populations.

To address these questions, we compile and analyze a data set that matches information on annual enrollments in federal crop insurance in each U.S. county for 123 different crops from 2015 to 2021 with county demographic data obtained from ERS (2022) and county-level measures of drought and excess precipitation on an annual basis.

Our analysis contributes to the emerging agricultural economics literature on structural inequities in the agri-food system (Collins et al., 2024; Giri et al., 2024; Horst and Marion, 2019; Mishra et al., 2024; Murphy, 2023). Previous studies have investigated racial and ethnic disparities in farmland ownership (Horst and Marion, 2019) and access to farm credit (Mishra et al., 2024). Others have focused on inequities with respect to use of government farm support (Murphy, 2023) and (in particular) ad hoc payments made to farmers (Giri et al., 2024; Murphy, 2023).

We also contribute to the well-established literature on the impacts of premium subsidies on the uptake and market-level effects of federal crop insurance (Goodwin et al., 2004; Goodwin and Smith, 2013; O'Donoghue, 2014; Tsiboe and Turner, 2023b; Young et al., 2001; Yu et al., 2018). Previous studies in this line of literature have analyzed the effects of crop insurance premium subsidies on agricultural land usage and production (Goodwin et al., 2004; Young et al., 2001), on producers' crop choices (Yu et al., 2018), and in terms of uptake of crop insurance policies (O'Donoghue, 2014; Tsiboe and Turner, 2023b). Within this line of literature, our study is perhaps most closely related to the works of Tsiboe and Turner (2023b) and Yu et al. (2018). Both of these studies identify the impacts of premium subsidies by looking at the (exogenous) timing of the Farm Bill cycle. Our empirical identification strategy is consistent with this approach.

To our knowledge, no previous studies have examined the impacts of federal crop insurance incentives offered to minority or historically underserved producers. We believe that – by filling this gap – our work contributes to the body of knowledge on federal crop insurance for several reasons. First, as discussed, through a combination of policy and other factors, minority producers have tended to locate geographically in areas of the country that face the types of weather risks most critically addressed by crop insurance. Nevertheless, farmers in highly productive regions (that are less prone to weather risk) receive double the government payments of producers in low productivity regions and are more likely to participate in crop insurance (Burchfield and Nelson,

[3]"Socially disadvantaged farmers," as used in this paper, is defined by the USDA as "an individual or entity who is a member of a socially disadvantaged group. A socially disadvantaged group is a group whose members have been subject to racial or ethnic prejudice because of their identity as a member of a group without regard to their individual qualities. Socially disadvantaged groups consist of the following: American Indians or Alaskan Natives, Asians, Blacks or African Americans, Native Hawaiians or other Pacific Islanders, Hispanics." https://www.nrcs.usda.gov/getting-assistance/underserved-farmers-ranchers.

2021). Further, agricultural production systems that tend to occupy marginal lands, such as livestock or high-tunnel production, are more likely to be owned by a minority producer (Dismukes et al., 1997). Concerns have been raised that base premium rates are not actuarially fair on marginal regions (GAO, 2015).

Our results indicate that – at least partly due to historic land distribution policies – minority and veteran farmers tend to be more exposed to both "tails" of weather risk. These producer groups are disproportionately located in regions of the U.S. with higher risks of drought and in regions with higher risks of excess precipitation. In spite of the higher risks faced by minority and veteran farmers, these producer groups had chronically lower use of crop insurance prior to the implementation of the 2018 Farm Bill. However, the incentive programs created under the 2018 Farm Bill have increased use of federal crop insurance among these vulnerable populations. This indicates that the host of efforts including premium subsidies, education, and wider arrays of policies authorized in the 2018 Farm Bill have impacted crop insurance use in target populations.

The remainder of this paper is organized as follows. Section 2 provides an overview of structural inequities in the U.S. food systems. It details the mechanics of federal crop insurance and then explains incentives for socially disadvantaged producers offered under the 2018 Farm Bill. Section 3 describes the data used in the empirical analysis. Section 4 describes the methods used to answer our two research objectives, and Section 5 reports results. In Section 6, we assess the sensitivity of our findings to alternative constructions of the dependent variable and explanatory variables of interest. Section 7 concludes with a brief discussion of the policy implications of our findings.

2. Background

2.1. Structural inequities in the U.S. food system

Approximately 94% of U.S. farm operations are white-owned (USDA National Agricultural Statistics Service, 2013). In contrast, farms owned by minority operators tend to be smaller – historically, almost half the size of farms owned by white counterparts (Dismukes et al., 1997). Previous research suggests that farm financial performance and other characteristics vary based on the racial profile of the owner, with Black[4] producers generally having less on-farm income, lower debt, and lower government payments (Collins et al., 2024; Horst and Marion, 2019). With regards to agricultural lending, minority producers often encounter disparities such as being approved for lower loan amounts, being subject to higher interest rates, and facing shorter loan maturities (i.e., less time to repay their loans) compared to their non-minority counterparts (Escalante et al., 2018).[5] Further, there are differences in default rates on USDA direct loans with higher delinquency rates among racial minority groups, women, and beginning farmers as compared to a non-Hispanic white male baseline (Vekemans et al., 2024). Further, minority-owned operations tend to specialize in livestock and specialty crop production (Miljkovic, 2005). Davis et al. (2024) found that beef cattle production by minority producers has not experienced the same rate of decline as cropland losses, but disparities in profitability and financial performance exist. These production differences likely exacerbate disparities in government program participation.

2.2. Federal crop insurance and the farm bill

The Federal Crop Insurance Program (FCIP) is designed to help producers mitigate their agricultural risk. The program is permanently authorized and is periodically amended through the Farm Bill. The FCIP is jointly administered by the USDA Risk Management Agency (RMA) and

[4] "Black" and "African American" will be used interchangeably in this paper.

[5] According to Ghimire et al. (2020), these differences may be the result of credit risk management considerations rather than racial discrimination.

the Federal Crop Insurance Corporation. These agencies evaluate new products and set actuarially fair premium rates based on the riskiness of the production area and practices of the producer (Glauber, 2013; Yu et al., 2018). Policies are then sold to producers by local crop insurance agents at a heavily subsidized rate.[6]

The present-day FCIP offers a wide variety of options producers can elect to customize a farm safety net instrument that addresses risk specific to their unique operating environment in the current year. These options include the type of outcome protected (yield, revenue, or margin); type of risk pooling (individual or group-based); level of on-farm risk aggregation (e.g., field, farm, or enterprise); level of coverage (catastrophic (CAT)); and commodity (row crop, livestock, or specialty crop coverage). Crop insurance coverage is available to agricultural producers of eligible crops in all 50 states and Puerto Rico. Participation is over 80% across all eligible field crops as of early 2023. However, 'misrating' in crop insurance premiums has been identified in some parts of the country (Chen et al., 2020) and the potential for misrating may create unintentional, disproportionate effects on Black producers of certain crops (Teal and Stevens, 2024). Further, while specialty crop insurance options are increasing, there may still be areas where historically underserved producers with highly diversified operations may not find benefit from crop insurance participation (Teal and Stevens, 2024).

Figure 1 summarizes the evolution and distribution of U.S. crop insurance participation between 2015 and 2021. In 2021, approximately 2.24 million FCIP policies were sold. The four most common row crops – corn, cotton, soybeans, and wheat – account for over half of the insurance policies sold. As shown in Panel B of the figure, revenue protection (RP) is the most common policy type purchased, accounting for more than 60% of policies sold. County-level participation is highest in the Midwest and Great Plains regions of the U.S. and along the Mississippi River (Panel C).

2.3. Farm bill incentives for socially disadvantaged farmers

The 2018 Farm Bill made several adjustments to the FCIP that may increase crop insurance use for agricultural risk management among socially disadvantaged groups.[7] Socially disadvantaged farmers – redefined under the 2018 Farm Bill to include minority and veteran producers – receive a 10-percentage-point increase in the base subsidy rate for federal crop insurance and waiver of administrative fees (USDA ERS, 2019). Veteran farmers for the purposes of farm bill programs specifically refer to those individuals honorably discharged from the armed services within the 5-year period prior to becoming a farm operator (USDA Risk Management Agency, 2023). In addition, under the 2018 Farm Bill, education partnership projects were expanded to assist the delivery of financial and risk management education to minority producers underserved by crop insurance.

Other changes under the 2018 Farm Bill benefit socially disadvantaged farm groups indirectly. For example, expanded coverage types and subsidies for livestock and specialty crop producers may have a disproportionately higher effect for minority producers, given their outsized participation with these commodities. Federally subsidized rainfall index insurance (a group-based policy) was made available for forage producers, and price and margin protection were made available for livestock producers. Livestock and dairy comprises the primary production for 48% of Black farmers (Mishra et al., 2024), and about 70% of Native American producers receive a majority of their farm income from livestock (Dismukes et al., 1997). Under the 2018 Farm Bill, subsidies for Livestock Risk Protection have also been increased, making it a viable price risk

[6]Current subsidy levels were set under the Agricultural Risk Protection Act of 2000. Subsidy levels are set at 67% subsidy for 50–55% coverage, 64% subsidy for 55–65% coverage, 59% subsidy for 65–75% coverage, 55% subsidy for 75–80% coverage, and 48% subsidy for 80–85% coverage.

[7]These changes are summarized in the USDA Economic Research Service (ERS) "Agriculture Improvement Act of 2018: Highlights and Implications" Report, available at https://www.ers.usda.gov/agriculture-improvement-act-of-2018-highlights-and-implications/beginning-socially-disadvantaged-and-veteran-farmers-and-ranchers/.

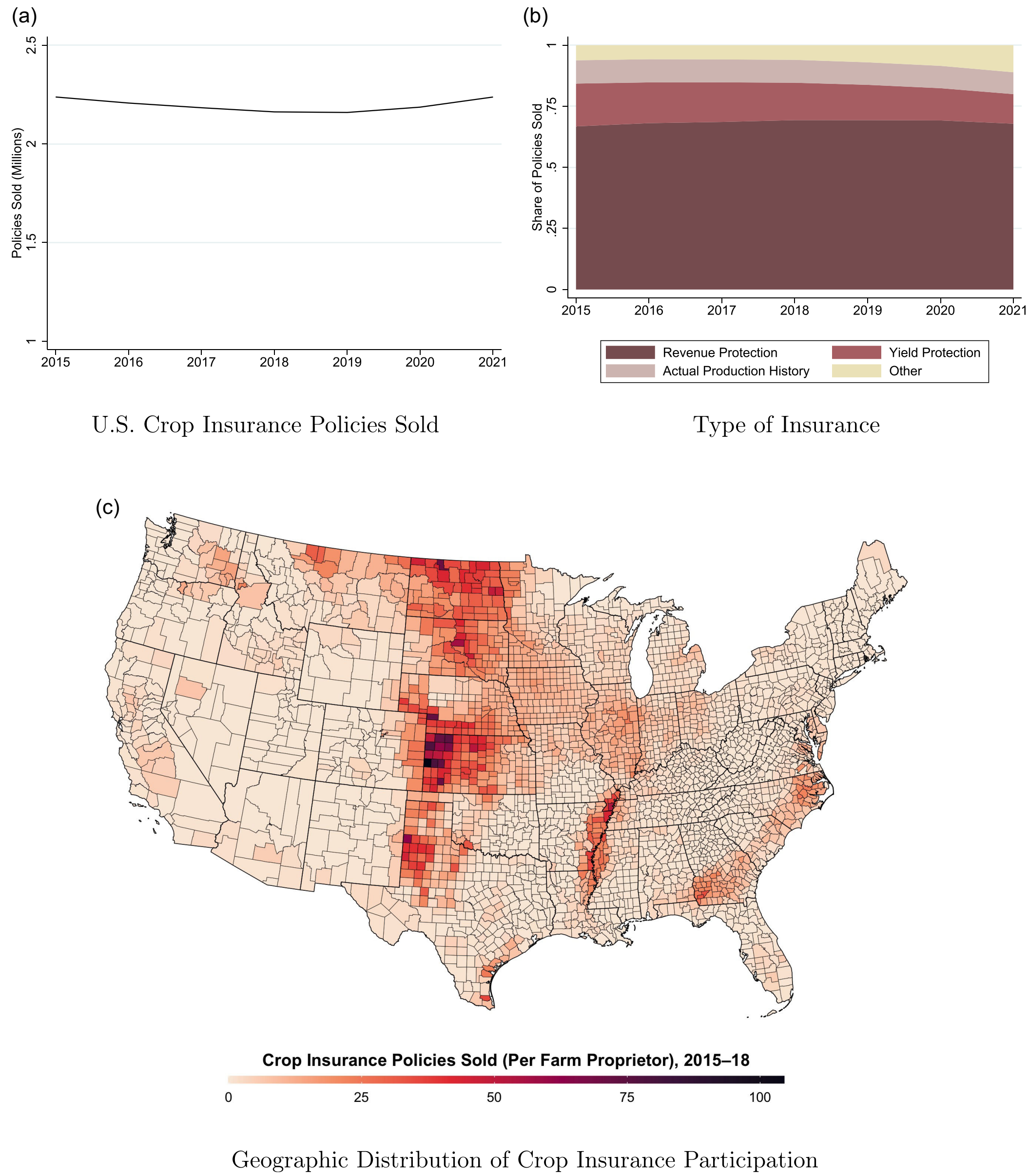

Figure 1. Evolution and distribution of U.S. crop insurance participation. *Notes:* Figure summarizes the evolution and distribution of U.S. crop insurance participation between 2015 and 2021. Panel A reports the number of policies sold in the U.S. each year. Panel B disaggregates these policies by type of insurance (i.e., revenue protection, yield protection, actual production history, or other). Panel C shows the number of crop insurance policies sold (per farm proprietor) in each U.S. county.

management tool for small livestock producers. The 2018 Farm Bill also expanded commodity coverage to include several additional specialty crop policies and designated a Specialty Crops Coordinator, as specialty crops are commonly raised by minority producers.

Finally, the 2018 Farm Bill expanded offerings for Whole-Farm Revenue Protection (WFRP) insurance. While whole-farm insurance is poorly adopted in general (<1% of policies sold nationally), it may be more beneficial to minority producers because it allows highly diversified

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crops on smaller acreages to be covered under a single insurance policy. Record requirements, which may have limited adoption of WFRP, were updated by RMA to improve ease of use. Section 11108 of the 2018 Farm Bill charged USDA RMA with completing a study to measure the adequacy of FCIP coverage for historically underserved producers. Using 2017 data, RMA found that participation rates for socially disadvantaged (38 to 51%) and veteran producers (62%) were lower than the participation rate across all producers (64%) (USDA Risk Management Agency, 2021). By crop, results found that low state participation rates were found more commonly for fruit crops or field crops used for cover crop or grazing; further, by region, western states where diverse farming operations were more frequently found to have underserved crops (USDA Risk Management Agency, 2021). In response to the 2018 Farm Bill, RMA expanded the availability of MPCI to an additional 318 crop-county combinations by 2020 (USDA Risk Management Agency, 2021). Together, the 2018 Farm Bill changes to the FCIP and other risk management programs combined to create an agricultural policy environment with more assurances and incentives for socially disadvantaged producers. Below we investigate the extent to which these changes translated into increased use of crop insurance for this vulnerable population.

3. Data

Our analysis incorporates data from three distinct categories of variables. First, we collected information on annual enrollments in federal crop insurance, which was gathered from the USDA Risk Management Agency. Our key outcome variable is the annual number of policies sold – pooled across all levels of coverage – for a given commodity in each U.S. county between 2015 and 2021. Previous literature has used national events – in this case the 2018 Farm Bill – as a potential source of exogenous structural change in FCIP (for example Connor and Katchova (2020), Schoengold et al. (2015) and Wang et al. (2021)). Additional discussion of the challenges in crop insurance data use can be found in Tsiboe and Turner (2023b).

Second, we obtained demographic data for each county, including the share of racial and ethnic minorities (Figure 2.a) and the share of veterans (Figure 2.b). Specific demographic information about producers in each county is not consistently available from sources such as the NASS Census of Agriculture, in which less than a quarter of U.S. counties have complete information on producers' racial and ethnic background.[8] Thus, we use the 2010 decennial census data (gathered from the ERS Rural Atlas) to proxy for the proportions of each racial or ethnic category within a given county (Figure 3).

To investigate the validity of proxying for producer demographics with county demographic information more broadly, Figure 4 illustrates the relationship between census demographic population shares and NASS producer demographics (only for the counties where such data is available). Across all four of the racial and ethnic groups that we focus on in this study, the correlation between the two ranges between 0.792 and 0.845, suggesting that census demographic data – which is not incomplete – is a strong proxy for the geographic distribution of socially disadvantaged farmers.

Finally, we used meteorological data to account for the incidence and severity of severe weather events. Specifically, we collected information regarding annual incidence of both drought and excess precipitation, which represent two of the more common weather hazards producers may be exposed to. Since 2000, about 70% of total indemnity payments on crop insurance were attributed to either drought and high temperatures or excess moisture (Tsiboe and Turner, 2023a). We collected annual precipitation data from the U.S. Center for Disease Control, which indicated the number of days in which a county received three or more inches of rainfall or snowfall

[8]Of the 3,075 counties reporting at least one producer to NASS in 2017, a total of 688 counties (22.4%) have complete producer counts for Black, Hispanic, Asian, and American Indian producers. Of these 688 counties, 57 are labeled by ERS as "farm dependent" (about 11% of the 507 farm dependent counties overall).

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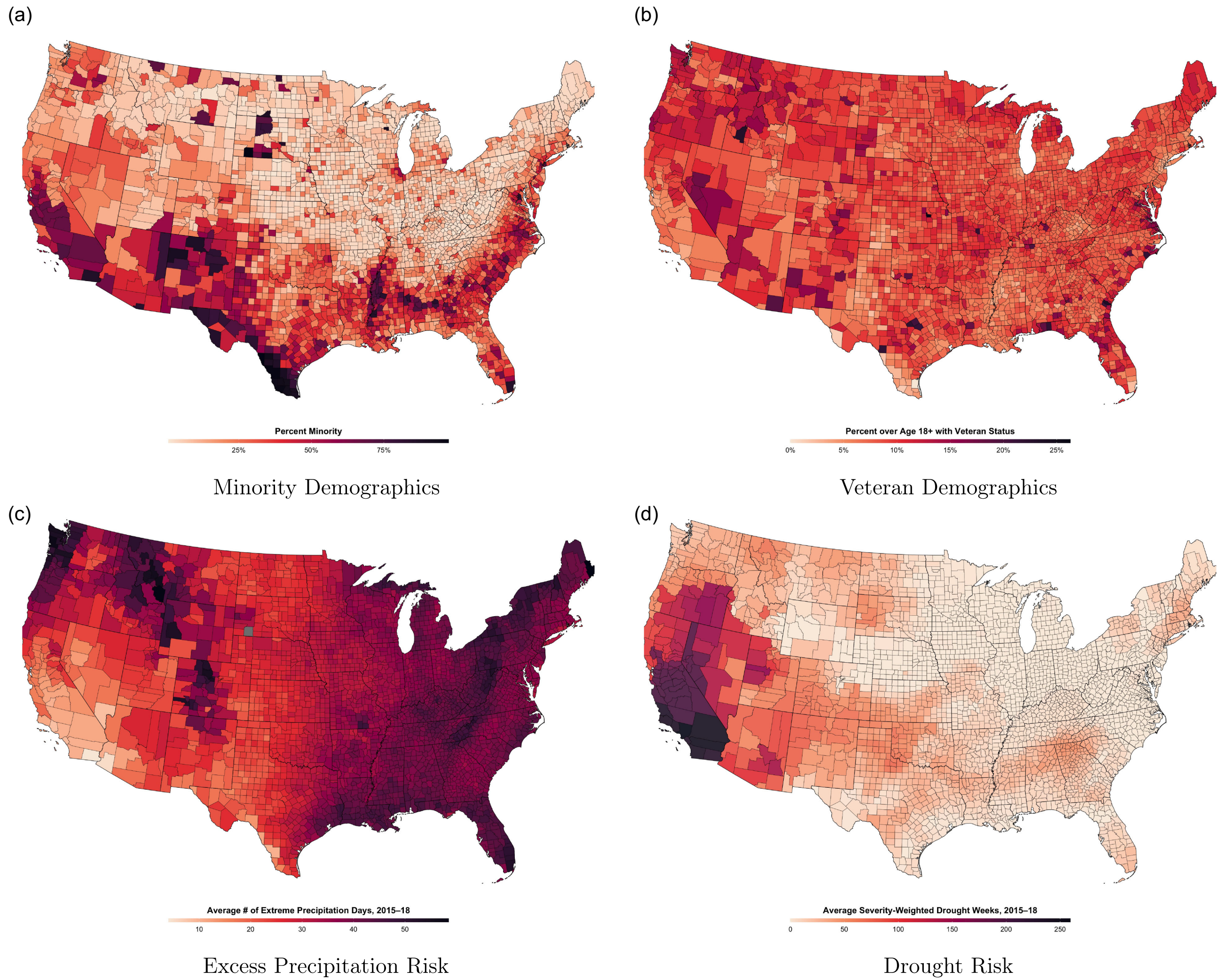

Figure 2. Distribution of agricultural risk and county demographics. *Notes:* Figure shows the share of racial and ethnic minorities (panel a) and the share of veterans (panel b) within a given county based on the 2010 decennial census. Panels c and d show the number of days in which a county received three or more inches of rainfall or snowfall and the county-level, growing-season-weighted index created by Haddock et al. (2023) to measure the incidence and severity of drought.

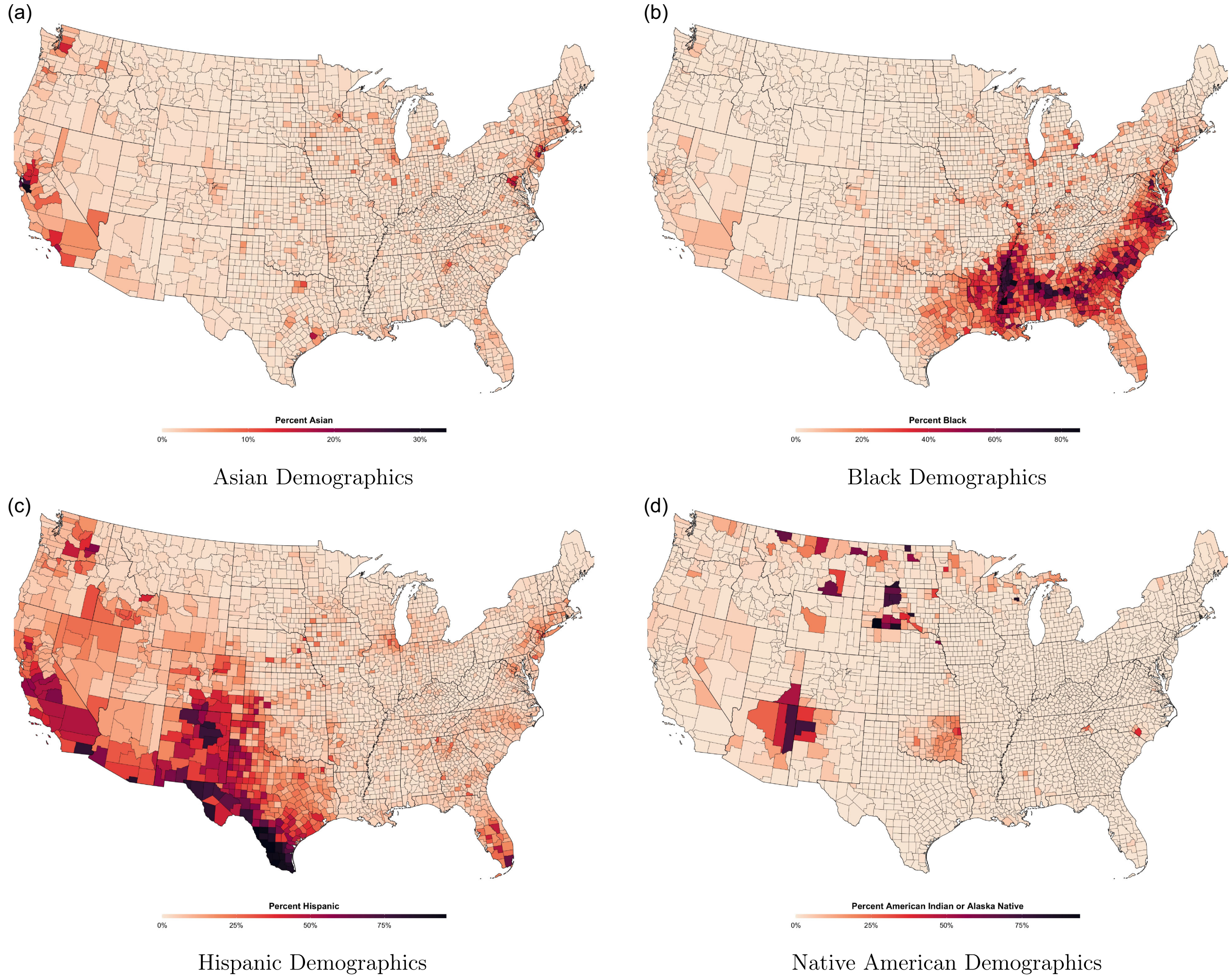

Figure 3. Distribution of minority demographic groups. *Notes:* Figure shows the proportions of each racial or ethnic category within a given county based on the 2010 decennial census.

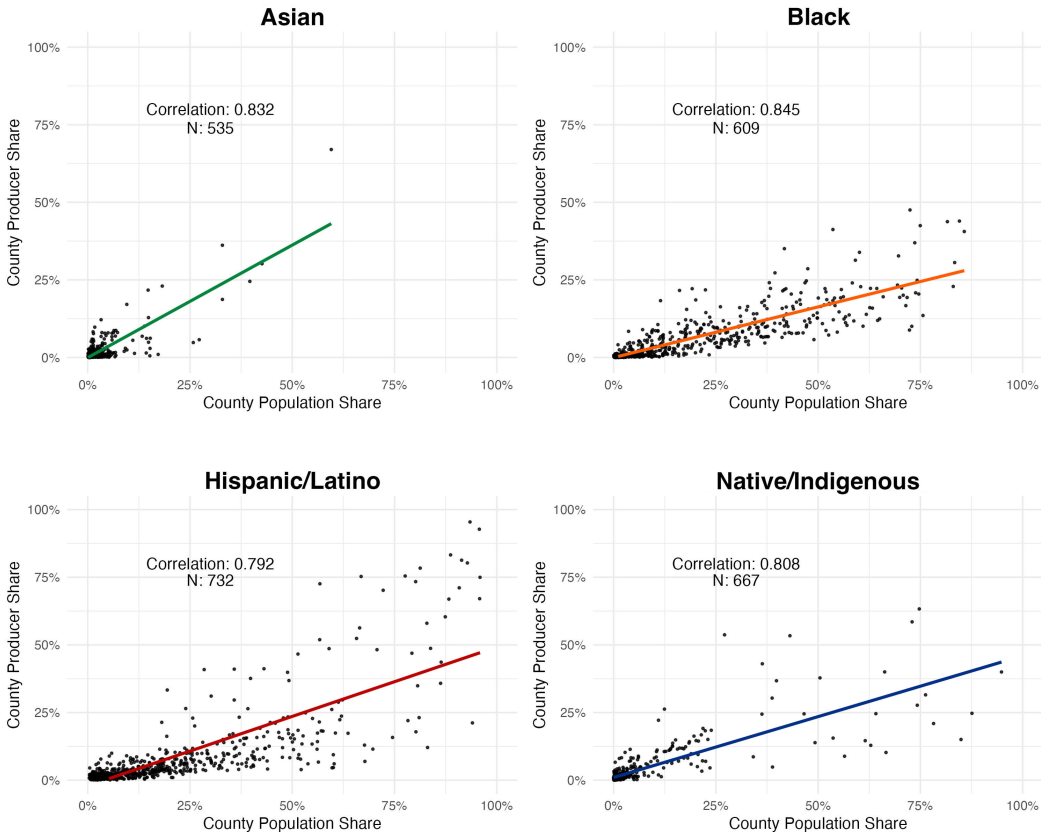

Figure 4. County and producer demographic correlations. *Notes:* Figure illustrates the relationship between census demographic population shares and NASS producer demographics (only for the counties where such data is available). Across all four of the racial and ethnic groups that we focus on in this study, the correlation between the two ranges between 0.79 and 0.85, suggesting that census demographic data – which is not incomplete – is a strong proxy for the geographic distribution of socially disadvantaged farmers. Each plot's N represents the number of counties for which complete USDA NASS data (on producer race/ethnicity) is available. This number should be understood in comparison with the over 3,100 counties in the U.S.

(Figure 2.c). To measure the incidence and severity of drought, we used a county-level, growing-season-weighted index created by Haddock et al. (2023) (Figure 2.d).

4. Methodology

We use the three data sources described above to compile a dataset with annual enrollments in federal crop insurance in each U.S. county for 123 different crops from 2015 to 2021, county demographics, and county-level measures for the presence and severity of drought and excess precipitation on an annual basis. We use this data to empirically map inequities in the domain of agricultural risk and investigate whether recent policy efforts have improved use of modern risk management tools among socially disadvantaged farmers.

Our empirical analysis is divided into two arms. First, in Section 4.1, we assess the presence and extent of structural inequities in U.S. agricultural risk management prior to the implementation of the 2018 Farm Bill. We evaluate these inequities in terms of the magnitude of agricultural risk factors socially disadvantaged farmers faced (measured using our drought and excess precipitation variables). We then ask whether – accounting for these risks – minority and veteran producers had unequal use of federal crop insurance to manage these risks.

Second, in Section 4.2, we use an event study design to investigate whether incentive programs adopted under the 2018 Farm Bill have increased use of federal crop insurance among minority and veteran producers. All U.S. counties are "treated" by the implementation of the 2018 Farm Bill. Therefore, we identify the success (or failure) of the 2018 Farm Bill at mitigating structural inequities in use of federal crop insurance by testing whether the *intensity* of this treatment (on policy enrollment outcomes) relates to a county's demographic composition.

4.1. Mapping structural inequities in agricultural risk management

We use a simple, pooled cross-section design to map structural inequities in U.S. agricultural risk management between 2015 and 2018 (i.e., prior to implementation of the 2018 Farm Bill). Note that with this cross-sectional design we make no claim of causality. Rather, the investigation is purely structural – is there a systematic relationship between the presence of minority and veteran demographics in a county and the agricultural production risk (and/or use of crop insurance) in the county?

Inequities in Agricultural Production Risk: To test whether the magnitude of agricultural risk in a given county was correlated with the presence of racial minorities and veterans, we estimate models where the dependent variable is specified as the Haddock et al. (2023) drought score for a given county in a given year or, alternatively, the number of days in which the county received three or more inches of rain or snowfall for the year. Our two (explanatory) variables of interest are the percentage of the county population that identifies as a racial minority and the percentage of the county population that are U.S. veterans. Note that – because these variables come from the decennial U.S. census – these demographic variables are time-invariant. In each model, we also include additional controls that measure the percentage of the county labor force that is employed in agriculture and the county's position along the Rural-Urban continuum. The Rural-Urban continuum (RUC) published by USDA Economic Research Service uses population size to distinguish metropolitan counties and degree of urbanization and distance to a metro area to distinguish non-metropolitan counties (https://www.ers.usda.gov/data-products/rural-urban-continuum-codes/documentation/ 2023). The RUC codes range from 1 to 9, with 1 being fully urban and 9 being fully rural.[9]

Differences in Use of Crop Insurance: We use a similar model to test whether the use of crop insurance was correlated with the presence of these demographic groups over the same period. The dependent variable in this model is the number of crop insurance policies sold for a given county-crop combination in a given year. Explanatory variables of interest, as well as the other model controls, are consistent with those described above. Additionally, in this model, we also include the Haddock et al. (2023) drought score and the number of days with $\geq$3 inches of precipitation as added model controls to account for the county's risk profile. We include the variables on both a contemporaneous and a 1-year lagged basis. Because planting and crop insurance decisions are made before actual weather patterns are known, the contemporaneous weather variable allows for the fact that farmers can use weather forecast information to create a fairly accurate opinion as to what weather will be for the upcoming year. The (somewhat myopic) lagged representation allows farmers to form expectations of the upcoming year based on the weather outcomes in the previous year.

Characterization of Racial Minority Demographics: We consider models where racial minorities are characterized as an aggregate "Minority" category as well as models where racial

[9]Note that – for these purposes – the Rural-Urban continuum is treated as a continuous variable for the purposes of interpretation. In reality, the variable is ordinal (rather than cardinal). Our results are robust to the specification of the Rural-Urban continuum as a categorical (rather than continuous) variable.

minorities are disaggregated into four separate explanatory variables: the percentage of county population that identifies as Asian, the percentage that identifies as Black, the percentage that identifies as Native American, and the percentage that identifies as Hispanic or Latino(a). The purpose for this aggregate versus disaggregate characterizations is straightforward. For the purposes of Farm Bill "socially disadvantaged farmers" definitions and incentives, these ethnic groups are effectively synonymous. However, from a modern economic geographical perspective (as well as from a historical land distribution perspective), these demographic groups are concentrated in different areas of the U.S. and face divergent discriminatory, social, and political hurdles to farming and risk management.

Functional Form: Because the dependent variables in both the "agricultural production risk" specifications and the "use of crop insurance" specifications are "count" variables, we fit all models using Poisson Pseudo-Maximum Likelihood (PPML) estimation.[10]

4.2. Mitigating structural inequities in agricultural risk management

We use an event study design to measure the effects of federal crop insurance incentive programs implemented under the 2018 Farm Bill on use of federal crop insurance among socially disadvantaged farmers. To do so, we use data for our entire sample period (2015–2021) to estimate the following model:

$$\text{Policies}_{ipt} = \beta_0 + \beta_1 \text{FB}_t + \beta_2 \left(\text{Minority}_i \times \text{FB}_t\right) + \beta_3 (\text{Veteran}_i \times \text{FB}_t) + \mathbf{X}'\omega + e_{ipt} \quad (1)$$

where dependent variable Policies_{ipt} denotes the number of crop insurance policies sold – pooled across all levels of coverage – for a given commodity p in a given county i in year t.

Treatment Effects: Variable FB_t is an indicator to denote years following implementation of the 2018 Farm Bill (i.e., the treatment period). The variable takes value one for all years on or after 2019, and is zero otherwise. As all counties were "treated" by the implementation of the 2018 Farm Bill, we identify the successes (or failures) of the 2018 Farm Bill in addressing differences in the use of federal crop insurance via the terms $\text{Minority}_i \times \text{FB}_t$ and $\text{Veteran}_i \times \text{FB}_t$, which interact our time-invariant demographic variables of interest with the treatment period indicator. This design tests whether the *intensity* of treatment relates to a county's population share of socially disadvantaged groups. As with the cross-sectional analysis above, we estimate equation (1) using specifications where racial minorities are characterized as an aggregate "Minority" category as well as models where racial minorities are disaggregated into four separate groups (Asian, Black, Native, and Hispanic/Lationo(a)). The "net" treatment effects of the 2018 Farm Bill differ for each county and are a function of the county demographic composition. These "net" effects are derived as the linear combinations $\hat{\beta}_1 + \hat{\beta}_2 \times \text{Minority}_i$ and $\hat{\beta}_1 + \hat{\beta}_3 \times \text{Veteran}_i$.

Model Fixed Effects and Additional Controls: Vector X in equation (1) includes panel fixed effects (i.e., intercepts for each county-crop combination). Thus, our estimates of β_1, β_2, and β_3 are estimated using only "within group" variation. Also included as controls in vector $\mathbf{X}$ are the Haddock et al. (2023) drought score and the number of days with $\geq$3 inches of precipitation to account for counties' time-varying risk profiles. As in the cross-sectional analysis, we include these weather variables on both a contemporaneous and a 1-year lagged basis.

Economic Significance of Crop Insurance Incentives: Even if the results from estimating equation (1) suggest that incentive programs implemented under the 2018 Farm Bill had a *statistically* significant effect at increasing the use of federal crop insurance, a remaining question is the *economic* significance of these results. To evaluate this, we use our econometric results to

[10]As a robustness check, we also re-ran all of our specifications using ordinary least squares (OLS). The results of the linear model are highly consistent with the results from the PPML model, both with respect to sign and statistical significance. The OLS results are not reported here but are available from the authors upon request.

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calculate the total number of additional federal crop insurance policies sold across the U.S. as a result of 2018 Farm Bill incentive programs for socially disadvantaged farmers.

5. Results

Section 5.1 reports results with respect to the presence and extent of structural inequities in U.S. agricultural risk management prior to the implementation of the 2018 Farm Bill. Section 5.2 reports the results of the event study design to investigate whether incentive programs adopted under the 2018 Farm Bill have increased use of federal crop insurance among minority and veteran producers.

5.1. Mapping structural inequities in agricultural risk management

Cross-sectional results in Table 1 suggest that structural inequities in U.S. agricultural risk management are substantial – both with respect to the magnitude of agricultural risk factors (Columns 1–4 of Table 1) and the utilization of federal crop insurance to manage these risks (Columns 5 and 6 of Table 1).

Inequities in Drought Risk: We refer first to the systematic relationship between socially disadvantaged farming and drought risk. As shown in Column (1) of Table 1, we see that counties with a larger minority share were statistically more prone to severe drought risk. A 1% increase in the share of the population who identifies as a racial minority is associated with a 1.59% increase (statistically significant at the 1% level) in drought severity.

When racial minority groups are disaggregated in Column (2), we see that this geographic relationship is primarily attributable to Asian, Native, and Hispanic populations. A 1% increase in Asian population share is associated with a 3.5% increase (statistically significant at the 1% level) in drought risk. For Native and Hispanic populations, the elasticities are 1.56% and 2.28% (both statistically significant at the 1%), respectively.

We also see a statistically significant relationship between the location of veteran farmers and drought risk. According to Column (1), a 1% increase in county veteran population share is associated with a 4.27% increase (statistically significant at the 1% level) in drought severity. We hypothesize that this relationship is, in part, attributable to the large clusters of veteran populations in counties with military bases (Figure 2.b).

Inequities in Excess Precipitation Risk: Referring to Columns (3) and (4) of Table 1, our results also suggest that socially disadvantaged farmers face higher risk of excess precipitation. As shown in Column (3), a 1% increase in minority populations is associated with a 1.97% increase (statistically significant at the 1% level) in the number of days with excess precipitation. When we disaggregate by minority groups by ethnicity in Column (4), we see that this result is associated with higher shares of counties' Black and Hispanic population. A 1% increase in the Black and Hispanic population shares are associated with 2.89% and 1.09% increases in the number of days with excess precipitation (both statistically significant at the 1% level). Again, this relationship also holds for veterans. According to Column (3), a 1% increase in a county's veteran share is associated with a 4.64% increase (statistically significant at the 1% level) in the number of days with excess precipitation.

Differences in the use of Crop Insurance: Although counties with higher minority populations face greater agricultural risk, Columns (5) and (6) of Table 1 suggest that – controlling for risk – these counties have statistically significantly less use of federal crop insurance. Referring to Column (5), we see that over the period of analysis, counties with a larger minority share had statistically significantly less enrollment in federal crop insurance (statistically significant at the 1% level). When we disaggregate racial minorities by ethnicity, this relationship remains statistically significant at the 1% level for Black, Native, and Hispanic American populations (Column 6). Results also hold for veterans in both Columns.

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Table 1. Mapping structural inequities in U.S. agricultural risk management

	(1)	(2)	(3)	(4)	(5)	(6)
	Drought Risk		Excess Moisture Risk		Use of Federal Crop Ins.	
Variables	Aggregated	Disaggregated	Aggregated	Disaggregated	Aggregated	Disaggregated
Minority (%)	0.0159***		0.0197***		−0.0079***	
	(0.0004)		(0.0003)		(0.0004)	
Disaggregated						
Asian (%)		0.0347***		0.0145		−0.0125
		(0.0081)		(0.0094)		(0.0101)
Black (%)		−0.0011		0.0289***		−0.0144***
		(0.0007)		(0.0004)		(0.0006)
Native (%)		0.0156***		−0.0108***		−0.0103***
		(0.0007)		(0.0016)		(0.0007)
Hispanic (%)		0.0228***		0.0109***		−0.0031***
		(0.0004)		(0.0005)		(0.0005)
Veteran (%)	0.0427***	0.0549***	0.0464***	0.0459***	−0.0731***	−0.0685***
	(0.0043)	(0.0042)	(0.0028)	(0.0029)	(0.0035)	(0.0034)
Ag. Emp. (%)	0.0394***	0.0317***	−0.0942***	−0.0781***	0.0118***	0.0098***
	(0.0013)	(0.0013)	(0.0021)	(0.0021)	(0.0009)	(0.0009)
Rural-Urban Cont.	0.0115**	0.0203***	0.0283***	0.0190***	0.0270***	0.0309***
	(0.0050)	(0.0054)	(0.0038)	(0.0041)	(0.0032)	(0.0036)
Drought					−0.0004	−0.0007***
					(0.0003)	(0.0003)
Drought (L)					−0.0054***	−0.0054***
					(0.0003)	(0.0003)

(*Continued*)

Table 1. (*Continued*)

Variables	(1) Drought Risk Aggregated	(2) Drought Risk Disaggregated	(3) Excess Moisture Risk Aggregated	(4) Excess Moisture Risk Disaggregated	(5) Use of Federal Crop Ins. Aggregated	(6) Use of Federal Crop Ins. Disaggregated
Ext. Moisture					−0.1097***	−0.0756***
					(0.0128)	(0.0132)
Ext. Moisture (L)					−0.0725***	−0.0468***
					(0.0118)	(0.0119)
Constant	1.5340***	1.4966***	−1.6672***	−1.6475***	5.5328***	5.4718***
	(0.0518)	(0.0554)	(0.0329)	(0.0385)	(0.0389)	(0.0422)
Observations	62,337	62,337	62,337	62,337	45,259	45,259

Robust standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

Table 2. Mitigating structural inequities under the 2018 farm bill

	(1)	(2)	(3)
	Crop Insurance Policies Sold		
Variables	ATE	HTE[a]	HTE[a] Disaggregated
Farm Bill	−0.0006	−0.0473***	−0.0359***
	(0.0006)	(0.0034)	(0.0034)
Heterogeneous Effects			
Minority (%) × Farm Bill		0.0009***	
		(0.0000)	
Asian (%) × Farm Bill			−0.0004
			(0.0006)
Black (%) × Farm Bill			0.0021***
			(0.0001)
Native (%) × Farm Bill			0.0002***
			(0.0001)
Hispanic (%) × Farm Bill			0.0001
			(0.0001)
Veteran (%) × Farm Bill		0.0039***	0.0028***
		(0.0004)	(0.0004)
Drought	−0.0000***	−0.0000***	0.0000
	(0.0000)	(0.0000)	(0.0000)
Drought (L)	0.0000	−0.0000	0.0001***
	(0.0000)	(0.0000)	(0.0000)
Ext. Moisture	−0.0018**	−0.0005	0.0004
	(0.0009)	(0.0009)	(0.0009)
Ext. Moisture (L)	−0.0023***	−0.0011	−0.0007
	(0.0008)	(0.0008)	(0.0008)
Constant	5.7829***	5.7824***	5.7810***
	(0.0006)	(0.0006)	(0.0006)
Observations	91,367	91,367	91,367

[a]The acronym HTE standards for "heterogeneous treatment effects."
Robust standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

5.2. Mitigating structural inequities in agricultural risk management

Table 2 reports the results of our event study analysis. Column (1) reports the "average treatment effect" (ATE) of the 2018 Farm Bill for all counties. The point estimate is near zero and is statistically insignificant. Thus, we conclude that the 2018 Farm Bill did not have a measurable effect on the crop insurance enrollments for the "average" U.S. county.

Columns (2) and (3) of the Table show the results where we include interactions between our 2018 Farm Bill indicator and our (time-invariant) measures of minority and veteran

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demographics. These results suggest that the incentive programs adopted under the 2018 Farm Bill have increased use of federal crop insurance among socially disadvantaged farm populations. Referring to Column (2) of the Table, we see that implementation of the 2018 Farm Bill generates a larger treatment effect for counties with a larger minority population. According to our results, a 1% increase in a county's minority share increases the estimated treatment effect of the 2018 Farm Bill on federal crop insurance sign-ups by 0.09% (statistically significant at the 1% level). When we run the model on a disaggregated basis, the effect is statistically significant at the 1% level for Black and Native populations. Interestingly, the magnitude of the estimated effect is ten times larger for Black Americans than for the Native populations. A 1% increase in the share of Black Americans in a county increases the estimated treatment effect by 0.21%.

The imposition of the 2018 Farm Bill also generated a statistically significant effect on crop insurance enrollment among veteran farmers. This effect is much larger in magnitude than for minority producers. According to Column (2) of Table 2, a 1% increase in the veteran population increases the treatment effect of the 2018 Farm Bill by 0.39%.[11]

The "Farm Bill" variable in Column (2) and Column (3) indicates the number of policies sold to non-historically underserved producers is significantly reduced after the 2018 farm bill, with an exception identified in Table 3 for "other" policy types. This may indicate an influence of consolidation in farm numbers generally, as revealed in the 2022 Census of Agriculture. Large numbers of counties experienced a decline in total producer numbers in 2022 versus the 2017 Census of Agriculture. Interestingly, the 2022 Census of Agriculture also showed increases in land owned or operated by producers that are American Indian or Alaska Native, Asian, and Black or African American. This reinforces the results in Column (2) and Column (3) for the interaction terms. This result opens up possibilities for future research.

"Net" Treatment Effects of the 2018 Farm Bill: Based on the results in Column (2) of Table 2, Figure 5 reports the "net" treatment effects in a given county, as a function of its demographic composition. These effects are derived as the linear combinations $\hat{\beta}_1 + \hat{\beta}_2 \times \text{Minority}_i$ and $\hat{\beta}_1 + \hat{\beta}_3 \times \text{Veteran}_i$. The vertical dashed lines in the Figure show the 25th and 75th percentiles for minority and veteran demographics for counties in our dataset.

Economic Significance of Crop Insurance Incentives: Figure 6 gauges the *economic* significance of the results in Table 2 using the aggregation procedure described in Section 4.2. This analysis suggests that incentive programs for minority farmers resulted in approximately 31,000 additional federal crop insurance policies sold per year (1.5% of U.S. policies). Additionally, the 2018 Farm Bill resulted in approximately 63,000 additional federal crop insurance policies sold per year (3.1% of U.S. policies) for veteran farmers.

6. Model robustness

In this Section, we conduct a number of additional analyses to gauge the reliability and robustness of our results. Specifically, we explore the sensitivity of our findings to alternative constructions of the dependent variable and explanatory variables of interest.

6.1. Impacts by crop insurance type

We first perform a robustness check to determine whether the generality of our findings holds across different types of crop insurance. To do so, we disaggregate our dependent variable $Policies_{ipt}$ from equation (1) into four different types of insurance – Revenue Protection (RP),

[11]We note that the estimated treatment effect for veterans falls in Column (3) compared to Column (2). This result is due to the correlation structure between variable Veteran (%) × Farm Bill and variable Minority (%) × Farm Bill in Column (2) and the disaggregated ethnicity variables in Column (3). The inclusion of the Asian, Native, and Hispanic treatment effects reduce the magnitude of the estimated Veteran effect.

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Table 3. Impacts of the 2018 farm bill by crop insurance type

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Revenue Protection		Yield Protection		APH		Other Policy	
VARIABLES	Aggregated	Disaggregated	Aggregated	Disaggregated	Aggregated	Disaggregated	Aggregated	Disaggregated
Farm Bill	−0.0210***	−0.0058**	−0.2158***	−0.2105***	−0.0794***	−0.0940***	0.1987***	0.3303***
	(0.0027)	(0.0028)	(0.0080)	(0.0078)	(0.0090)	(0.0095)	(0.0307)	(0.0302)
Heterogeneous Effects								
Minority (%) × Farm Bill	0.0010***		0.0004***		0.0008***		0.0012***	
	(0.0000)		(0.0001)		(0.0001)		(0.0004)	
Asian (%) × Farm Bill		−0.0052***		0.0044***		0.0000		−0.0022
		(0.0005)		(0.0015)		(0.0018)		(0.0053)
Black (%) × Farm Bill		0.0015***		−0.0000		0.0004**		0.0158***
		(0.0001)		(0.0001)		(0.0002)		(0.0007)
Native (%) × Farm Bill		0.0011***		0.0024***		−0.0003		−0.0043***
		(0.0001)		(0.0002)		(0.0002)		(0.0007)
Hispanic (%) × Farm Bill		0.0005***		0.0002		0.0015***		−0.0064***
		(0.0001)		(0.0001)		(0.0001)		(0.0004)
Veteran (%) × Farm Bill	0.0014***	0.0003	0.0019**	0.0010	0.0022**	0.0040***	0.0189***	0.0019
	(0.0003)	(0.0003)	(0.0008)	(0.0008)	(0.0009)	(0.0010)	(0.0033)	(0.0031)
Drought	0.0000***	0.0000***	−0.0006***	−0.0006***	0.0000	−0.0000	0.0009***	0.0015***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Drought (L1)	−0.0001***	−0.0001***	−0.0002***	−0.0002***	0.0002***	0.0001***	0.0006***	0.0014***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0001)	(0.0001)
Ext. Moisture	0.0021***	0.0019***	0.0041**	0.0036**	0.0084***	0.0081**	−0.0083	0.0112
	(0.0007)	(0.0007)	(0.0018)	(0.0018)	(0.0032)	(0.0032)	(0.0079)	(0.0078)

(*Continued*)

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Table 3. (*Continued*)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Revenue Protection		Yield Protection		APH		Other Policy	
VARIABLES	Aggregated	Disaggregated	Aggregated	Disaggregated	Aggregated	Disaggregated	Aggregated	Disaggregated
Ext. Moisture (L1)	−0.0001	−0.0006	0.0113***	0.0108***	0.0073**	0.0073**	−0.0275***	−0.0177**
	(0.0006)	(0.0006)	(0.0016)	(0.0016)	(0.0030)	(0.0030)	(0.0076)	(0.0075)
Constant	5.8491***	5.8489***	4.2795***	4.2798***	4.6387***	4.6396***	3.4123***	3.3773***
	(0.0005)	(0.0005)	(0.0015)	(0.0015)	(0.0016)	(0.0016)	(0.0071)	(0.0072)
Observations	54,502	54,502	53,006	53,006	26,963	26,963	61,759	61,759

Robust standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

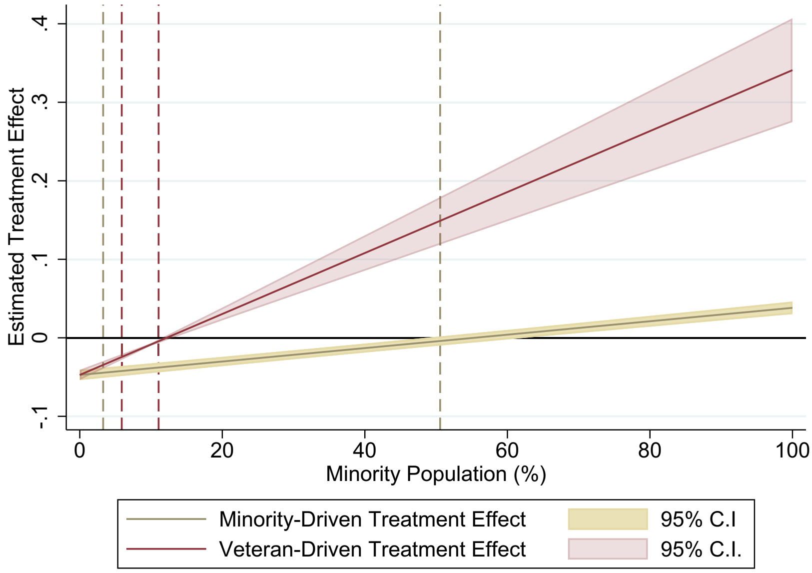

Figure 5. Estimated "net" treatment effects of the 2018 farm bill. *Notes:* Figure reports the "net" treatment effects in a given county, as a function of its demographic composition. These effects are derived as the linear combinations $\hat{\beta}_1 + \hat{\beta}_2 \times \text{Minority}_i$ and $\hat{\beta}_1 + \hat{\beta}_3 \times \text{Veteran}_i$. The vertical dashed lines in the Figure show the 25th and 75th percentiles for minority and veteran demographics for counties in our dataset.

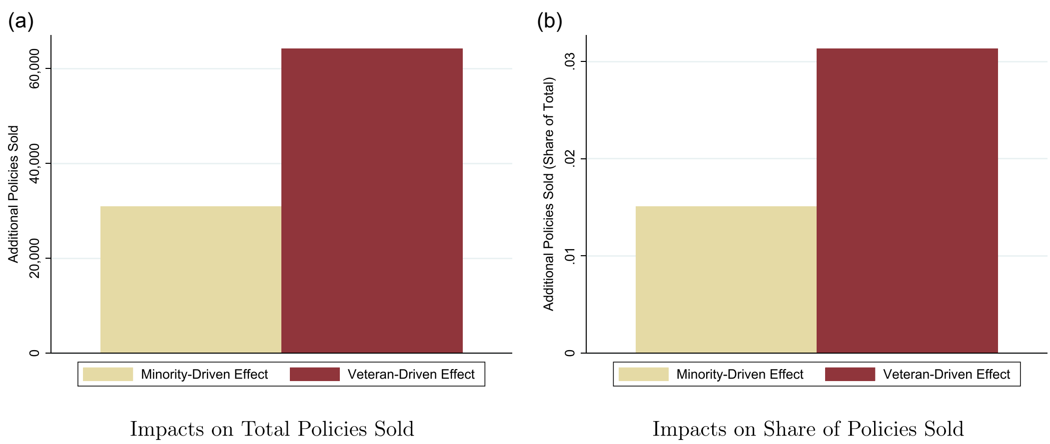

Figure 6. Aggregated effects of farm bill incentives on crop insurance enrollment. *Notes:* Figure summarizes the aggregated effects of 2018 Farm Bill incentive programs for socially disadvantaged farmers and veterans on federal crop insurance policies sold. Panel (a) reports these results in terms of the total number of additional policies sold. Panel (b) shows these same results as the share of total federal crop insurance policies sold.

Yield Protection (YP), Actual Production History (APH), and "Other" Policies. As in our original analysis, for each of these different types of insurance, we compute the annual number of policies sold – pooled across all levels of coverage – for a given commodity in each U.S. county between 2015 and 2021. We then re-estimate equation (1) separately for RP, YP, APH, and "Other" crop insurance policies sold as dependent variable.

Table 3 reports the results of this robustness check. These results suggest that the impacts of the 2018 Farm Bill on crop insurance uptake among socially disadvantaged farmers hold across each type of insurance. The largest impacts for minorities appear to be for RP and "other" insurance policies. A 1% increase in a county's minority population increases the treatment effect for RP coverage by 0.10% and for "other" coverage by 0.12%, compared with 0.08% for APH and 0.02% for YP.

However, the different types of crop insurance are designed to protect against risk differently and against different sources of risk. As discussed above, minority groups are geographically concentrated in different parts of the U.S., and, thus, may face different sources of risk. So, even though we see an increase in all types of crop insurance among socially disadvantaged farmers that is associated with the 2018 Farm Bill, the results for any given crop insurance type may be driven by a subset of racial minorities.

To investigate this, Table 3 also shows the impacts of the 2018 Farm Bill on different crop insurance types disaggregated by minority group. The increase in revenue protection and "other" policies appears to have been primarily driven by Black populations (both effects statistically significant at the 1% level). In contrast, the increase in yield protection plans appears to have been driven by Asian populations (statistically significant at the 1% level). Native populations were a major driver of the increase in revenue protection and yield protection plans among socially disadvantaged farmers (both effects statistically significant at the 1% level). Hispanic populations contributed to the increase in revenue protection plans and APH policies among socially disadvantaged farmers (both effects statistically significant at the 1% level).

Still referring to Table 3, we see that – for veterans – the largest impact appears to be for APH insurance. As shown in Column (5), a 1% increase in the share of veterans in a given county increases the treatment effect of the 2018 Farm Bill for APH coverage by 0.22%, compared with 0.19% for YP, 0.14% for RP, and 0.12% for "other."

6.2. Impact on acres under revenue protection

We next investigate the extent to which our results are a function of our choice to use number of policies sold as the dependent variable for our analysis rather than acreage. As discussed in the Introduction, our identification strategy is most closely related to the works of Tsiboe and Turner (2023b) and Yu et al. (2018) in that both of these studies identify the impacts of premium subsidies by looking at the (exogenous) timing of the Farm Bill cycle. However, our approach differs from these studies in that our baseline models uses the number of crop insurance policies sold as the dependent variable, whereas Tsiboe and Turner (2023b) and Yu et al. (2018) analyze the effects of Farm Bill policy changes on insured acreage. This difference is a matter of necessity rather than choice. Because our analysis measures effects across the full range of insured commodities, many of the insurance schemes are measured in units other than acreage (e.g., colonies, tons, and trees).

To determine whether our results are an artifact of our dependent variable choice rather than the true effect of the policy treatment, we re-estimate the analyses described in Sections 4.1 and 4.2 substituting the dependent variable as the number of acres in a county covered by a revenue protection insurance policy.

Table 4 reports the results of this robustness check. Columns (1) and (2) show the results of the cross-sectional analysis from Section 4.1, and Columns (3) and (4) show the results measuring the impacts of the 2018 Farm Bill. Consistent to our baseline findings, we see in Column (1) that – prior to the 2018 Farm Bill – the presence of social minorities and veterans in a county was negatively correlated with the number of crop acreage with revenue protection insurance. These relationships are statistically significant at the 1% level.

When we disaggregate minority groups in Column (2) of Table 4, we see that the negative correlation between social minorities and county-level RP acreage holds for Black populations, Native populations, and Hispanic populations. For each of these demographic groups, the negative relationship with RP acreage is statistically significant at the 1% level.

Results in Column (3) of Table 4 are also consistent with our baseline findings of 2018 Farm Bill incentives on crop insurance enrollment among socially disadvantaged farmers.

Table 4. RP acreage as an alternative dependent variable

	(1)	(2)	(3)	(4)
	Cross-Sectional Analysis		Farm Bill HTE	
Variables	Aggregated	Disaggregated	Aggregated	Disaggregated
Minority (%)	−0.0169***			
	(0.0008)			
Disaggregated				
Asian (%)		0.0059		
		(0.0145)		
Black (%)		−0.0225***		
		(0.0014)		
Native (%)		−0.0104***		
		(0.0016)		
Hispanic (%)		−0.0157***		
		(0.0012)		
Veteran (%)	−0.0885***	−0.0873***		
	(0.0062)	(0.0061)		
Farm Bill			0.0069	0.0236**
			(0.0085)	(0.0092)
Heterogeneous Effects				
Minority (%) × Farm Bill			0.0002*	
			(0.0001)	
Asian (%) × Farm Bill				−0.0051***
				(0.0012)
Black (%) × Farm Bill				0.0010***
				(0.0002)
Native (%) × Farm Bill				0.0001
				(0.0003)
Hispanic (%) × Farm Bill				−0.0005**
				(0.0002)
Veteran (%) × Farm Bill			0.0013	−0.0000
			(0.0009)	(0.0010)
Ag. Emp. (%)	0.0082***	0.0079***		
	(0.0017)	(0.0017)		
Rural-Urban Cont.	0.0256***	0.0273***		
	(0.0052)	(0.0057)		
Drought	−0.0019***	−0.0022***	0.0001***	0.0001***
	(0.0005)	(0.0005)	(0.0000)	(0.0000)

(*Continued*)

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Table 4. (*Continued*)

	(1)	(2)	(3)	(4)
	Cross-Sectional Analysis		Farm Bill HTE	
Variables	Aggregated	Disaggregated	Aggregated	Disaggregated
Drought (L1)	−0.0055***	−0.0057***	0.0001	0.0001***
	(0.0007)	(0.0007)	(0.0000)	(0.0000)
Ext. Moisture	−0.1568***	−0.1261***	0.0050***	0.0049***
	(0.0215)	(0.0221)	(0.0018)	(0.0018)
Ext. Moisture (L1)	−0.1501***	−0.1238***	−0.0026	−0.0029
	(0.0197)	(0.0197)	(0.0018)	(0.0018)
Constant	10.4356***	10.3778***	11.1702***	11.1697***
	(0.0658)	(0.0682)	(0.0014)	(0.0014)
Observations	45,259	45,259	51,164	51,164

Robust standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

The coefficients on our heterogeneous treatment effect variables ("Minority (%) × Farm Bill" and "Veteran (%) × Farm Bill") are both positive, though the veteran-driven effect is statistically insignificant at conventional levels. Interestingly, when we disaggregate across social minorities in Column (4) of the Table, we see that this effect is driven exclusively by an increase in uptake among Black farmers.

6.3. Two-step analysis with imputation

As discussed in Section 3, our baseline analysis uses county population demographic data to proxy for county farm operator demographics. We do so because NASS farm operator data are substantially incomplete and population demographics correlate well with producer demographics (see Figure 4).

In this robustness check, we attempt to incorporate the producer demographic data more directly into the analysis. To do so, we conduct a two-step approach with data imputation. We first regress the available county-level producer demographic data against the county population demographic data as shown in Figure 4. After doing so, we then predict producer demographic information for all counties, including imputing demographic data for counties for which this information is not reported. After doing so, we re-estimate the models described in Sections 4.1 and 4.2 substituting our demographic variables of interest with the predicted values from this first-stage regression.

The results of this analysis are reported in Table 5. Columns (1) and (2) report results of the cross-sectional analysis described in Sections 4.1. These results are directly comparable to those reported in Columns (5) and (6) of Table 1.

Columns (3) and (4) of Table 5 report results measuring the impacts of the 2018 Farm Bill as described in Section 4.2. These results are directly comparable to those in Columns (2) and (3) of Table 2. We note that the socially disadvantaged producer demographic variables shown in Columns (3) and (4) of Table 5 are akin to variables their treatment effect equivalents in Table 2. For example, the coefficient estimate on "Black Hat (%)" in Column (4) of Table 5 is compared to the coefficient estimate "Black (%) × Farm Bill" in Column (3) of Table 2.

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Table 5. Results from two-stage analysis with imputation

	(1)	(2)	(3)	(4)
	Cross-Sectional Analysis		2018 Farm Bill Effects	
Variables	Aggregated	Disaggregated	Aggregated	Disaggregated
Farm Bill			−0.0576***	−0.0355***
			(0.0037)	(0.0033)
Veteran (%)	−0.0732***	−0.0684***	0.0040***	0.0027***
	(0.0035)	(0.0034)	(0.0004)	(0.0004)
Minority Hat (%)	−3.8585***		0.4278***	
	(0.2037)		(0.0227)	
Asian Hat (%)		−1.6446		−0.0683
		(1.3653)		(0.0813)
Black Hat (%)		−4.3715***		0.6281***
		(0.1753)		(0.0218)
Native Hat (%)		−2.2533***		0.0117
		(0.1565)		(0.0125)
Hispanic Hat (%)		−0.6105***		0.0497***
		(0.1040)		(0.0158)
Ag. Emp (%)	0.0119***	0.0098***		
	(0.0009)	(0.0009)		
Rural-Urban Cont.	0.0274***	0.0308***		
	(0.0032)	(0.0036)		
Drought	−0.0004	−0.0007***	−0.0000***	0.0000
	(0.0003)	(0.0003)	(0.0000)	(0.0000)
Drought (L)	−0.0055***	−0.0054***	−0.0000	0.0001***
	(0.0003)	(0.0003)	(0.0000)	(0.0000)
Ext. Moisture	−0.1101***	−0.0753***	−0.0005	0.0004
	(0.0128)	(0.0132)	(0.0009)	(0.0009)
Ext. Moisture (L)	−0.0730***	−0.0465***	−0.0011	−0.0007
	(0.0118)	(0.0119)	(0.0008)	(0.0008)
Constant	5.6131***	5.4792***	5.7824***	5.7810***
	(0.0410)	(0.0415)	(0.0006)	(0.0006)
Observations	45,259	45,259	91,367	91,367

Robust standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

This comparison across Table 5 and Tables 1 and 2 suggests that the coefficient estimates from the two-step imputation approach are similar in sign and statistical significance to our baseline estimates. However, the estimates in Table 5 are generally larger in magnitude than those in the baseline.

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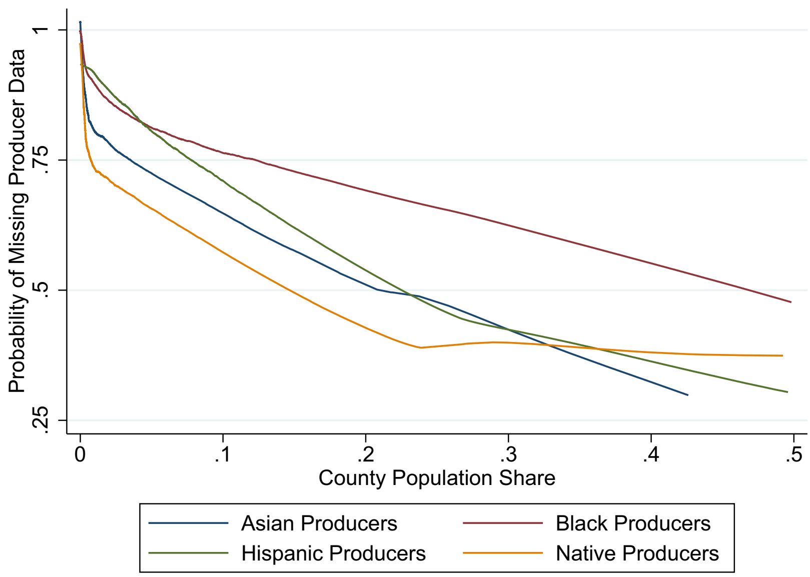

Figure 7. Systematic reporting bias in county producer data. *Notes:* Figure plots the probability that producer information for a given ethnic group is omitted for a given county as a function of the county population share for that ethnic group.

This is almost certainly due to the fact that the two-step approach with imputation is biased by the fact that the counties with missing data are systematically those with lower representation from socially disadvantaged producers. Figure 7 provides evidence of the systematic reporting bias with respect to producer demographic data. The Figure plots the probability that producer information for a given ethnic group is omitted for a given county as a function of the county population share for that ethnic group. As shown in the Figure, counties with a smaller population share for a given minority group are much more likely to be missing producer data for that ethnic group. This creates bias in the two-stage estimates and further supports our baseline approach.

6.4. Alternative risk exposure measures

To assess the robustness of our findings to the risk exposure measures used, we expanded our analysis to incorporate additional models using county-specific analogues of base rates for crop insurance. These analogues, encompassing multiperil risks including weather-related factors, offer a localized assessment of risk specific to each county. As shown in Table 6, we evaluated two measures: the average base rate estimated by the Risk Management Agency (RMA) and a target rate empirically derived from summary of business data, adhering to methodologies from Tsiboe and Turner (2023b). To manage missing values in both rates, we employed regression analyses with state and year fixed effects, using the resulting predictions for data imputation. Presented in Table 6, our results affirm that the percentages of minority and veteran populations significantly influence the calculated risk measures, supporting the robustness of our preferred Drought Risk and Excess Moisture Risk indices. Despite their insights, these alternative measures cover a smaller sample (13,059 vs. 62,337), justifying the continuation of our original model configurations. Moreover, historical data from the Federal Crop Insurance Program (FCIP) emphasize the dominance of weather-related risks, with drought and high temperatures comprising 42% of total indemnity payments since 2000, and excess moisture contributing to another 28%. These findings underscore the significance of our selected indices in capturing the major risks affecting U.S. agriculture, reinforcing the validity of our approach.

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Table 6. Alternative risk exposure measure results

Variables	(1) Target rate	(2) Target rate (Imputation)	(3) RMA rate	(4) RMA rate (Imputation)
Minority (%)	0.0010***	0.0010***	0.0010***	0.0007***
	(0.0000)	(0.0000)	(0.0002)	(0.0000)
Veterans (%)	0.0018***	0.0018***	0.0088***	0.0013***
	(0.0003)	(0.0003)	(0.0009)	(0.0002)
Ag Emp (%)	−0.0013***	−0.0013***	−0.0057***	−0.0013***
	(0.0001)	(0.0001)	(0.0006)	(0.0001)
Rural-Urban Cont.	0.0070***	0.0069***	0.0072***	0.0053***
	(0.0003)	(0.0003)	(0.0005)	(0.0002)
Drought	0.0003***	0.0003***	0.0001***	0.0002***
	(0.0000)	(0.0000)	(0.0001)	(0.0000)
Drought (L)	0.0002***	0.0002***	−0.0001**	0.0001***
	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Extreme Moisture	0.0043***	0.0042***	−0.0001	0.0014*
	(0.0011)	(0.0011)	(0.0030)	(0.0008)
Extreme Moisture (L)	0.0078***	0.0078***	0.0021	0.0042***
	(0.0011)	(0.0011)	(0.0028)	(0.0008)
Constant	0.0481***	0.0485***	−0.0183**	0.0352***
	(0.0028)	(0.0028)	(0.0084)	(0.0022)
Observations	13,059	13,302	1,400	13,302

Robust standard errors in parentheses.
***$p < 0.01$, **$p < 0.05$, *$p < 0.1$.

7. Conclusion

Racial inequality is fundamentally intertwined with the economic geography of agriculture in the United States. Recently, the USDA implemented a series of policies aimed at addressing these structural inequities. This study seeks to analyze agricultural risk inequities in the domain of agricultural risk and examine whether incentive programs established by the 2018 Farm Bill have improved socially disadvantaged farmers' access to modern risk management tools. While "access" has multiple facets, many of which cannot be directly measured, this study specifically examined access as measured by the purchase of crop insurance policies proxying the ability to purchase insurance and affordability.

Our findings demonstrate that minority and veteran farmers are more vulnerable to both ends of the spectrum with regard to weather-related risks. These specific groups of producers are disproportionately situated in regions of the United States that face heightened risks of drought and excess precipitation. Prior to the implementation of the 2018 Farm Bill, minority and veteran farmers consistently had lower utilization of crop insurance despite facing greater risks. However, the incentive programs introduced under the 2018 Farm Bill have contributed to an increase in use of federal crop insurance among these vulnerable populations.

The 2018 Farm Bill has increased the use of crop insurance in areas with higher populations of Black, Native American, and Hispanic producers. Increased insurance use consequently improved

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the ability to offset farm risk (Ifft et al., 2015), it has likely enhanced farm revenues in the wake of poor market conditions (Coble and Barnett, 2013), and – at the macro level – it has contributed to a more resilient food supply (Bullock and Steinbach, 2023). However, we note that benefits may not all be positive. Critics contend that the societal costs of subsidized crop insurance may manifest in several undesirable ways. According to Skees (1999), these subsidies may encourage riskier behavior among farmers and facilitate the redistribution of wealth from taxpayers in the form of transfer payments. Additionally, Yu et al. (2018) highlight another potential concern – the promotion of excessive monoculture acreage, which can lead to negative environmental impacts.

Finally, as with any research, our analysis is not without limitations. For our event study estimates to be interpreted causally, one must rely on relatively strong identifying assumptions. The estimation approach in equation (1) implicitly assumes a zero time trend in the dependent variable. In other words, one must assume that – in the absence of the 2018 Farm Bill – outcome variables would be, on average, at their pre-2018 Farm Bill levels.

Further, while we believe we have captured the predominant effects of the 2018 Farm Bill on crop insurance uptake among socially disadvantaged farmers, our study necessarily focuses on the extensive margin of this effect (i.e., the number of policies sold). We have not analyzed the *intensive* margin of these impacts, but we believe it is likely that – for socially disadvantaged producers who were already purchasing crop insurance – the 2018 Farm Bill may have encouraged enrollment in higher coverage levels. To this extent, our estimates may represent a lower bound (i.e., a conservative estimate) of the true effects of the 2018 Farm Bill on crop insurance uptake among socially disadvantaged farmers. It remains an open question how persistent this impact will be. For example, if – in the short run – farmers who were induced to enroll in crop insurance do not realize the benefits of the safety net (either because weather is favorable or prices or high), they may choose to forego the instrument in the future due to the associated costs. As we continue in the development period for the next Farm Bill, these issues may continue to be monitored and crop insurance offerings refined to support risk management among socially disadvantaged producers.

Data availability statement. The data that support the findings of this study are openly available. Annual crop insurance data was obtained from the USDA Risk Management Agency Summaries of Business at https://www.rma.usda.gov/SummaryOfBusiness. The 2017 Census of Agriculture data was obtained from the USDA National Agricultural Statistics Service https://www.nass.usda.gov/AgCensus/. The 2010 U.S. Census data was obtained from the U.S. Census Bureau at https://data.census.gov/. Precipitation data was obtained from the U.S. Centers for Disease Control at https://ephtracking.cdc.gov. Drought data was obtained from the U.S. Drought Monitor at https://droughtmonitor.unl.edu.

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