

Government payments and farm debt utilization during the pandemic

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Abstract

Purpose – This study examines the heterogeneous relationship between ad-hoc support policies, high government payments, low interest rates and farm debt use across farms of different sizes and across farm operators of different races, genders and experiences to inform the 2024 Farm Bill discussions.

Design/methodology/approach – Utilizing USDA's Agricultural Resource Management Survey data for 2020 and 2021, this study characterizes the differences in short-term farm debt use and the amount of short-term debt during the COVID-19 pandemic period across several farm and farmer types using double selection LASSO and regression analysis.

Findings – Results show positive associations between government payments and debt use for all farm types and farmer demographics except for residence farms and non-white farmers, which may be due to their limited access to credit. Findings also indicate that farms that could already access credit, like commercial farms, increased their short-term debt during the pandemic per the decrease in interest rates. Moreover, the 2018 Farm Bill extended certain commodity support and direct and guaranteed loan program participation provisions that were previously more closely restricted. Beginning farmers seemed more likely to use short-term debt in response to higher pandemic government payments than their more experienced counterparts.

Practical implications – The insights from this study are timely and useful for policymakers for designing and implementing programs related to the new 2024 Farm Bill.

JEL Classification — Q14, Q18, E43, H3

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Originality/value – One of the explanations for the results is that beginning farmers have been more likely to use debt than most other groups of operators, signaling the success of special credit provisions. Our results are relevant to making upcoming policies related to female and nonwhite farm and ranch operators.

Keywords Agricultural finance, Farm debt, Credit use, Quantitative easing

Paper type Research paper

Introduction

The COVID-19 pandemic posed significant challenges for farmers, intensifying pre-existing issues (Kauffman, 2013; Marchant and Wang, 2018; Zhang, 2021; Thilmany *et al.*, 2022) while introducing new uncertainties in the supply chain, input costs, marketing strategies, and market demand (Johansson *et al.*, 2021; McLaughlin *et al.*, 2023). In response, the government support was augmented under the 2018 Farm Bill with several provisions aimed at increasing access to credit. Much of this support was gradually withdrawn as the pandemic receded, assuming it was no longer needed. However, access to credit has remained crucial for both the survival and growth of farm operations (Key, 2022), both during an economic challenge and afterward. Therefore, understanding the factors related with access to and use of debt can reveal ongoing vulnerabilities and risks that farmers face, which can limit access to capital and hinder growth. In this study, we contribute to this line of literature and the 2024 Farm Bill discussions by examining the differences in short-term debt use during the pandemic across farms of various sizes, as well as among farm operators of different races, genders, and levels of experience.

Farmers and agricultural operations exhibit varying levels of debt and financial vulnerability, influenced by operation size, operator diversity, market access, and management practices. Previous studies have highlighted disparities among farm operators and operation types in farm survival, financial performance and financial position (Fairlie *et al.*, 2022; Jablonski *et al.*, 2022; Giri *et al.*, 2022; Giri and Subedi, 2024). Additionally, inequalities in credit access have been shown to persist in programs like the Paycheck Protection Programs (Sant'Anna *et al.*, 2023), USDA loan programs (Escalante *et al.*, 2018) and non-traditional lending (McDonald *et al.*, 2021).

During the peak pandemic time, farmers received only \$5.9 billion in Paycheck Protection Program (PPP) loans, far less than the total amount that the farm sector could have received (Giri *et al.*, 2021b), indicating selective utilization possibly due to a lack of awareness about government programs. Subedi and Giri (2024) also highlight that producers use several sources of credit that their choice of lender varies based on the type of loan (real estate or non-real estate) and farm size. Furthermore, racial inequities in access to relief programs were also highlighted during the initial phase of the Coronavirus Food Assistance Program (CFAP) (Reiley, 2021), the primary relief program from USDA for producers impacted by the COVID pandemic. This highlights some selection in awareness about and access to the government programs and support made available during the pandemic. Without an investigation into the heterogeneity in previous utilization, ensuring balanced access to information and resources may continue to be difficult in future programs like the upcoming 2024 Farm Bill.

This study explores the heterogeneity in short-term debt use and the degree of indebtedness across farm sizes, and operator gender, race, and levels of experience. Specifically, by analyzing the USDA's Agricultural Resource Management Survey (ARMS) data for 2020 and 2021, we examine how short-term debt use and amounts changed due to pandemic-specific provisions. We only consider loans with a repayment period of less than a year. In 2020 and 2021, ARMS also collected comprehensive information on COVID-19 government payments, making this a suitable data source to conduct a comprehensive comparison of access to short-term debt during the pandemic. We use a combination of machine learning methods and economic intuition in the form of post-double selection LASSO estimation. Therefore, we contribute to the relatively new literature that uses machine learning methods to predict several outcomes in the agricultural finance domain (Ifft *et al.*, 2018; Chen *et al.*, 2021; Storm *et al.*, 2020; Lu *et al.*, 2022).

Record-high government payments and near-zero interest rates, along with more guaranteed loans, provided higher liquidity and favorable credit conditions for the farm sector, expectedly alleviating financial challenges and increasing access to credit across all types of farmers. Analyzing whether such an effect was experienced unilaterally or differentially among farms by sizes and operator demographics is highly relevant for evaluating and considering the updates to debt-related provisions in the next Farm Bill. This enables policymakers to tailor future Farm Bill provisions to meet the specific financial needs of various farm operations, contributing to more effective agricultural policy design.

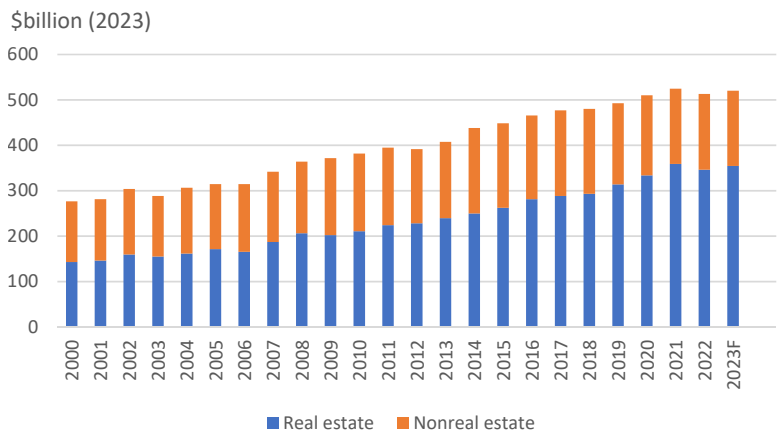
We find positive associations between government payments and short-term debt use for all farm types and farmer demographics, except for residence farms and non-white farm operators, suggesting their limited access to credit. A priori, one might expect similar limitations for beginning farmers, but their debt use is at par with, if not higher than, their more experienced counterparts. This may stem from previous Farm Bill provisions, demonstrating that special provisions improved access to credit for this group. Moreover, estimations indicate substantial variation in how government payments may have impacted the amounts of short-term debt across farms and farm operators. We observe insignificant changes in short-term debt when pandemic-related government payments increased during the pandemic. Conversely, lower interest rates during the pandemic are significantly associated with higher short-term debt use for all farm and farmer categories other than female operators. Lower interest rates are also associated with higher amounts of short-term debt for all farm and farmer categories except female and non-white operators. Our results also indicate that farms that could already access credit, like commercial farms, increased their short-term debt during the pandemic in association with lower interest rates. One explanation of these results is that while government payments provided stability, they did not necessarily encourage additional borrowing. Instead, the borrowing behavior appears more responsive to the cost of credit, as evidenced by the strong association between lower interest rates and increased short-term debt.

Debt for US Farms

The Agriculture Improvement Act of 2018, also called the 2018 Farm Act, provides critical support to farmers who face limited access to credit through traditional lending markets. Title V of the 2018 Farm Act details these provisions related to farm debt and grants USDA the authority to establish credit-related programs. These programs specifically target individuals who encounter difficulties accessing credit from conventional sources. Furthermore, the 2018 Farm Act focuses on supporting credit access for beginning farmers, farmers with limited financial means, and military veterans (USDA ERS, 2019a). Although credit provisions by the government, including this Farm Act, are set to support all farmers facing financial challenges, recent literature highlights several disparities in access to financial support (Sant'Anna *et al.*, 2023; McDonald *et al.*, 2021; Ghimire *et al.*, 2020), and farm debt is one such support.

The overall farm debt had been steeply rising before the pandemic; however, real farm debt fell for the first time in a decade during the pandemic. After the pandemic, farm sector debt continued to increase and was forecast to exceed half a trillion dollars in 2023 (Figure 1). This comes with a risk of higher farm leverages if farm incomes or asset values fall (Ifft *et al.*, 2015), placing farmers in a critical position. As farm incomes are heterogeneous, the changes in aggregate farm debt before, during, and after the pandemic convey a distributional impact on farmers during the pandemic when financial stress was high. Farm sector debt includes both real estate as well as non-real estate debt, or alternatively is comprised of short-term and long-term loans, where debt use varies significantly by farm type and farm income. As the pandemic would primarily impact the short-term financial health of farm operations, this study focuses only on short-term debt.

Several farm and farmer characteristics are related to overall as well as short-term debt use. Ifft *et al.* (2014) highlighted the role of farm size, commodity specialization, and farmer



Note(s): F = Forecast. Values are adjusted for inflation using the U.S. Bureau of Economic Analysis Gross Domestic Product Price Index (BEA API series code: A191RG) rebased to 2023 by USDA, Economic Research Service
Source(s): USDA, Economic Research Service, Farm Income and Wealth Statistics. Data as of August 31 (2023)

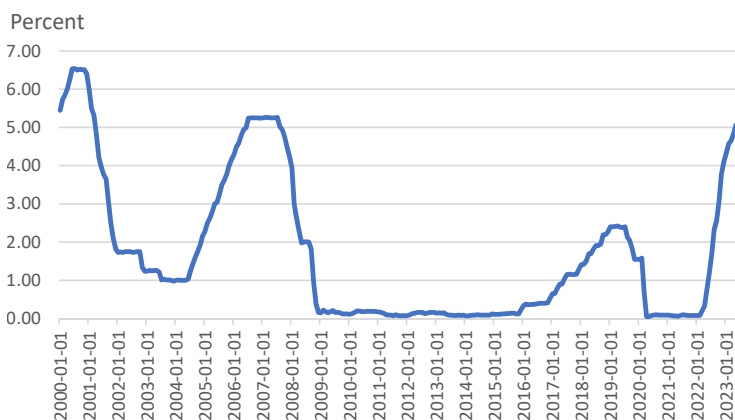
Figure 1.
Real farm debt

characteristics in determining debt use and magnitude. They found that large-scale family farms (with annual gross cash income of \$1 million or more) held the largest share of farm business debt; dairy farm operations, and those specializing in poultry had the highest average debt-to-asset ratios that decreased as the operator's age increased. Additional factors that are related to debt use and composition are government payments (Kropp and Katchova, 2011; Katchova, 2005), interest rates (Martinez *et al.*, 2023), financial vulnerability, and cash flow (Prager *et al.*, 2018), status as a beginning farmer (Dodson and Ahrendsen, 2016; Tulman *et al.*, 2016) and current leverage (Brewer *et al.*, 2014). We include all of these factors and measure their relative importance by grouping farms by their size, financial status, and operator characteristics. This allows us to look at the role of government payments in addressing financial needs of each group separately, identifying the most effective utilization of government support, along with assessing debt use in light of the low interest rates during the pandemic.

Government payments and interest rates during the pandemic

Recent USDA data shows that producers had record-high net cash incomes of \$149.3 billion and \$202.2 billion in 2021 and 2022, respectively, which at \$148.6 billion in 2023 is expected to remain higher than the pre-pandemic average (USDA ERS, 2023). Although record-high commodity prices boosted cash receipts, a major component was the rise in government payments. Direct government payments of more than \$45 billion in 2020 were the highest on record in both nominal and real terms (Giri *et al.*, 2022). Additionally, the Federal Reserve Bank maintained historically low interest rates during the pandemic in 2020 and 2021, as depicted in Figure 2. This suggests that the farm sector was financially stronger during the pandemic compared to the period before, placing them in a favorable position to access credit. Higher government payments improve liquidity while lower interest rates make it easier to access credit, refinance debt, and revise farm investments, making it a favorable time for the farm sector.

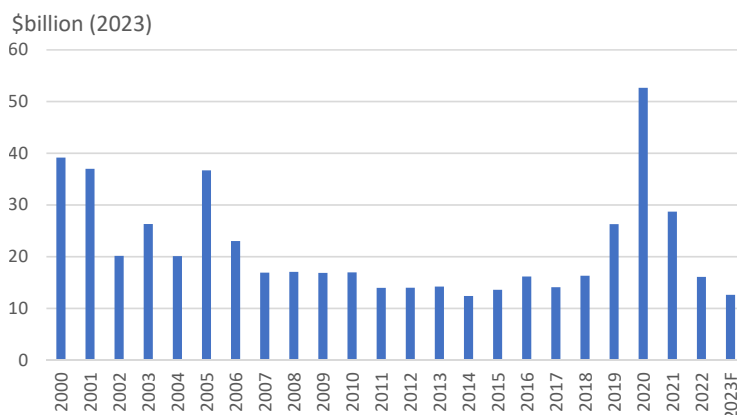
Figure 3, based on data from the August 31, 2023, release of the Farm Income and Wealth Statistics data product by the USDA's Economic Research Service, illustrates the nominal



Note(s): The rates are seasonally unadjusted monthly rates

Source(s): Economic Data, St. Louis Fed as of 08/07/2023

Figure 2.
Federal funds rate



Note(s): F = Forecast. Values are adjusted for inflation using the U.S. Bureau of Economic Analysis Gross Domestic Product Price Index (BEA API series code: A191RG) rebased to 2023 by USDA, Economic Research Service

Source(s): USDA, Economic Research Service, Farm Income and Wealth Statistics. Data as of August 31 (2023)

Figure 3.
Direct government
payments

government payments from 2000 through 2023. The 2020 direct payments reached record highs due to COVID-19 assistance, particularly through the Coronavirus Food Assistance Program (CFAP). In fact, CFAP alone distributed more payments than the total average payments to the farm sector over the preceding 20 pre-pandemic years. Notably, a study by [Giri et al. \(2021a\)](#) revealed that nearly all producers, approximately 97% based on cash receipts, were eligible to receive CFAP payments, making it one of the most comprehensive USDA programs in history. According to the USDA-ERS ARMS web tool ([2023](#)), 40% of all farm operations received some form of government payments in 2020. This marked a

substantial increase from the 31% observed in the preceding year (2019) and the 34% in the subsequent year (2021). As eligibility was high across the board, one might expect that short-term debt needs would be substituted by the government payments, decreasing both debt use, and the amounts of short-term debt.

Moreover, beginning in March 2021, the Federal Open Market Committee (FOMC) of the Federal Reserve System initiated a series of eight consecutive rate hikes through March 2023 to combat elevated and persistent inflation. [Figure 2](#) illustrates the short-term federal funds rate, which increased to 4.65% in March 2023, contrasting sharply with the less than one percent rate observed in March 2020. An increase in loan interest rates directly translates to higher interest expenses for farm operations, potentially leading to reduced loan demand. The USDA-ERS forecasts that interest expenses in 2023 will be the fastest-growing category among production expenses, with sector-level interest expenses estimated at \$33.85 billion, reflecting a \$6.21 billion increase, or 22%, compared to the \$27.64 billion recorded in 2022 ([Giri and Subedi, 2023](#)). This further supports the notion of debt being substituted to some extent with government payments and presents a unique opportunity to examine the effects of interest rate fluctuations on farm debt. This underscores the importance of understanding the lasting implications of interest rate changes observed during the pandemic and the study period for farm operations, particularly for those considering new loans or lacking fixed interest rate arrangements.

Data

This study uses 2020 and 2021 Phase 3 of the USDA's Agricultural Resource Management Survey (ARMS), which annually collects data from a nationally representative cross-section of about 30,000 farms across 48 contiguous states in the US. ARMS is also the only annual source of information about the financial well-being of the farm sector and detailed farm operation characteristics. Since the 2020 and 2021 ARMS collected data on government payments, including those from COVID-19 related programs, it allows an empirical examination of the tradeoffs among various sources of credit and cash flow constraint relaxation faced by farmers. Using the pooled data for 2020 and 2021 also allows us to capture the plausibly unexpected changes in interest rates as they sharply fell in 2020 and started rising again in 2021. We use this data to explore descriptive statistics related to debt use, farm debt amount, and pandemic support as they vary by farm size, financial conditions, and operator demographics. Subsequently, we leverage a shrinkage model to identify the most important characteristics that determine debt use for various farm and farmer types.

Our main outcome variables, short-term debt use and short-term debt amount, both pertain to production or other loans with a repayment period of one year or less. Short-term debt use is a binary variable for identifying the farm operations that held any short-term debt owed on December 31st of the respective year, while short-term debt amount is a sum of the balance owed on all short-term loans. Both outcomes are denoted by y_i in estimation equations. We group all lender types together and only classify debt as either short-term or not to capture the changes in farm liquidity and short-term debt brought about by the pandemic and pandemic-related support.

We begin with two possible determinants of short-term debt use and the degree of indebtedness. First, the average interest rates on production or other loans with a repayment period of one year or less, denoted int_i , and second, the pandemic related government payments, denoted gov_i for farm i . The pandemic related government payments include all the COVID-19 related grants, funds, and loans available for 2020 and 2021. These are only the financial payments received by operations (or operators). Both variables are included as our primary control variables, and referred to as model variables in the LASSO. In addition to the two model variables, several farm and farmer characteristics are considered; they are described in [Table 1](#), and summarized by farm and operator categories in [Tables 1 and 2](#). [Table 1](#)

Variable	Description	All farms	Residence	Intermediate	Commercial
Overall Debt Use (1/0)	1 if farmer has any loans; 0 otherwise	0.29	0.22	0.27	0.64
Short-Term Debt Use (1/0)	1 if farmer has any loans with a repayment period of 1 year or less; 0 otherwise	0.26	0.21	0.25	0.59
Debt to Asset Ratio	Ratio of farm debt to farm assets	0.08	0.05	0.07	0.22
Short-Term Debt Amount (1,000 \$)	Total amount of loans with a repayment period of 1 year or less (short-term loans) (million \$)	85.20	25.61	48.30	488.77
Short-Term Interest Rate (%)	Average interest rate across all short-term loans weighted by the loan balance (%)	0.38	0.22	0.37	1.18
Overall Interest Rate (%)	Average interest rate across all loans weighted by the loan balance (%)	1.23	0.96	1.18	2.71
Covid government payments (1,000 \$)	All COVID-19 related government payments (million \$)	5.66	0.87	2.46	38.85
Producer payments (1,000 \$)	All Pandemic Assistance for Producers – it is included in the total Covid Government payments (million \$)	2.89	0.36	1.11	20.67
Farm Assets Sold (\$)	Income from farm asset sales (million \$)	7.18	5.70	4.97	21.36
Farm Investment (1,000 \$)	All improvements on fam real estate and farm operation (million \$)	25.78	10.96	15.96	128.24
Labor Cost (1,000 \$)	Wages and salaries for all hired farm and ranch labor, including producer and their household (million \$)	26.21	1.90	6.10	206.98
Gross Farm Income (1,000 \$)	Gross farm income (million \$)	181.59	31.81	69.64	1,257.38
Total Off-Farm Income (1,000 \$)	Total off-farm income (million \$) of the principal operator's household	102.42	128.74	74.03	66.90
Return On Assets (%)	Rate of return on assets (%)	−0.08	−0.12	−0.09	0.10
Acreage	Total acres operated (owned and leased)	402.85	139.91	321.79	1922.58
Contracts Use	Proportion of production under contracts	0.05	0.02	0.06	0.19
Diversification	Entropy index of diversification	0.11	0.09	0.11	0.19
Land Tenure	Ratio of owned to operated land	1.20	1.26	1.23	0.84
Age	Operator age (years)	62.16	60.77	65.64	57.67
Assets (million \$)	Total assets (million \$)	1.51	0.86	1.22	5.51
Experience	Operator experience in number of years	27.64	24.48	31.39	30.80

Table 1.
Summary statistics by
farm type
(continued)

Variable	Description	All farms	Residence	Intermediate	Commercial
Male (1/0)	1 if the primary operator is male; 0 otherwise	0.86	0.85	0.85	0.94
White (1/0)	1 if the primary operator is white; 0 otherwise	0.96	0.96	0.96	0.98
Crop Insurance Use (1/0)	1 if the producers received crop insurance payments; 0 otherwise	0.15	0.07	0.12	0.59
Education	Education of primary producer (categorical variable ranges from 1 to 5): 1 = did not graduate from high school; 2 = graduated high school degree or received GED; 3 = attended college but did not graduate; 4 = graduated from college; 5 = attended graduate school or higher	2.93	2.99	2.81	2.99
Individual Farm (1/0)	1 if the farm is operated as a sole proprietorship; 0 otherwise	0.88	0.91	0.91	0.62
Land Sold (1/0)	1 if any farm real estate was sold during the last year; 0 otherwise	0.01	0.01	0.01	0.02
Crop Farm (1/0)	1 if the operation is a crop farm; 0 if it is a livestock, ranch, pasture, or other operation	0.35	0.28	0.36	0.68
Number of Observations	Number of Observations in ARMS sample	21,293	5,882	7,126	8,285
Number of Represented Farms	Total farms represented by the USDA ARMS data weights	3,315,326	1,768,514	1,177,989	368,824

Note(s): The table presents the descriptions of variables used in the study along with the summary statistics for the entire sample in our analysis (column titled “All Farms”), and the sample divided by farm types according to the USDA criteria for defining Residence, Intermediate, and Commercial farm operations

Source(s): Authors own work

Table 1.

separately presents the summary statistics for residence, intermediate, and commercial farms, while [Table 2](#) summarizes the data by farmer gender, race and experience.

Additionally, the key factors we consider in our study can further be classified into supply and demand side factors affecting short term debt use. Supply factors refer to the conditions and constraints set by lenders that affect the availability of credit, such as interest rates, lending policies, and government support programs. Lower interest rates during the pandemic made credit more accessible, and government payment programs provided direct payments and guarantees that influenced lenders’ willingness to extend credit. Therefore, our two model variables are both supply side factors. Their relationship with debt use during the pandemic is also related to the demand side factors. Demand side factors pertain to the needs and preferences of farmers seeking credit, including financial needs, risk tolerance, and awareness of available programs. The remaining farm and farmer specific control variables, described in [Table 1](#), therefore, depict the demand side determinants of debt use. Additionally, government payments may also be considered a demand side factor since it can affect the need for loans.

	Male	Female	Non-white	White	Experienced	Beginning
Overall Debt Use (1/0)	0.30	0.19	0.24	0.29	0.28	0.31
Short-Term Debt Use (1/0)	0.28	0.17	0.21	0.27	0.26	0.28
Debt to Asset Ratio	0.08	0.06	0.07	0.08	0.07	0.12
Short-Term Debt Amount (1,000 \$)	94.00	31.47	67.30	85.88	88.39	70.19
Short-Term Interest Rate (%)	0.41	0.17	0.33	0.38	0.38	0.37
Overall Interest Rate (%)	1.29	0.86	1.04	1.24	1.21	1.33
Covid government payments (1,000 \$)	6.07	3.15	3.76	5.73	6.03	3.93
Producer payments (1,000 \$)	3.16	1.22	1.18	2.96	3.16	1.64
Farm Assets Sold (\$)	8.19	1.04	10.10	7.07	8.32	1.81
Farm Investment (1,000 \$)	28.28	10.54	19.52	26.02	26.63	21.79
Labor Cost (1,000 \$)	28.10	14.68	28.51	26.12	27.80	18.74
Gross Farm Income (1,000 \$)	201.12	62.44	106.27	184.46	195.69	115.22
Total Off-Farm Income (1,000 \$)	102.51	101.85	86.30	103.03	97.82	124.07
Return On Assets (%)	-0.07	-0.17	-0.14	-0.08	-0.07	-0.14
Acreage	434.31	210.89	230.77	409.41	437.33	240.54
Contracts Use	0.05	0.03	0.05	0.05	0.05	0.05
Diversification	0.11	0.09	0.08	0.11	0.11	0.09
Land Tenure	1.19	1.30	0.91	1.21	1.18	1.33
Age	62.15	62.21	60.84	62.21	64.28	52.15
Assets (million \$)	1.59	0.99	1.10	1.52	1.62	0.99
Experience	28.41	22.91	25.78	27.71	32.21	6.09
Male (1/0)	1.00	0.00	0.78	0.86	0.88	0.77
White (1/0)	0.97	0.94	0.00	1.00	0.96	0.97
Crop Insurance Use (1/0)	0.16	0.04	0.06	0.15	0.16	0.10
Education	2.90	3.09	2.70	2.94	2.89	3.10
Individual Farm (1/0)	0.88	0.84	0.93	0.88	0.88	0.89
Land Sold (1/0)	0.01	0.01	0.01	0.01	0.01	0.00
Crop Farm (1/0)	0.37	0.21	0.20	0.36	0.36	0.29
Number of Observations	19,615	1,678	588	20,705	18,896	2,397
Number of Represented Farms	2,848,565	466,762	121,796	3,193,530	2,734,508	580,818

Note(s): The table presents the summary statistics for the sample divided by gender, race, and experience

Source(s): Authors own work

Table 2.
Summary statistics by
type of operator

Following USDA's definitions, residence farms are those with gross cash farm income less than \$350,000 and where the principal operator has either retired from farming or has a primary occupation other than farming; intermediate farms are those with gross cash farm income less than \$350,000 and a principal operator whose primary occupation is farming; and commercial farms as those with more than \$350,000 in gross cash farm income and nonfamily farms. Since race and farmer experience are key variables for our analysis, we drop the observations where these are missing, which were about 10% of the pooled sample. We further define beginning farm operators as those with 10 years or less of farming experience (Key and Lyons, 2019; Jablonski *et al.*, 2022).

Table 1 presents the averages of debt use and debt amounts, our primary outcome variables, and several farm and farmer characteristics used as control variables in our analysis for all farms, along with the subsamples of residence, intermediate, and commercial farms. The summary statistics show that debt use increases with farm size and is much higher for commercial farms compared to residence or intermediate farms, perhaps due to higher reliance on leverage and easier access to credit for a larger-size farm operation, also indicated by their debt-to-asset ratios of 5%, 7%, and 22%, respectively. The average

interest rate across all debt is the highest for commercial farms, suggesting a relation to their higher debt utilization. Several other variables highlight differences in farms, a notable one being a lower ratio of male operators for residence and intermediate farms compared to commercial farms in [Table 1](#). This motivates an investigation into the differences in farms based on operator characteristics, which are presented in [Table 2](#).

[Table 2](#) displays the averages of the same farm and farmer variables for six categories of primary farm operators: male, female, non-white, white, experienced, and beginning operators. Among these, beginning farmers have the highest debt use of 31% compared to the lowest use by female and non-white operators, 19% and 23%, respectively. All of these individual farm operator categories have a lower debt use and debt-to-asset ratio than commercial farms. That is because select farms from each operator category comprise the financially vulnerable sample of farm operations.

During the pandemic, the average COVID-19 related government payments were highest for commercial farms at \$38,846, with intermediate farms falling second at \$2,460 ([Table 1](#)). Moreover, on average, male farm operators received almost twice as much COVID-19 government payments at about \$6,070 compared to female operators who received \$3,151, though their gross farm income and acreage was also much larger ([Table 2](#)). Beginning farmers rank fourth in the category of farm operators in the ranking of payments, only above female and non-white operators, at \$3,930. When gross cash income is accounted for, commercial farms, male operators, white operators and experienced operators all received about \$30 of government payment per \$1,000 of gross farm income. Female farm operators received the highest amounts of support per \$1,000 in their gross farm income at \$50, followed by non-white and beginning operators and intermediate farms at about \$35 with the lowest support being utilized by residence farms at \$27 per \$1,000 in gross farm income. Higher amounts of government payment utilization, therefore, does not seem to have a clear correlation with lower debt needs or use during the pandemic. Instead, the categories of farms and farm operators with the highest COVID-19 government payments were often the ones with higher debt use both overall and short-term.

Methods

Our study follows [Belloni et al. \(2014\)](#) and utilizes the double selection LASSO (Least Absolute Shrinkage and Selection Operator) for model selection followed by an OLS regression ([StataCorp, 2021](#)) in analyzing the role of government payments and interest rates on farm debt use during the COVID-19 pandemic period. The approach assumes only that farm debt use is related to interest rates and government payments, and the rest of the control variables that influence farm debt use are selected during the estimation process. The empirical approach combines the use of machine learning methods with economic theory to select an appropriate set of controls for short-term debt use and amount of debt. We begin with the following model signifying the data generating process

$$y_i = \alpha_0 + \alpha_{int} int_i + \alpha_{gov} gov_i + g(z_i) + \epsilon_i \quad (1)$$

where the outcome variable y_i is either short-term debt use or the amount of short-term debt for farm i , and int_i and gov_i are model variables referring to the interest rate and government payments, respectively. The variables z_i are other relevant control variables, and an unknown function $g(z_i)$ represents the relationship between other control variables and debt use. The LASSO estimation does not assume which other control variables will be included in the model and in what functional form (for example, as interaction terms with other control variables). For our study, we include farm and operator characteristics that have typically been used in previous studies (crop insurance ([Ifft et al., 2015](#)), commodity specialization and farmer characteristics ([Ifft et al., 2014](#)), farm financials ([Prager et al., 2018](#)), race and gender

(Escalante *et al.*, 2018; Sant'Anna *et al.*, 2023)) on farm debt use in the set z_i . Then, we use linear approximation of the function $g(z_i)$ function with all the control variables in Tables 1 and 2 and all interactions between the categorical and continuous variables to construct an exhaustive list of controls x_i . This transforms the model to:

$$y_i = \alpha_0 + \alpha_{int} int_i + \alpha_{gov} gov_i + x_i' \alpha_z + r_{zi} + \epsilon_i \quad (2)$$

where $x_i' \alpha_z$ is the linear approximation of $g(z_i)$, and r_{zi} is the resulting approximation error. $x_i' \alpha_z$ contains all the control variables in Tables 1 and 2 and all interactions between the categorical and continuous variables, resulting in a fully saturated model with over 200 variables, from which LASSO would select the list of variables that belong in the final regression. Since there are a large number of variables in x_i (i.e. x_i is high dimensional), estimation and inference may be challenging. The assumption of sparsity, stating that only a small number of variables need to be selected in the linear approximation of $g(z_i)$ to make the approximation error r_{zi} small relative to the estimation error ϵ_i (Belloni *et al.*, 2014). Therefore, we apply the double selection LASSO method to select the variables that approximate $g(z_i)$ reasonably enough for r_{zi} to be relatively small.

The variables selection, or alternatively the approximation of $g(z_i)$, which belongs in the true unobserved model, is done in two steps. First, we estimate a linear LASSO of y_i on x_i (not including the main variables of interest, int_i and gov_i) and denote the vector of estimated coefficients θ . Specifically, we use the Rigorous LASSO estimator from Belloni *et al.* (2012) to solve the following optimization problem to select a subset of controls:

$$\min_{\theta \in \mathbb{R}^p} \mathbb{E}_n \left[(y_i - x_i' \theta)^2 \right] + \frac{\lambda}{n} \sum_{j=1}^p |\hat{l}_j \theta_j| \quad (3)$$

where λ is the penalty level, p is the number of variables in x , n is the sample size, and $\hat{l}_j$ are variable-specific penalty loadings for each θ_j which are selected according to Belloni *et al.* (2012) to accommodate the heteroscedastic and non-Gaussian error. The LASSO penalty

term in equation (3), $\frac{\lambda}{n} \sum_{j=1}^p |\hat{l}_j \theta_j|$, forces the coefficients of variables explaining the least variation towards zero, allowing us to select a subset from control variables x_i that have non-zero θ s from the LASSO optimization.

In the second step, we estimate two additional LASSO models, one for each of the main model variables, int_i and gov_i , respectively on all the control variables x_i . The optimization problem is solved again to choose the variables with the non-zero coefficients from the estimated coefficient vectors δ and γ resulting from LASSO estimation for int_i and gov_i , respectively, on the control variables x_i . That is, we select the relevant control variables using LASSO from the following optimization problems:

$$\min_{\delta \in \mathbb{R}^p} \mathbb{E}_n \left[(int_i - x_i' \delta)^2 \right] + \frac{\lambda}{n} \sum_{j=1}^p |\hat{l}_j \delta_j| \quad (4a)$$

and

$$\min_{\gamma \in \mathbb{R}^p} \mathbb{E}_n \left[(gov_i - x_i' \gamma)^2 \right] + \frac{\lambda}{n} \sum_{j=1}^p |\hat{l}_j \gamma_j| \quad (4b)$$

Identifying the main variables associated with either interest rate, int_i , or government payments, gov_i , explicitly and ensuring their inclusion in the following regression minimizes the omitted variable bias. In our study, these steps determine the main farm and operator characteristics that affect farm debt use in addition to interest rates and government payments, while also allowing for heterogeneity among different farm types.

Finally, we use $\tilde{x}_i$ to denote the set of selected controls after the two selection estimations depicted by [equations \(3\) and \(4a and 4b\)](#), i.e. LASSO double selection, and estimate the following reduced form model using least squares:

$$y_i = \beta_0 + \beta_{int} int_i + \beta_{gov} gov_i + \beta_x \tilde{x}_i + \epsilon_i \quad (5)$$

Utilizing the LASSO two-step selection process combined with estimating [equation \(5\)](#) using OLS on a subset of controls represented by $\tilde{x}_i$ offers a significant advantage over either method alone. This approach allows us to observe and verify the relevance of the selected variables $\tilde{x}_i$ based on contextual knowledge and literature, ensuring that approximation error r_{zi} is small relative to ϵ_i . Estimating an OLS regression on contextually motivated interactions involving over 200 variables without the LASSO selection would result in high variance in the OLS estimates, especially given the sample size and model complexity. Conversely, relying solely on LASSO without monitoring the double selection process might lead to the exclusion of essential variables, causing omitted variable bias. Therefore, our chosen post double selection LASSO OLS method enhances overall accuracy by combining the strengths of both LASSO and OLS approaches.

An additional contribution of our study is that the LASSO can determine which other farm and farmer characteristics in addition to interest rates and government payments, are selected as the main variables explaining the variation in farm debt use. This allows us to study the heterogeneity in the two outcome variables, short-term debt use and the amount of short-term debt, by grouping farmers into different samples based on farm size, farm financial status, and operator race, gender, and experience. We use the ARMS survey main weights during both LASSO steps. For the final post-double selection estimation in [equation \(5\)](#), we use the main weights to estimate the coefficients and the 30 replicate weights and the delete-a-group jackknife method for the re-sampling process to calculate the standard errors ([Dubman, 2000; USDA-ERS, 2024](#)).

Results and discussion

The empirical results are discussed in the following sequence. We begin with a comparative analysis of the key factors associated with short-term debt use during the pandemic to understand any credit access constraints. We divide our sample into groups based on farm operation size, beginning versus established farmer status, and race and gender of the primary operator. This allows us to map patterns in debt use, highlighting the implications for Farm Bill provisions. Following that, we consider the variations in the short-term degree of indebtedness conditional on debt use to highlight whether government payments had comparable effects on credit access and financial constraints across diverse groups of farms and farmers.

Determinants of short-term debt use during the pandemic

[Tables 3 and 4](#) present estimations of short-term debt usage, highlighting the differences in factors associated with debt use across different farm types and farm operator demographics. The results depict that higher government payments during the COVID-19 pandemic were associated with increased short-term debt use for all farm types and farmer demographics other than residence farms and non-white operators. This suggests that non-

	All farms	Residence	Intermediate	Commercial
Covid government payments (million \$)	0.630 ^{***} (0.0863)	2.787 (1.955)	3.642 ^{***} (1.059)	0.458 ^{***} (0.0688)
Short-Term Interest Rate (%)	0.0505 ^{***} (0.00432)	0.0547 ^{***} (0.00895)	0.0575 ^{***} (0.00806)	0.0216 ^{***} (0.00456)
Crop Insurance Use (1/0)	0.0553 (0.0596)	0.0481 (0.0766)		0.155 ^{***} (0.0345)
Individual Farm (1/0)	−0.0505 (0.0999)			
Farm Investment (million \$)	0.00803 (0.0457)			
Gross Farm Income (million \$)	0.00582 (0.0193)	0.826 (0.532)	0.590 (0.472)	0.00859 ^{***} (0.00300)
Return on Assets (%)	−0.00236 (0.0327)			
Contracts Use	0.0395 (0.0268)			
Diversification (0–1)	−0.203 (0.149)			
Age (years)	−0.00698 ^{***} (0.00155)	−0.00702 ^{***} (0.000680)	−0.00567 ^{***} (0.00110)	−0.00416 ^{***} (0.00108)
Total Assets (million \$)	0.00505 ^{***} (0.00166)			
Male (1/0)		0.0411 (0.0282)		
Education				−0.0215 (0.0138)
Constant	0.661 ^{***} (0.100)	0.531 ^{***} (0.0562)	0.532 ^{***} (0.0832)	0.680 ^{***} (0.0845)
Observations	21,293	5,882	7,126	8,285
Represented Farms	3,315,326	1,768,514	1,177,989	368,824
R ²	0.185	0.159	0.162	0.105
Number of Double Selection Lasso Controls	32	10	8	15
<i>Number of Double Selection LASSO Interactions Related to</i>				
Gender	3	1	1	1
Race	3	1	1	3
Farm characteristics	11	4	4	6
Other farmer characteristics	6			1
Note(s): This table shows the estimation results for equation (5) $y_i = \beta_0 + \beta_{int} int_i + \beta_{gov} gov_i + \beta_x \tilde{x}_i + \varepsilon_i$ where y_i refers to the binary variable short-term debt use. LASSO selected interactions within $\tilde{x}$ are classified as being related to gender, race, farm characteristics, and other farmer characteristics at the bottom of the table depicting the relevance of each category of controls for the estimated association. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ Source(s): Authors own work				

Table 3.
Post double selection
LASSO OLS for short-
term debt use:
farm types

Table 4.
Post double selection
LASSO OLS for short-
term debt use: gender,
race, and experience

	Male	Female	Non-white	White	Experienced	Beginning
Covid government payments (million \$)	0.599*** (0.0946)	1.207*** (0.399)	0.582 (0.436)	0.647*** (0.0827)	0.576*** (0.0893)	0.941** (0.360)
Short-Term Interest Rate (%)	0.0506*** (0.00405)	0.0521 (0.0412)	0.0634*** (0.0196)	0.0502*** (0.00453)	0.0530*** (0.00357)	0.0385** (0.0147)
Crop Insurance Use (1/0)	0.102*** (0.0342)			0.0617 (0.0603)	0.109*** (0.0372)	
Individual Farm (1/0)	0.102 (0.0767)			−0.0470 (0.103)	0.00850 (0.0875)	
Farm Investment (million \$)	0.0160 (0.0422)			0.00756 (0.0457)	0.00871 (0.0493)	
Gross Farm Income (million \$)	0.0118** (0.00458)			0.0101 (0.0217)	0.0149 (0.0278)	
Age (years)	−0.00502*** (0.00118)			−0.00696*** (0.00164)	−0.00675*** (0.00133)	−0.00631*** (0.00116)
Acreage (acres)	−0.00000349 (0.00000212)				−0.00000711 (0.00000988)	
Return on Assets (%)		0.0170 (0.0523)		0.00639 (0.0154)		
Contracts Use Diversification (0–1)			0.329** (0.120)	0.0374 (0.0261)		0.172* (0.0940)
Total Assets (million \$)				−0.236 (0.155)	−0.199 (0.127)	
Land Tenure (ratio)				0.00541*** (0.00171)	0.00512*** (0.00174)	
Constant	0.548*** (0.0767)	0.159*** (0.0184)	0.167*** (0.0314)	0.659*** (0.105)	0.663*** (0.0926)	−0.000510 (0.00206)
Observations	19,615	1,678	588	20,705	18,896	2,397
Represented Farms	2,848,565	466,762	121,796	3,193,530	2,734,508	580,818

(continued)

	Male	Female	Non-white	White	Experienced	Beginning
R^2	0.185	0.0640	0.124	0.186	0.201	0.121
Number of Double Selection Lasso Controls	23	12	2	29	27	8
<i>Number of Double Selection LASSO Interactions Related to</i>						
Gender				3	3	1
Race	2	4			2	
Farm characteristics	11	4	1	11	10	4
Other farmer characteristics	4	3		6	4	
Note(s): This table shows the estimation results for equation (5) $y_i = \beta_0 + \beta_{int} int_i + \beta_{gov} gov_i + \beta_x \tilde{x}_i + \varepsilon_i$ where y_i refers to the binary variable short-term debt use. LASSO selected interactions within $\tilde{x}$ are classified as being related to gender, race, farm characteristics, and other farmer characteristics at the bottom of the table depicting the relevance of each category of controls for the estimated association. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$						
Source(s): Authors own work						

Table 4.

white farm operators may have limited access to credit, or, despite the available programs, they may have faced other barriers that present in a lower debt use for them. Interestingly, despite being a group typically expected to face credit limitations, beginning farmers displayed higher debt use, likely due to specific provisions in previous Farm Bills, demonstrating that special provisions could provide easier access to credit for this group [1]. This overall positive correlation suggests that farms that received higher government support payments during the pandemic may have been more likely to experience cash constraints, necessitating debt use to address their financial needs.

Results also show a positive association between interest rates and short-term debt use across all farm sizes and most operator types, except for female operators, where the association is insignificant. This aligns with the idea that farms using debt typically face higher loan interest rates. Notably, non-white operators had the highest significant increase in debt use with higher interest rates (6.34%), while beginning farmers (3.85%) and commercial farms (2.16%) showed the lowest significant increases. Higher debt use due to higher interest rates and accessible government support may stem from persistently lower net cash incomes (Giri and Subedi, 2023). It could indicate that farm operations could not avoid higher interest rates to relieve short-term liquidity constraints. Conversely, increases in debt use (for beginning and commercial farms, along with female operators) as interest rates increase but remain quite low during the pandemic, might result from either stable farm financials, as often observed among large commercial farm operations, or limited access to credit. If farm operators faced challenges in accessing credit, changes in interest rates would not be significantly related to their debt use, as observed among female operators.

A notable phenomenon presented in Tables 3 and 4 is the selection of variables explaining debt use and the relationship between debt use, COVID-19 government payments, and interest rates. LASSO selected different controls based on farm type (residence, intermediate, and commercial farms) and farmer demographics (male, female, white, non-white, experienced, and beginning), as shown in Tables 3 and 4. The variables selected by LASSO, significant or insignificant, highlight the most important characteristics that explain debt use in each farm type and farmer group. While gross farm income remains important for residence, intermediate and commercial farms along with male, white and experienced farm operators, its absence in explaining debt use for female, non-white and beginning farm operators highlights that once gender, experience, or race are accounted for, farm income no longer explains unique variation in debt use. Table 4 further verifies this by highlighting the differences in both the number and types of variables selected as most important in explaining debt use for white and non-white operators. Notably, fewer variables were selected for the farm and farmer categories traditionally expected to face higher challenges. Residence and intermediate farms had only 10 and 8 critical determinants for debt use, respectively, while commercial farms had 15 influential factors. Similarly, 2, 8, and 12 variables were selected for the subsamples of non-white, beginning, and female farmers, respectively, compared to 29, 27, and 23 variables for the categories of white, experienced and male farm operators, respectively. This underscores the significance of size, experience, and farmer demographics as crucial factors influencing debt use, diminishing the explanatory power of other determinants sometimes including farm financials.

The double selection by LASSO includes the variables that explain the most variation in the outcome. Even if some estimates are insignificant, the inclusion of each variable in underscores its importance in relation to the outcome (short-term debt use) and model variables (interest rates and government payments). This difference in variable selection by LASSO emphasizes the relative importance of factors such as farm financials, race, and gender in explaining variations in binary debt use and continuous debt utilization.

Overall, we also observe the interaction of supply and demand factors in explaining debt use across different farm sizes and operator characteristics. Larger commercial farms

typically have better access to credit due to stronger financial positions and collateral availability, benefiting more from favorable supply factors like low interest rates. In contrast, residence and intermediate farms may face greater challenges due to stricter lending criteria and less collateral. Traditionally financially vulnerable groups might have higher demand for credit but face significant supply-side barriers due to perceived higher risk by lenders (Thilmany *et al.*, 2022), even with government support programs in place. Non-white and female operators may often face additional supply-side constraints, such as discriminatory lending practices or lack of targeted support (Atkins *et al.*, 2022; Sant'Anna *et al.*, 2023) despite possibly having a similar or greater demand for credit compared to their white and male counterparts, which may explain their relatively lower debt use and less farm financial factors being selected by LASSO. Beginning farmers, despite higher demand for credit to establish their operations, might benefit from specific provisions in the Farm Bill that ease supply-side constraints.

Degree of indebtedness

Next, we examine the association between government payments and interest rates and farms' level of indebtedness using the amount of short-term debt. The amount of short-term debt represents the dollar value (in millions of dollars) of loans with a duration of less than one year. The results, specifically estimated using equation (5) for the subset of farms that have obtained short-term debt, are presented in Tables 5 and 6.

Results in Table 5 present the estimations for all farms, residence, intermediate, and commercial farms while Table 6 includes estimations for male, female, non-white, white, experienced, and beginning farm operators. The findings indicate that increased pandemic-related government payments were not significantly associated with lower short-term debt for any farm type or farmer group. However, we observe a weak negative coefficient for residence and intermediate farms, and non-white farm operators. An association between lower debt and higher government payments indicates a substitution effect between the two sources of financial support, debt and government payments, in addressing a farm operation's financial needs. The farms where government payments may have substituted short-term debt were residence and intermediate farms, and non-white operators.

Overall, once we restrict the estimation to a sample of those with short-term debt, the average change in short-term debt is not significantly associated with pandemic-related government payments during 2020 and 2021 for these farmers likely due to a high variation in the access to credit as well as the decision to use short-term debt. Some farms may have increased their debt use due to a combination of very favorable credit terms (low interest rates) and stronger financial conditions from pandemic-related assistance. The farms that did not increase their debt amounts could either have chosen not to do so, or they may have restricted access to credit.

On the other hand, the favorable credit conditions during the pandemic allowed farms that could arguably access credit more easily, like commercial farms and white or experienced farm operators to increase their short-term debt during the pandemic in response to lower interest rates. Our findings show that a one percentage point decrease in the short-term interest rate is significantly associated with an increase of \$17,500 in short-term debt for the sample of all farms. Despite the relatively low average short-term interest rate for debt holders during the pandemic (as shown in Figure 3), our estimate suggests that a decrease in the already low interest rate was associated with a significant increase in the amount of short-term debt. Notably, this relationship was primarily driven by commercial farms, as evidenced by the fourth column in Table 5. For these farms, a one percentage point decrease in the short-term interest rate was associated with an average increase of \$47,600 in short-term debt. Experienced and white operators followed this with an average increase in

Table 5.
Post double selection
LASSO OLS for the
amount of short-term
debt: farm types

	All farms	Residence	Intermediate	Commercial
Covid government payments (million \$)	0.315 (0.445)	−1.565 (1.221)	−0.884 (0.865)	0.183 (0.494)
Short-Term Interest Rate (%)	−0.0175*** (0.00237)	−0.00883*** (0.00171)	−0.00952*** (0.00207)	−0.0476*** (0.00497)
Crop Insurance Use (1/0)	0.0357 (0.0361)	−0.0808* (0.0392)		
Individual Farm (1/0)	−0.0787 (0.0582)			0.0728 (0.0722)
Farm Investment (million \$)	0.197** (0.0940)			0.179 (0.113)
Gross Farm Income (million \$)	0.0982*** (0.0287)	0.774*** (0.153)	0.383 (0.226)	0.107*** (0.0273)
Return on Assets (%)	0.0424 (0.163)			
Total Assets (million \$)	0.0380*** (0.0103)		0.0246*** (0.00695)	0.0370*** (0.0114)
Contracts Use		0.0397 (0.0529)		
Constant	0.239*** (0.0444)	0.0723*** (0.00913)	0.0699*** (0.00847)	0.442*** (0.0675)
Observations	9,270	1,576	2,462	5,232
Represented Farms	876,416	365,133	293,307	217,976
R ²	0.383	0.232	0.211	0.282
Number of Double Selection Lasso Controls	21	11	6	6
<i>Number of Double Selection LASSO Interactions Related to</i>				
Gender	1	2	1	
Race	1	1		
Farm characteristics	8	5	3	2
Other farmer characteristics	5			
Note(s): This table shows the estimation results for equation (5) $y_i = \beta_0 + \beta_{int} int_i + \beta_{gov} gov_i + \beta_x \tilde{x}_i + \varepsilon_i$ where y_i refers to the dollar amount of short-term debt. LASSO selected interactions within $\tilde{x}$ are classified as being related to gender, race, farm characteristics, and other farmer characteristics at the bottom of the table depicting the relevance of each category of controls for the estimated association. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$				
Source(s): Authors own work				

	Male	Female	Non-white	White	Experienced	Beginning
Covid government payments (million \$)	0.373 (0.431)	2.302 (3.108)	−1.360 (3.538)	0.408 (0.452)	0.392 (0.451)	0.0274 (1.166)
Short-Term Interest Rate (%)	−0.0189*** (0.00250)	0.00188 (0.00955)	−0.0206 (0.0160)	−0.0175*** (0.00240)	−0.0190*** (0.00259)	−0.0115* (0.00560)
Crop Insurance Use (1/0)	0.0397 (0.0275)			0.0460 (0.0348)	0.0439 (0.0410)	
Individual Farm (1/0)	−0.0915 (0.0607)			−0.0658 (0.0594)	−0.0814 (0.0746)	
Farm Investment (million \$)	0.202* (0.107)	0.403 (0.465)		0.185* (0.0925)	0.212* (0.112)	0.0497 (0.157)
Gross Farm Income (million \$)	0.0873*** (0.0266)			0.102*** (0.0294)	0.0895*** (0.0304)	0.219** (0.0833)
Education (categorical)	0.00178 (0.00845)				0.00577 (0.00881)	
Acreage (acres)	−0.00000827 (0.0000216)	−0.0000288 (0.0000418)			−0.00000913 (0.0000201)	
Total Assets (million \$)	0.0382*** (0.0107)	0.0916 (0.0581)		0.0372*** (0.0105)	0.0376*** (0.0110)	0.0383 (0.0274)
Diversification (0–1)				0.0279 (0.0796)		
Return on Assets (%)				0.0115 (0.170)	−0.00793 (0.194)	−0.233 (0.403)
Contracts Use Male (1/0)						0.262*** (0.0834)
Constant	0.260*** (0.0479)	0.0368 (0.0624)	0.284*** (0.0668)	0.228*** (0.0416)	0.0660** (0.0273)	0.0961*** (0.0215)
Observations	8,841	429	232	9,038	8,327	943
Represented Farms	796,811	79,605	25,931	850,485	715,296	161,120

(continued)

Table 6. Post double selection LASSO OLS for the amount of short-term debt: gender, race, and experience

Table 6.

	Male	Female	Non-white	White	Experienced	Beginning
R^2	0.375	0.367	0.545	0.381	0.372	0.481
Number of Double Selection Lasso Controls	21	10	13	19	24	8
<i>Number of Double Selection LASSO Interactions Related to</i>						
Gender				1	1	
Race	3	1	2		2	
Farm characteristics	7	5	5	8	8	2
Other farmer characteristics	4	1	6	3	4	1
Note(s): This table shows the estimation results for equation (5) $y_i = \beta_0 + \beta_{int} int_i + \beta_{gov} gov_i + \beta_x \tilde{x}_i + \varepsilon_i$ where y_i refers to the dollar amount of short-term debt. LASSO selected interactions within $\tilde{x}$ are classified as being related to gender, race, farm characteristics, and other farmer characteristics at the bottom of the table depicting the relevance of each category of controls for the estimated association. Standard errors in parentheses. $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.01$						
Source(s): Authors own work						

short-term debt of \$19,000, and \$18,900 for a percentage point decrease in the short-term interest rate, respectively. As the prevailing interest rate was very low, an increase in the interest rate may not necessarily increase interest expense significantly for commercial farms and white or experienced operators, perhaps allowing them to gain advantage of COVID-19 easing policies.

Consistent with previous estimations, LASSO selected a smaller number of controls for the subsamples of smaller sized farms, and female, non-white, beginning farm operators compared to commercial farms, and farms with male, white, and experienced operators highlighting the explaining power of size, gender, race, and experience in farm debt.

Robustness

To ensure that the LASSO selection of control variables does not introduce regularization bias or omitted variable bias, we also estimated [equation \(5\)](#) using the entire sample of all farms (column 1 in [Tables 1, 3, and 5](#)). In this approach, the variables selected for the overall sample are used consistently across all subsamples, providing a uniform set of variables for all regressions. This consistency allows for direct comparison of coefficients across all estimations. The results for the two variables of interest in these models are shown in [Table 7](#), which presents estimates using both the LASSO selection process and the same set of variables.

The estimated coefficients and their precision closely match the results presented in [Tables 3–6](#). Given this similarity, one might question the necessity of using LASSO selection. The key advantage of LASSO is that it identifies the most parsimonious set of variables that explain sufficient variation in the outcome variable. In other words, when a variable is selected by LASSO, it highlights its relative importance in explaining variations in debt use.

Our analysis shows significant differences in the factors influencing debt use among different groups. As seen in [Tables 3 and 4](#), fewer variables were selected for categories traditionally facing higher challenges. For example, residence and intermediate farms had only 10 and 8 critical determinants for debt use, respectively, compared to 15 for commercial farms. More notably, 2, 8, and 12 variables were selected for the subsamples of non-white, beginning, and female farmers, respectively, compared to 29, 27, and 23 variables for the categories of white, experienced and male farm operators, respectively. Therefore, this selection of variables highlights the significance of operator's gender, race, experience and the size of a farm operation in their respective debt use. It also indicates the diminishing role of other major determinants like farm financials relative to farmer demographics.

[Table 6](#) further illustrates these differences. For non-white operators, debt utilization is influenced by 13 variables, with only a few being financial factors. In contrast, for white farmers, 19 variables are relevant, including several financial characteristics. This suggests that debt utilization for white farmers is driven by numerous farm-specific financial factors, whereas for non-white farmers, race plays a more dominant role. Note that our results and LASSO selection does not serve as evidence of discrimination, rather, it underscores the homogeneity of specific farmer groups' financial characteristics, resulting in lower debt use for the entire demographic. This finding is essential for designing support programs such as the Farm Bill credit provisions. It suggests that systematic trends in debt utilization among groups like female and non-white operators may stem from barriers not reflected in farm financial statements.

Policy implications and conclusions

Our study yields two critical findings that bear significant implications for the forthcoming 2024 Farm Bill discussions. Firstly, it sheds light on the debt use by farmers during the

Results related to table	Sample/Column title	Estimates from Tables 3–6				New estimates with the same set of variables in all estimations			
		Covid government payments (million \$)		Average interest rate for short-term debt		Covid government payments (million \$)		Average interest rate for short-term debt	
		Estimate	SE	Estimate	SE	Estimate	SE	Estimate	SE
Table 3: Short-Term Debt Use	All Farms	0.630***	−0.0863	0.0505***	−0.00432	0.630***	−0.0863	0.0505***	−0.00432
	Residence	2.787	−1.955	0.0547***	−0.00895	2.825	−2.005	0.0550***	−0.00913
	Intermediate	3.642***	−1.059	0.0575***	−0.00806	3.576***	−1.021	0.0568***	−0.00802
	Commercial	0.458***	−0.0688	0.0216***	−0.00456	0.421***	−0.0673	0.0217***	−0.00445
Table 4: Short-Term Debt Use	Male	0.599***	−0.0946	0.0506***	−0.00405	0.579***	−0.0903	0.0505***	−0.00397
	Female	1.207***	−0.399	0.0521	−0.0412	0.721	−0.562	0.0475	−0.0329
	Non-White	0.582	−0.436	0.0634***	−0.0196	0.393	−0.759	0.0718***	−0.0189
	White	0.647***	−0.0827	0.0502***	−0.00453	0.637***	−0.0851	0.0501***	−0.00447
Table 5: Short-Term Debt Utilization	Experienced	0.576***	−0.0893	0.0530***	−0.00357	0.568***	−0.0875	0.0531***	−0.00352
	Beginning	0.941**	−0.36	0.0385**	−0.0147	0.824**	−0.368	0.0394***	−0.0139
	All Farms	0.315	−0.445	−0.0175***	−0.00237	0.315	−0.445	−0.0175***	−0.00237
	Residence	−1.565	−1.221	−0.00883***	−0.00171	−1.367	−1.075	−0.00842***	−0.0014
Table 6: Short-Term Debt Utilization	Intermediate	−0.884	−0.865	−0.00952***	−0.00207	−1.296	−0.873	−0.0101***	−0.00231
	Commercial	0.183	−0.494	−0.0476***	−0.00497	0.139	−0.451	−0.0469***	−0.00542
	Male	0.373	−0.431	−0.0189***	−0.0025	0.383	−0.44	−0.0188***	−0.00246
	Female	2.302	−3.108	0.00188	−0.00955	−0.139	−2.93	0.00131	−0.00843
	Non-White	−1.36	−3.538	−0.0206	−0.016	0.604	−1.719	−0.0144	−0.0123
	White	0.408	−0.452	−0.0175***	−0.0024	0.401	−0.454	−0.0175***	−0.00234
	Experienced	0.392	−0.451	−0.0190***	−0.00259	0.398	−0.46	−0.0187***	−0.00247
	Beginning	0.0274	−1.166	−0.0115*	−0.0056	−0.109	−0.928	−0.0128***	−0.00457

Note(s): This table shows the estimated coefficients of the two variables of interest resulting from equation (5) $y_i = \beta_0 + \beta_{int} int_i + \beta_{gov} gov_i + \beta_x \tilde{x}_i + \varepsilon_i$ where y_i refers to the binary short-term debt use for Tables 3 and 4, while it is dollar amount of short-term debt for Tables 5 and 6. Column “Current estimates in the paper” repeats the coefficients from previous tables while “New estimates with the same set of variables in all estimations” estimates equation (5) with LASSO selected $\tilde{x}$ from the sample of “All Farms” for all the other sub samples. Standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Source(s): Authors own work

COVID-19 pandemic, providing valuable insights into potential liquidity constraints that led farmers to seek loans. This observation is underscored by the substantial associations between changes in interest rates and debt use among farmers, regardless of whether interest rates increased or decreased. The presence of these significant associations indicates that farmers, particularly those expected to face financial challenges, recognized the need for farm debt. Notably, our study reveals that non-white farm operators exhibited the most substantial increase in debt use when facing higher interest rates. We observed beginning farm operators and commercial farms recorded the smallest increases in debt use. This pattern suggests that their existing access to credit may have been associated with higher debt use even when interest rates were higher, potentially as a response to cash constraints during the pandemic.

Furthermore, the 2018 Farm Bill introduced crucial debt-related provisions that aimed to assist farmers who lacked access to traditional debt sources. This legislative support explains, in part, the positive association observed between interest rates and debt use across various farm typologies and farm operator categories. Notably, the Farm Bill significantly increased the total loan authorization levels for direct and guaranteed farm loan programs from \$4.226 billion to \$10 billion per fiscal year between 2019 and 2023, maintaining a consistent 30–70% allocation between direct and guaranteed loans (USDA ERS, 2019a, b). This expansion in available credit may have reduced competition between farm operations when seeking debt, fostering more equitable access. The contribution of our study lies in providing updated insights, specifically during the pandemic, characterized by historically low interest rates and record-high government payments. Overall, our study enhances the understanding of adapting policies related to interest rates, government payments, loan programs, and debt restructuring in the post-pandemic era to support farmers, manage financial risks, and optimize credit markets. These insights are particularly pertinent to the upcoming 2024 Farm Bill.

Note

1. The 2018 Farm Bill included several key provisions to support this group. Some specific examples are detailed here. For Payment Acres, beginning farmers were exempted from the 10 base acres requirement. Advanced Payments saw an increase in allowable advance payment to at least 50%. The Soil Health Program offered higher rental rates and cost-share for planting cover crops. Emergency Conservation provided up to 90% cost-share for disaster rehabilitation. Additionally, the Farm Ownership Loans reduced or waived the 3-year experience requirement for eligibility (USDA ERS, 2019b).

References

- Atkins, R., Cook, L. and Seamans, R. (2022), "Discrimination in lending? Evidence from the paycheck protection program", *Small Business Economics*, Vol. 58 No. 2, pp. 1-23, doi: [10.1007/s11187-021-00533-1](https://doi.org/10.1007/s11187-021-00533-1).
- Belloni, A., Chen, D., Chernozhukov, V. and Hansen, C. (2012), "Sparse models and methods for optimal instruments with an application to eminent domain", *Econometrica*, Vol. 80 No. 6, pp. 2369-2429.
- Belloni, A., Chernozhukov, V. and Hansen, C. (2014), "Inference on treatment effects after selection among high-dimensional controls", *Review of Economic Studies*, Vol. 81 No. 2, pp. 608-650, doi: [10.1093/restud/rdt044](https://doi.org/10.1093/restud/rdt044).
- Brewer, B.E., Wilson, C.A., Featherstone, A.M. and Langemeier, M.R. (2014), "Multiple vs single lending relationships in the agricultural sector", *Agricultural Finance Review*, Vol. 74 No. 1, pp. 55-68, doi: [10.1108/af-04-2013-0014](https://doi.org/10.1108/af-04-2013-0014).

- Chen, J., Katchova, A.L. and Zhou, C. (2021), "Agricultural loan delinquency prediction using machine learning methods", *International Food and Agribusiness Management Review*, Vol. 24 No. 5, pp. 797-812, doi: [10.22434/IFAMR2020.0019](https://doi.org/10.22434/IFAMR2020.0019).
- Dodson, C.B. and Ahrendsen, B.L. (2016), "Beginning farmer credit and the farm Service agency's role", *Choices*, Vol. 31 No. 4, pp. 1-9.
- Dubman, R. (2000), "Variance estimation with USDA's farm costs and returns surveys and agricultural resource management study surveys", ERS Staff Papers, United States Department of Agriculture, Economic Research Service, Staff Report No. 276685.
- Escalante, C.L., Osinubi, A., Dodson, C. and Taylor, C.E. (2018), "Looking beyond farm loan approval decisions: loan pricing and nonpricing terms for socially disadvantaged farm borrowers", *Journal of Applied Agricultural Economics*, Vol. 50 No. 1, pp. 129-148, doi: [10.1017/aae.2017.25](https://doi.org/10.1017/aae.2017.25).
- Fairlie, R., Robb, A. and Robinson, D.T. (2022), "Black and white: access to capital among minority-owned start-ups", *Management Science*, Vol. 68 No. 4, pp. 2377-2400, doi: [10.1287/mnsc.2021.3998](https://doi.org/10.1287/mnsc.2021.3998).
- Ghimire, J., Escalante, C.L., Ghimire, R. and Dodson, C.B. (2020), "Do farm service agency borrowers' double minority labels lead to more unfavorable loan packaging terms?", *Agricultural Finance Review*, Vol. 80 No. 5, pp. 633-646, doi: [10.1108/afr-03-2020-0038](https://doi.org/10.1108/afr-03-2020-0038).
- Giri, A.K. and Subedi, D. (2023), "Increases in US Farm debt and interest expenses minimally affect sector's financial position in the short-term, as measured by liquidity and solvency ratios", *USDA Amber Waves*, United States Department of Agriculture, Economic Research Service, available at: <https://ers.usda.gov/amber-waves/2023/august/increases-in-u-s-farm-debt-and-interest-expenses-minimally-affect-sector-s-financial-position-in-the-short-term-as-measured-by-liquidity-and-solvency-ratios/>
- Giri, A.K. and Subedi, D. (2024), "Increases in US Farm debt and interest expenses minimally affect sector's financial position in the short-term, as measured by liquidity and solvency ratios", in *Amber Waves: The Economics of Food, Farming, Natural Resources, and Rural America*.
- Giri, A.K., McDonald, T., Subedi, D. and Whitt, C. (2021a), "Financial assistance for farm operations and farm households in the face of COVID-19", COVID-19 Working Paper, United States Department of Agriculture, Economic Research Service.
- Giri, A.K., Subedi, D., Peterson, E.W.F. and McDonald, T.M. (2021b), "Impact of the paycheck protection program on US Producers", *Choices*, Vol. 36 No. 3, pp. 1-7.
- Giri, A.K., Subedi, D. and Kassel, K. (2022), "Analysis of the payments from the coronavirus food assistance program and the market facilitation program to minority producers", *Applied Economic Perspectives and Policy*, Vol. 46, pp. 1-13, doi: [10.1002/aep.13325](https://doi.org/10.1002/aep.13325).
- Ifft, J., Novini, A. and Patrick, K. (2014), "Debt use by US farm businesses", USDA-ERS economic information bulletin, United States department of agriculture, Economic Research Service No. 122.
- Ifft, J.E., Kuethe, T. and Morehart, M. (2015), "Does federal crop insurance lead to higher farm debt use? Evidence from the Agricultural Resource Management Survey (ARMS)", *Agricultural Finance Review*, Vol. 75 No. 3, pp. 349-367, doi: [10.1108/afr-06-2014-0017](https://doi.org/10.1108/afr-06-2014-0017).
- Ifft, J., Kuhns, R. and Patrick, K. (2018), "Can machine learning improve prediction—an application with farm survey data", *International Food and Agribusiness Management Review*, Vol. 21 No. 8, pp. 1083-1098, doi: [10.22434/ifamr2017.0098](https://doi.org/10.22434/ifamr2017.0098).
- Jablonski, B.B.R., Key, N., Hadrich, J., Bauman, A., Campbell, S., Thilmany, D. and Sullins, M. (2022), "Opportunities to support beginning farmers and ranchers in the 2023 Farm Bill", *Applied Economic Perspectives and Policy*, Vol. 44 No. 3, pp. 1177-1194, doi: [10.1002/aep.13256](https://doi.org/10.1002/aep.13256).
- Johansson, R., Hungerford, A., Sewadeh, M. and Effland, A. (2021), "Unprecedented crisis calls for unprecedented policy responses", *Applied Economic Perspectives and Policy*, Vol. 43 No. 1, pp. 120-131, doi: [10.1002/aep.13128](https://doi.org/10.1002/aep.13128).

- Katchova, A.L. (2005), "Factors affecting farm credit use", *Agricultural Finance Review*, Vol. 65 No. 2, pp. 17-29, doi: [10.1108/00214660580001164](https://doi.org/10.1108/00214660580001164).
- Kauffman, N.S. (2013), "Credit markets and land ownership for young and beginning farmers", *Choices*, Vol. 28 No. 2, pp. 1-5.
- Key, N. (2022), "The determinants of beginning farm success", *Journal of Applied Agricultural Economics*, Vol. 54 No. 2, pp. 199-223, doi: [10.1017/aae.2022.6](https://doi.org/10.1017/aae.2022.6).
- Key, N. and Lyons, G. (2019), "An overview of beginning farms and farmers", Economic Brief, United States Department of Agriculture, Economic Research Service No. 29.
- Kropp, J.D. and Katchova, A.L. (2011), "The effects of direct payments on liquidity and repayment capacity of beginning farmers", *Agricultural Finance Review*, Vol. 71 No. 3, pp. 347-365, doi: [10.1108/00021461111177611](https://doi.org/10.1108/00021461111177611).
- Lu, L., Tian, G. and Hatzenbuehler, P. (2022), "How agricultural economists are using big data: a review", *China Agricultural Economic Review*, Vol. 14 No. 3, pp. 494-508, doi: [10.1108/caer-09-2021-0167](https://doi.org/10.1108/caer-09-2021-0167).
- Marchant, M.A. and Wang, H.H. (2018), "US-China trade dispute and potential impacts on agriculture", *Choices*, Vol. 33 No. 2, pp. 1-3.
- Martinez, C., Boyer, C.N., Yu, T.-H., Smith, A.S. and Rabinowitz, A. (2023), "Ad hoc government payments impact on non-real estate farm debt", *Agricultural Finance Review*, Vol. 83 No. 1, pp. 83-95, doi: [10.1108/afr-09-2021-0129](https://doi.org/10.1108/afr-09-2021-0129).
- McDonald, T.M., Law, J., Giri, A.K. and Subedi, D. (2021), "The role of nontraditional lending for socially disadvantaged and financially stressed farmers", *Agricultural Finance Review*, Vol. 82 No. 2, pp. 247-267, doi: [10.1108/afr-06-2021-0072](https://doi.org/10.1108/afr-06-2021-0072).
- McLaughlin, P.W., Stevens, A., Arita, S. and Dong, X. (2023), "Stocking up and stocking out: food retail stock-outs, consumer demand, and prices during the COVID-19 pandemic in 2020", *Applied Economic Perspectives and Policy*, Vol. 45 No. 3, pp. 1618-1633, doi: [10.1002/aep.13362](https://doi.org/10.1002/aep.13362).
- Prager, D.L., Burns, C.B. and Miller, N.J. (2018), "How do financially vulnerable farms finance debt in periods of falling prices?", *Agricultural Finance Review*, Vol. 78 No. 4, pp. 412-424, doi: [10.1108/afr-08-2017-0066](https://doi.org/10.1108/afr-08-2017-0066).
- Reiley, L. (2021), "Agriculture secretary Tom Vilsack says only 0.1 percent of Trump administration's Covid farm relief went to black farmers", *The Washington Post*, available at: <https://www.washingtonpost.com/business/2021/03/25/vilsack-interview-usda-rescue-plan/> (accessed 20 September 2023).
- Sant'Anna, A.C., Kim, K.N. and Demko, I. (2023), "Limits to capital: assessing the role of race on the paycheck protection program for African American farmers in America", *Applied Economic Perspectives and Policy*, Vol. 46, pp. 1-17, doi: [10.1002/aep.13338](https://doi.org/10.1002/aep.13338).
- StataCorp (2021), "Stata LASSO reference manual, Stata release 17", available at: <https://www.stata.com/features/overview/LASSO-model-selection-prediction/> (accessed 7 May 2023).
- Storm, H., Baylis, K. and Heckelee, T. (2020), "Machine learning in agricultural and applied economics", *European Review of Agricultural Economics*, Vol. 47 No. 3, pp. 849-892, doi: [10.1093/erae/jbz033](https://doi.org/10.1093/erae/jbz033).
- Subedi, D. and Giri, A.K. (2024), "Debt use by US farm businesses, 2012-2021", (Report No. EIB-273), US Department of Agriculture, Economic Research Service.
- Thilmany, D., Bauman, A., Hadrich, J., Jablonski, B.B.R. and Sullins, M. (2022), "Unique financing strategies among beginning farmers and ranchers: differences among multigenerational and beginning operations", *Agricultural Finance Review*, Vol. 82 No. 2, pp. 285-309, doi: [10.1108/afr-05-2021-0070](https://doi.org/10.1108/afr-05-2021-0070).
- Tulman, S., Williams, R., Higgins, N., Gerling, M., Dodson, C. and McWilliams, B. (2016), "USDA microloans for farmers: participation patterns and effects of outreach", Economic Research Reports, United States Department of Agriculture, Economic Research Services No. 222.

- US Department of Agriculture, Economic Research Service (2019a), “Agriculture improvement Act of 2018: highlights and implications – credit”, available at: <https://www.ers.usda.gov/agriculture-improvement-act-of-2018-highlights-and-implications/credit/> (accessed 7 September 2023).
- US Department of Agriculture, Economic Research Service (2019b), “Beginning, socially disadvantaged, and veteran farmers and ranchers”, available at: <https://www.ers.usda.gov/topics/farm-bill/2018-farm-bill/beginning-socially-disadvantaged-and-veteran-farmers-and-ranchers/> (accessed 23 July 2024).
- US Department of Agriculture, Economic Research Service (2023), “Farm income and Wealth statistics”, available at: <https://www.ers.usda.gov/data-products/farm-income-and-wealth-statistics/> (accessed 7 September 2023).
- US Department of Agriculture, Economic Research Service (2024), “Agricultural resource management survey documentation”, available at: <https://www.ers.usda.gov/data-products/arms-farm-financial-and-crop-production-practices/documentation/> (accessed 16 April 2024).
- US Department of Agriculture, Economic Research Service and National Agricultural Statistics Service (NASS), Agricultural Resource Management Survey (2023), “ARMS Webtool”, Data as of August 31, 2023, available at: <https://my.data.ers.usda.gov/arms/tailored-reports> (accessed 7 September 2023).
- Zhang, W. (2021), “The case for healthy US-China agricultural trade relations despite deglobalization pressures”, *Applied Economic Perspectives and Policy*, Vol. 43 No. 1, pp. 225-247, doi: [10.1002/aapp.13115](https://doi.org/10.1002/aapp.13115).

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