Impact of Interest Rate Changes and Government Payments on Farm Operation's Debt

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Abstract

The farm debt dynamics, which provide an insight into the financial health of farmers, before, during, and after the pandemic, convey a heterogenous impact of the quantitative easing policies on the agricultural sector in the US. While high government payments and low interest rates were intended to counter financial stress, their dynamic and aggregate impact is unclear. Our study utilizes the double selection LASSO (Least Absolute Shrinkage and Selection Operator) method for model selection in ARMS data to analyze the role of government payments and interest rates on farm credit used during the COVID-19 pandemic period. The findings and insights from this study are timely, and could be useful for policymakers and lenders for designing and implementing programs to support agricultural producers.

Keywords: Farm debt, agricultural finance, quantitative easing, credit use.
JEL Codes: E43, H3, Q14, Q18.

Introduction

US agricultural sector debt is indicative of agricultural operations' financial health, stability, and risk management; therefore, understanding farm debt dynamics can help identify potential vulnerabilities and risks faced by farmers. The coronavirus pandemic exacerbated several challenges for farmers that existed pre-pandemic (Kauffman, 2013; Marchant & Wang, 2018; Zhang, 2021; Thilmany et al., 2022) while introducing new hurdles and uncertainties along the supply chain, inputs (and their costs), marketing strategies, and market demand, among many others (Giri et al., 2022a). While specific quantitative easing measures by the government would counter the financial challenges for agricultural producers to some extent, an in-depth analysis of the farm sector debt is necessary for researchers and policymakers to identify how the policies related to interest rates, government payments, loan programs, and debt restructuring may be adapted in the post-pandemic economy to support farmers, mitigate financial risks, and enhance the efficiency of credit markets.

This study seeks to understand the heterogeneous impact of two policy instruments, interest rates, and government payments, on farm sector debt during COVID-19. We specifically seek to understand the heterogeneous relationship between near-zero interest rates, record-high government payments, and loan demand by producers. We control for documented factors important for farm debt (Katchova, 2005) and separate the potentially constrained groups of farmers to test the hypothesis that a decrease in interest rates would significantly impact farm debt for financially vulnerable farms. Moreover, if the binary demand for credit stems from a need to finance day-to-day expenses and increase liquidity, demand for loans will decrease when government payments are high. On the other hand, if the demand for loans stems from a need for capital-intensive projects, we would expect that government payments would play a less

significant effect on farm credit demand. We also anticipate that the estimated effect would differ for different farm types.

Our findings suggest that while interest rates and government payments are significantly associated with both overall and short-term credit use, government payments matter more in explaining short-term credit use than overall credit use. This is because the likelihood of receiving government payments is expected to rise with financial need and provide a strengthened impact on the demand for credit during the pandemic. On the other hand, neither interest rates nor pandemic-related government payments provided during the COVID-19 pandemic explain the overall degree of indebtedness for farms of any size or financial condition, but there is a very strong relationship between both variables and the amount of short-term credit. A one percentage point decrease in the short-term interest rate is significantly associated with an increase of $22,900 in short-term loans, while the short-term credit increases by $93 per $100 of pandemic-related government payments. This speaks to the financial constraints faced by farmers during the pandemic that these policy instruments were meant to relieve.

We plan to further explore how these changes impact farm investment and costs in the next steps. We will expand our examination to farm investments and costs to understand whether labor supply shocks, arguably a causal impact of the pandemic, combined with financial support and favorable credit conditions, converted to higher labor costs for farmers and promoted higher mechanization. While access to credit and direct support are both expected to have relieved financial stress, exploring other aspects of farm financial decision-making (farm investment) and economic pressures (costs) will allow for a more comprehensive understanding of the farm sector's financial health, stability, and risk.

Background

Farm debt had been steeply rising before the pandemic, but real farm debt fell for the first time in a decade during the pandemic. After the pandemic, farm sector debt has been increasing again and is forecast to continue to increase and exceed half a trillion dollars in 2022 and 2023 (Figure 1). The changes in aggregate farm debt before, during, and after the pandemic convey a heterogenous impact on farmers during the pandemic when financial stress was high. Farm sector debt includes both real estate as well as non-real estate, or alternatively short-term and long-term loans, where credit use varies significantly by farm type and farm income. Ifft et al. (2014) highlighted the role of farm size, commodity specialization, and farmer characteristics in determining credit use and magnitude. They found that large-scale family farms[1] 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 operator's age increased. The most important factors that impact credit use and composition that have been highlighted in other research are government payments (Kropp & Katchova, 2011; Katchova, 2015), financial vulnerability and cash flow (Prager et al., 2018), and current leverage (Brewer et al., 2014). Previous studies on the relationship between interest rates and farm debt using ARMS are rare, though economic theory would suggest that interest rate increases would be associated with lower loan demand by farm operations.

Recent USDA data shows that producers had record-high net cash incomes of $149.5 billion and $189.9 billion in 2021 and 2022, respectively. Net cash income is expected to be at $150.6 billion in 2023 which is higher than the pre-pandemic average. Although record-high commodity prices boosted cash receipts, a major component was the rise in government payments and favorable

[1] Farms with annual gross cash farm income of $1 million or more.

trade agreements. During the pandemic in 2020 and 2021, government payments to farmers exceeded historical levels. Direct government payments of more than $45 billion in 2020 were the highest on record in both nominal and real terms. As expected, a large driver of high government payments for various support programs includes the coronavirus pandemic support. Additionally, the pandemic also led the Federal Reserve Bank to lower the interest rates to near zero, essentially increasing access to credit. Lower interest rates make it easier to access credit, refinance debt, and revise farm investments.

The government payments' magnitude and reach far exceeded anything observed before the pandemic. Figure 2 shows the government payments in nominal terms from 2000 through 2023 using data from the most recent release (February 7, 2023) of the Farm Income and Wealth Statistics data product of the USDA's Economic Research Service. The 2020 direct payments were record-high because of the COVID-19-assistance (Giri et al., 2022a). In fact, the Coronavirus Food Assistance Program (CFAP), the primary COVID relief program of the USDA, made more in payments than the average total payments to the farm sector for the past 20 pre-pandemic years (Giri et al., 2022b). Giri et al. (2021a) found that almost all producers, 97 percent measured by cash receipts, were eligible to receive CFAP payments, which suggests this was one of the most comprehensive USDA programs in history. Based on the USDA-ERS ARMS web tool (2023), 40 percent of all farm operations received some government payments in 2020, which was significantly higher than 31 percent in the preceding year (2019) and 34 percent in the succeeding year (2021). Generally, less than 30 percent of farm operations received some government payment in previous years.

Additionally, to keep the economy running smoothly and ensure enough liquidity, the Federal Open Market Committee (FOMC), which sets the short-term federal funds rate, had set rates at

record low levels in 2020 and 2021 (Figure 3)[2]. However, since March 2021, to tame high and persistent inflation, the FOMC has already increased the short-term federal funds rate eight times through March 2023. Figure 3 shows the short-term federal funds rate at 4.65 percent in March 2023 compared to less than one percent in March 2020. This offers a unique source of variation in such a short period, allowing for an investigation of interest rate changes on farm debt. An increase in interest rate translates to an increase in interest expenses for farm operations which can lead to lower demand for loans. The USDA-ERS has forecasted interest expenses in 2023 to be the fastest-increasing category among production expense categories. Sector-level interest expenses are forecast at $33.85 billion for 2023, an increase of $6.21 billion, or 22 percent, compared with interest expenses of $27.64 billion in 2022. This shows that interest expenses will continue to be higher for farm operations that will take new loans and for those that do not have their interest rates locked in. Therefore, the impact of interest rate changes observed during the pandemic (and study period) will remain relevant for the upcoming years.

Methods

This study follows Belloni et al. (2014) and utilizes the double selection LASSO (Least Absolute Shrinkage and Selection Operator) method for model selection in analyzing the role of government payments and interest rates on farm credit use during the COVID-19 pandemic period. The empirical approach combines the use of machine learning methods with economic theory to select an appropriate set of controls for several farm debt variables. The model is given as

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

[2] The short-term federal funds rate either directly or indirectly influence other interest rates in the United States (St. Louis Fed, 2023).

Where y_i is the outcome variable and will take four different values ($y_i \in (overall\ credit\ use,\ short\ term\ credit\ use,\ degree\ of\ indebtedness,\ amount\ of\ short\ term\ debt)$), int_i and gov_i refer to the interest rate and government payments, respectively, and are model variables whose impact we are interested in measuring, while z_i are the control variables to condition on for the estimation, where the $g(z_i)$ function is unknown. The control variables include farm and operator characteristics that are typically used in previous studies on farm credit use. We linearly approximate the $g(z_i)$ function by including all linear combinations and interactions of the available control variables x_i. The resulting model is:

$$y_i = \alpha_{int}\, int_i + \alpha_{gov}\, gov_i + x'_i\beta_z + r_{zi} + \epsilon_i \qquad (2)$$

where $x'_i\beta_z$ is the linear approximation of $g(z_i)$, and r_{zi} is the resulting approximation error. The x_i variables (but not their interaction terms) that are used to approximate z_i are presented in tables 1 and 2 as *Control Variables*. The full set of x_i variables include all interactions between the categorical and continuous variables in z_i. As such, we estimate a fully saturated model, making the total number of variables over 100, from which the Lasso would need to select from. Since there are a large number of variables in x_i (i.e., x_i is high dimensional), estimation and inference are challenging. Under the assumption of sparsity, only a small number of non-zero coefficients in the $g(z_i)$ set are needed to make the approximation error r_{zi} small relative to the estimation error ϵ_i, making the estimation simpler. Therefore, we apply the double selection Lasso method to select the appropriate controls for the model in two steps.

First, we use a linear lasso of y_i on x_i (not including the main model variables, int_i and gov_i) and denote their coefficients β_y. Specifically, we use the Rigorous Lasso estimator from Belloni et al. (2012) to solve the following optimization problem to select a subset of high dimensional controls:

$$\min_{\beta_y \in \mathbb{R}_p} \mathbb{E}_n \left[\left(y_i - x_i' \beta_y \right)^2 \right] + \frac{\lambda}{n} \sum_{j=1}^{p} \left| \widehat{l_j} \, \beta_{yj} \right| \qquad (3)$$

where λ is the penalty level, p is the number of variables in x, n is the sample size, and $\widehat{l_j}$'s are variable-specific penalty loadings for each β_{yj} which are selected according to Belloni et al. (2012) to accommodate the heteroscedastic and non-Gaussian error. The first step concludes by selecting the control variables x_i with non-zero β_y's from the Rigorous Lasso optimization.

In the second step, we estimate two lasso models, one for each of the main model variables, int_i and gov_i, respectively on the relevant control variables x_i. The optimization problem is solved again to choose the non-zero coefficients β_{int} and β_{gov}, respectively on the relevant control variables x_i. That is, we select the control variables using Lasso in both of the following optimization problems:

$$\min_{\beta_{int} \in \mathbb{R}_p} \mathbb{E}_n [(int_i - x_i' \beta_{int})^2] + \frac{\lambda}{n} \sum_{j=1}^{p} \left| \widehat{l_j} \, \beta_{intj} \right| \qquad (4)$$

and

$$\min_{\beta_{gov} \in \mathbb{R}_p} \mathbb{E}_n \left[\left(gov_i - x_i' \beta_{gov} \right)^2 \right] + \frac{\lambda}{n} \sum_{j=1}^{p} \left| \widehat{l_j} \, \beta_{govj} \right| \qquad (5)$$

Let $\widetilde{x_i}$ denote the union of the set of all controls x_i with non-zero coefficients retained after both steps. Then, after the double selection from Lasso, we estimate the following reduced form model using least squares:

$$y_i = \alpha_{int} \, int_i + \alpha_{gov} \, gov_i + \beta \, \widetilde{x_i} + \varepsilon_i \qquad (6)$$

and report the post double selection lasso estimation results in the following section. We use the ARMS survey main weights during both lasso steps. For the final post-double selection estimation in equation (6), we use the main and replicate weights and the jackknife method for calculating the standard errors (Dubman, 2000).

Data

This study uses the recent waves of the USDA's Agricultural Resource Management Survey (ARMS) as it collects data on government support payments, including from COVID-19 specific programs, farmer credit practices and utilization, and detailed farm operations. 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. ARMS also collect data on interest rates paid on loans, which we use in the analysis. Restricting our analysis to 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. The outcome variables: whether the farm has credit use (indicator variable), whether the farm has short term credit use (indicator variable), the degree of indebtedness (debt-to-asset ratio), and the dollar amount of short-term credit, were all constructed from the ARMS data.

The summary statistics of the outcome, model, and control variables is presented in tables 1 and 2 for the entire sample and debtors, respectively. Moreover, we separately present the summary statistics for farms of small, medium, and commercial size along with financially vulnerable farms that are in a critical condition. Financially vulnerable farms are defined in ARMS as those with debt-to-assets ratio above 0.40 and negative net farm income. We see from tables 1 and 2 that credit use increases with farm size and is highest for commercial farms, and also is also highest

for financially vulnerable farms. The average interest rate across all loans is higher for farms of larger size and of financially vulnerable status. The total COVID government payments (measured in millions of dollars) are highest for commercial farms. Similar trends are found for farm that are debtors (with positive levels of debt) in table 2.

Results and Discussion

We measure the impact of two main variables, interest rates paid on loans and government payments received, on farm debt through four different variables: $y_i \in (overall\ credit\ use,\ short\ term\ credit\ use,\ degree\ of\ indebtedness,\ amount\ of\ short\ term\ debt)$. The estimation for the first two variables identifies the most important determinants of debt use while the last two shed light on the factors that are most relevant for the amount of credit utilization during the COVID-19 period for US farmers. Tables 3-6 present the post double selection Lasso OLS results (corresponding to equation 6) for each of the outcome variables where interest rates (int_i) and government payments (gov_i) are the model variables and all control variables in table 1, along with the interactions of all categorical and continuous variables as selected in $\widetilde{x_i}$. Column 1 estimates include all farms for 2020 and 2021 for a pooled model, while the next four columns are estimated for a subsample of farms based on farm size and financial condition as titled in the column.

Credit Use

Table 3 presents the estimates for the model with overall credit use as the dependent variable. Results indicate that farms of different sizes experience similar impacts of interest rates on their credit use. The positive and significant coefficient on interest rates aligns with expectations, as farms that use credit are expected to have higher interest rates compared to farms that do not use credit and have zero interest rates. Additionally, farms of all sizes are significantly more likely to

utilize credit if they receive higher pandemic-related government payments during COVID-19. The positive and significant association between government payments and credit use may be because farms eligible for higher amounts of government support payments during the pandemic are also likely to be cash-constrained and in need of credit. On the other hand, for financially vulnerable farms, neither the interest rate nor government payments are significantly associated with credit use. This suggests that lower interests rates or additional COVID support payments did not result in higher credit use for financially vulnerable farms.

It is also interesting to note the control variables selected by the double selection Lasso based on farm size and the financially vulnerable status of the farm. Eight variables are identified as important control variables for credit use when considering all farms (column “All Farms”). These variables include farm and operator characteristics such as receiving crop insurance payments, being an individual farm, gross farm income, operator age, farm investment, labor cost, and others (results shown in the "All Farms" column of Table 3). Although the double selection Lasso method informs the inclusion of these variables in the final model, none of their coefficients are significant in the final estimation reported in Table 3. In the final model, labor cost, the proportion of production under contracts, and operator age play a significant role in determining credit use. Furthermore, farm investment, gross farm income, return on assets, and total assets have an additional impact on farms.

As we move across the columns in Table 3, the selected variables change to reflect the most relevant controls for each farm typology (small, medium, and commercial farms) and financially vulnerable farms. While gross farm income and operator age remain important across all farm sizes, they are not selected in the sample for financially vulnerable farms. The ratio of owned to operated land, interactions of education with farm investment and labor cost, and interactions of

receiving crop insurance with returns on assets and age are among the most important controls for financially vulnerable farms. However, the R-squared for the estimation of financially vulnerable farms remains the lowest, and no significant coefficients on model or control variables are observed. Double selection by Lasso includes the variables that explain the most variation in the outcome, so despite the insignificant estimates, the inclusion of each variable in any given estimation highlights the importance of its relationship with the dependent and model variables. This meticulous selection of controls provides an insight into the aspects of heterogeneity among farms that should be considered for any future studies and policy decisions concerning farm credit.

Table 4 identifies the most important controls for short-term credit use to assess the impact of interest rates and government payments during COVID-19. Short-term credit specifically refers to the utilization of loans with a repayment period of one year or less. Therefore, the model variables include the average interest rate for all short-term loans undertaken by a farmer instead of the average interest rate for all loans as in the previous analysis. Results indicate that the coefficients on interest rates in the model for short-term credit remain positive and significant for all farm sizes for similar reasons as discussed earlier. However, the magnitudes of these coefficients in the short-term credit model are smaller compared to the model for all credit (that includes short-term and long-term credit), which may be due to the smaller, near-zero interest rates during COVID-19. Furthermore, the coefficients on pandemic-related government payments in Table 4 for short-term credit are much larger than those in Table 3, suggesting a stronger correlation between receiving COVID-19 support payments and taking short-term loans. The largest association between COVID-19 government payments and short-term credit use exists for medium, and commercial farms. The association is insignificant for small farms and financially vulnerable farms.

Degree of Indebtedness

Next, we examine the influence of interest rates and government payments on farms' level of indebtedness using two additional outcomes: the degree of indebtedness and the amount of short-term debt. The degree of indebtedness is measured using the debt-to-asset ratio, while 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 for the subset of farms that have obtained credit, are presented in Tables 5 and 6, respectively.

Results in Table 5 indicate that neither interest rates nor pandemic-related government payments provided during the COVID-19 pandemic significantly explain the degree of indebtedness for farms of any size or financial condition. This lack of statistical significance aligns with expectations for the period, as substantial credit accumulation before the pandemic may have been driven by other factors unrelated to interest rates or recent government support. Furthermore, this finding is consistent with previous research conducted by Katchova (2005). Therefore, we focus our analysis on the impact of policy instruments on short-term farm credit, given that any effects that occur within the two-year study period are more likely to manifest in short-term loans than long-term loans.

Results for the amount of short-term credit obtained are presented in Table 6, where the amount of debt is measured in millions of dollars. Our findings indicate that a one percentage point decrease in the short-term interest rate is significantly associated with an increase of $22,900 in the amount of short-term loans. Despite the relatively low average short-term interest rate for creditors during the pandemic (as shown in Table 2), our estimate suggests that even small variations in the already low-interest rate could substantially impact farm debt. Notably, the impact is primarily driven by financially vulnerable farms, as evidenced by the last column in table 6. For these farms, a

percentage point decrease in the short-term interest rate is associated with a $32,700 increase in short-term loans. Financially vulnerable farms likely faced greater challenges during the pandemic, making it essential for them to obtain credit and relieve their persistent financial constraint that is unaffected by COVID-19. But the credit conditions during the study period make it ideal for them to obtain credit at lower interest rates. Since the financially vulnerable farms that face difficulty securing credit would not be able to do so during the pandemic, we did not observe any effect of the interest rate on their likelihood of obtaining credit in either credit use estimations (Tables 3 and 4).

Additionally, the pandemic-related government payments estimate is only significant for the pooled "All Farms" sample with a positive coefficient of 0.930. This translates to a short-term credit increase of $93 per $100 of pandemic-related government payments. There seems to be an almost one-to-one relationship between short-term credit and pandemic-related government payments during the study period. That is most likely due to a combination of very favorable credit terms (low interest rates) and the overlap among the farms that are eligible for higher pandemic-related assistance and have financial constraints that can be relaxed through short-term credit. We do not observe a significant association between short-term credit use and government payments for any specific farm size or financially vulnerable farms.

Conclusions

While farm debt is expected to rise in 2023 (US Department of Agriculture, 2023), questions remain about the distribution of farm debt among farms of different types, sizes, and financial constraints. Farm debt rose steeply before the pandemic, but 2019 also witnessed a six-year peak in delinquency rates for large commercial farmers (Kreitman, 2021), and real farm debt fell for the first time in a decade during the pandemic. The changes in aggregate farm debt before, during, and

after the pandemic convey a heterogenous impact on farms during the pandemic when financial stress was high. High government payments and low interest rates were intended to counter financial stress, but their overall and aggregate impact is unclear. Our study contributes by offering unique insights into the different impacts of the two instruments used during the pandemic to support farmers.

Overall, our research aims to understand the impact of interest rate changes on producers with heterogenous demand for credit from different sources conditional on their endogenous credit and cash flow constraints. Understanding the impact of interest rate changes, record high government payments in 2020, and substantially high payments (above 20-year average) in 2021 on (low) loan demand is of interest to stakeholders, including policymakers, agricultural financial institutions, and producers.

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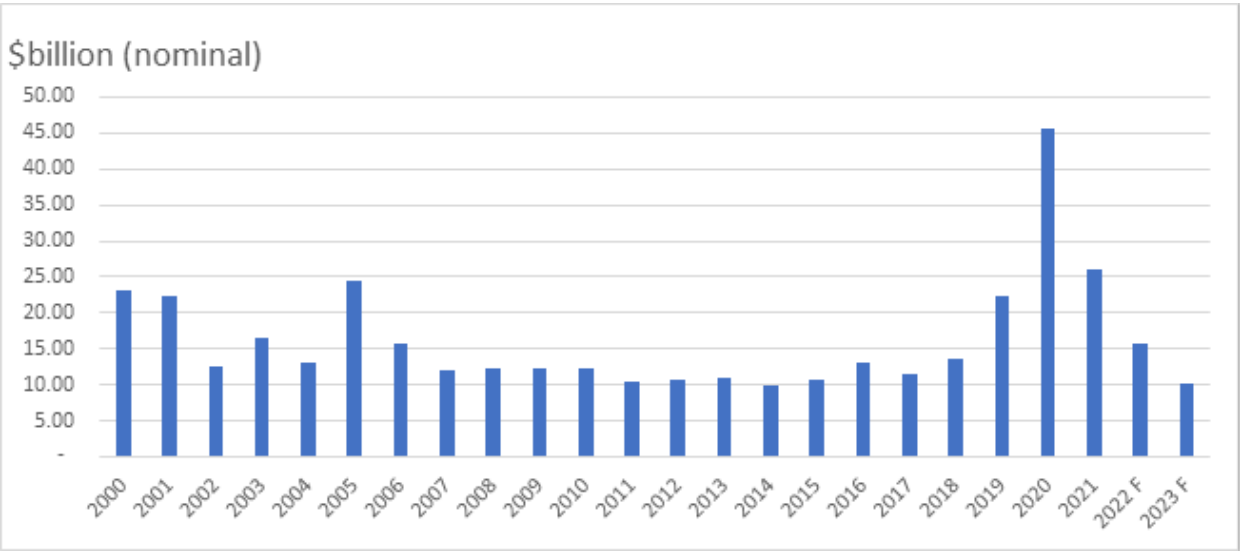
Figures and Tables

Figure 1. Total debt (nominal $)

Note: F= Forecast.

Source: USDA, Economic Research Service, Farm Income and Wealth Statistics. Data as of February 7, 2023.

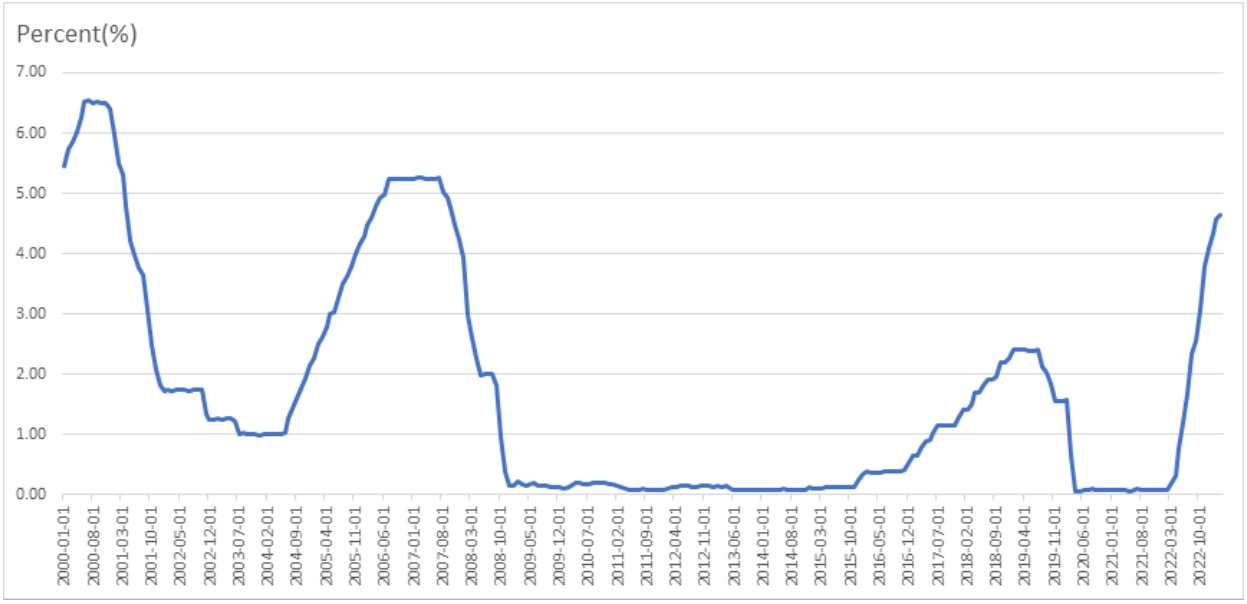
Figure 2. Direct government payments



Note: F= Forecast.

Source: USDA, Economic Research Service, Farm Income and Wealth Statistics. Data as of February 7, 2023.

Figure 3. Federal funds rate



Note: The rates are seasonally unadjusted monthly rates.

Source: Economic Data, St. Louis Fed as of 04/07/2023.

Table 1. Summary Statistics

	All Farms	*Small*	*Medium*	*Commercial*	*Financially Vulnerable*
Outcome Variables					
Credit Use 1/0	.2688479	.2128736	.2403818	.6274522	.9911561
Short Term Credit Use 1/0	.2462853	.196268	.2180029	.5770985	.9551154
Debt to Assets Ratio	.0736334	.0472067	.0654484	.2237859	.8359517
$ Short Term Credit	.0829866	.0242946	.043237	.495094	.3858174
Model Variables					
Short term credit interest rate	.3572569	.2039934	.333971	1.139921	1.003954
Average Interest Rate Across all Loans	1.155504	.9107189	1.049081	2.657896	4.1428
Total COVID government payments	.0055716	.0008443	.0021922	.0394127	.0063274
Control Variables					
Farm Investment	.0251988	.0106585	.014975	.1286652	.0517149
Labor Cost	.0299604	.001893	.0053092	.247603	.0394225
Receiving Crop Insurance 1/0	.1400267	.0673081	.1126905	.5707467	.1661008
Crop Farm 1/0	.3420506	.2727382	.3374627	.6743427	.3274116
Return on Assets	-.0880137	-.1165421	-.0985608	.0803174	-.2154922
Acreage	425.4419	147.504	316.78	2086.934	420.2263
Diversification Index	.1067722	.0902197	.1044484	.1906034	.1148672
Ratio of Owned to Operated Land	1.212174	1.278514	1.232372	.8365152	.7790602
Total Assets	1.559959	.8933439	1.229726	5.798685	.8990175
Operator Age	61.52306	60.85439	63.47184	57.46393	52.50596
Operator Education (categorical)	2.83081	2.959881	2.650076	2.901959	2.694694
Individual Farms	.8749113	.9072222	.9035656	.6233569	.8045461
Land Sold	.0097371	.008922	.0090681	.0158865	.0092349
Income from farm machine/real estate sales	.0072409	.0052567	.0057953	.0215444	.0031176
Machinery sold at loss 1/0	.0008578	.0009498	.0006812	.0010827	0
Gross Farm Income	.1967951	.0311325	.0646269	1.432798	.1842671
Total Off-Farm Income	.0983082	.1260949	.0727267	.0650469	.1068075
Proportion of Production under Contracts	.0486535	.0170947	.0520401	.179991	.0818723
Number of Population Farms	4014418	1987074	1590897	436447.1	83588

Table 2. Summary Statistics for Farms with Debt

	All Farms	*Small*	*Medium*	*Commercial*	*Financially Vulnerable*
Outcome Variables					
Credit Use 1/0	1	1	1	1	1
Short Term Credit Use 1/0	.9160768	.9219934	.9069029	.919749	.9636378
Debt to Assets Ratio	.2729794	.2204673	.2711412	.356658	.8379195
$ Short Term Credit	.3086751	.114127	.1798678	.7890546	.38926
Model Variables					
Short term credit interest rate	1.328844	.9582841	1.389336	1.816746	1.012912
Average Interest Rate Across all Loans	4.297984	4.278214	4.364228	4.236014	4.179765
Total COVID government payments	.0153704	.0021538	.0049636	.050318	.0063839
Control Variables					
Farm Investment	.063732	.0263168	.0305264	.1678948	.0519674
Labor Cost	.0741762	.0034301	.0107807	.2719823	.0397741
Receiving Crop Insurance 1/0	.3022123	.1455682	.2173147	.6627259	.1641513
Crop Farm 1/0	.4372085	.3023866	.4010607	.6959374	.3269015
Return on Assets	-.0194023	-.0534655	-.0575881	.0865378	-.2043303
Acreage	779.602	216.3022	512.2131	2023.09	423.6423
Diversification Index	.1391037	.1038382	.1272301	.2101569	.1144053
Ratio of Owned to Operated Land	1.180226	1.111803	1.55336	.7648433	.7860116
Total Assets	2.553091	1.11616	1.6034	6.098826	.9065184
Operator Age	56.77493	54.30012	60.03174	56.04957	52.52139
Operator Education (categorical)	2.828427	2.941935	2.655319	2.894843	2.700569
Individual Farms	.8271554	.9171234	.8607708	.6412458	.8029641
Land Sold	.0145249	.0150241	.010994	.0186847	.0093173
Income from farm machine/real estate sales	.0146946	.0132762	.0104169	.0228591	.0031454
Machinery sold at loss 1/0	.0017014	.0020242	.0016027	.0013408	0
Gross Farm Income	.4931437	.056908	.1191343	1.689258	.1857213
Total Off-Farm Income	.0999101	.1402288	.0769338	.0697182	.1068465
Proportion of Production under Contracts	.1021046	.0371091	.1028913	.2013999	.0826028
Number of Population Farms	1079268	422996	382423	273850	82849

Table 3. Post Double Selection Lasso OLS for Credit Use

	All Farms	Small	Medium	Commercial	Vulnerable
Average Interest Rate Across all Loans	0.189***	0.192***	0.184***	0.183***	0.0223
	(0.00346)	(0.00754)	(0.00463)	(0.00385)	(0.0162)
Total COVID government payments	0.141***	1.323*	1.218**	0.103***	0.0846
	(0.0439)	(0.762)	(0.456)	(0.0330)	(0.0741)
Receiving Crop Insurance 1/0	0.0326*	0.0221		0.0264*	
	(0.0169)	(0.0501)		(0.0149)	
Individual Farms	-0.0397			-0.0260	
	(0.0402)			(0.0456)	
Farm Investment	0.0172			0.00400	
	(0.0164)			(0.0157)	
Labor Cost	-0.00798***			-0.00543**	
	(0.00269)			(0.00225)	
Gross Farm Income	0.000591	0.346**	0.168	0.000524	
	(0.000955)	(0.128)	(0.111)	(0.000938)	
Proportion of Production under Contracts	0.0104*				
	(0.00575)				
Diversification Index	-0.00600				
	(0.0264)				
Operator Age	-0.00185***	-0.00149***	-0.00109***	-0.00186**	
	(0.000536)	(0.000230)	(0.000299)	(0.000706)	
Total Assets	0.000328			0.000267	0.00299
	(0.000402)			(0.000260)	(0.00293)
Receiving Crop Insurance 1/0=1 # Total Off-Farm Income	0.0402	0.200**			
	(0.0486)	(0.0744)			
Receiving Crop Insurance 1/0=1 # Diversification Index	0.0901	0.0130	0.121***	0.140***	
	(0.0620)	(0.157)	(0.0410)	(0.0504)	
Crop Farm 1/0=1 # Acreage	0.000000523			-0.00000126	
	(0.00000213)			(0.00000215)	
Crop Farm 1/0=1 # Diversification Index	0.0390				
	(0.0262)				
some college # Gross Farm Income	0.00762**			0.00749***	
	(0.00320)			(0.00238)	
college degree # Gross Farm Income	0.00321**				
	(0.00145)				

high school or GED # Total Off-Farm Income	0.00720 (0.0225)				
some college # Proportion of Production under Contracts	0.0445 (0.0304)				
high school or GED # Ratio of Owned to Operated Land	-0.00120 (0.000738)		-0.00303** (0.00137)		
Ratio of Owned to Operated Land					0.0146 (0.0249)
Individual Farms=1 # Farm Investment	0.0531*** (0.0188)		0.0702 (0.0429)	0.0315 (0.0206)	
Individual Farms=1 # Gross Farm Income	0.00279* (0.00146)	0.00873 (0.0969)	0.0642 (0.0960)	0.00231** (0.00105)	
Individual Farms=1 # Return on Assets	0.00527* (0.00277)				-0.0159 (0.0278)
Individual Farms=1 # Acreage	0.000000536 (0.00000140)				
Individual Farms=1 # Operator Age	0.000382 (0.000602)			0.000361 (0.000726)	
Individual Farms=1 # Total Assets	0.00141* (0.000693)				
Land Sold=1 # Gross Farm Income	0.0145 (0.00918)				
Receiving Crop Insurance 1/0=1 # Gross Farm Income		-0.287 (0.181)		0.000980 (0.00107)	
Receiving Crop Insurance 1/0=1 # Acreage			0.00000852 (0.00000714)		
Individual Farms=1 # Diversification Index			-0.0661* (0.0342)		
Operator Education (categorical)				-0.000527 (0.00662)	
Crop Farm 1/0=1 # Farm Investment				0.00867 (0.0236)	
college degree # Farm Investment				0.0289 (0.0247)	

college degree # Return on Assets				0.00166	-0.0723
				(0.00370)	(0.0669)
Land Sold=1 # Farm Investment				0.101	
				(0.0851)	
Receiving Crop Insurance 1/0=1 # Return on Assets					0.0834
					(0.0700)
Receiving Crop Insurance 1/0=1 # Operator Age					0.000269
					(0.000570)
some college # Labor Cost					0.00971
					(0.0284)
Individual Farms=1 # Ratio of Owned to Operated Land					0.0266
					(0.0316)
Constant	0.164***	0.115***	0.103***	0.204***	0.862***
	(0.0372)	(0.0163)	(0.0199)	(0.0527)	(0.0993)
Observations	25557	6541	9086	9930	617
Represented Farms	4014418	1987074	1590897	436447	83588
R^2	0.849	0.848	0.836	0.810	0.146
Number of Double Selection Lasso Controls	8	7	8	19	8

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4. Post Double Selection Lasso OLS for Short-Term Credit Use

	All Farms	Small	Medium	Commercial	Vulnerable
Short-term credit interest rate	0.0559***	0.0568***	0.0641***	0.0263***	-0.00920
	(0.00393)	(0.00879)	(0.00652)	(0.00443)	(0.00866)
Total COVID government payments	0.626***	3.241	4.027***	0.383***	-0.0606
	(0.0650)	(1.940)	(1.018)	(0.0577)	(0.273)
Receiving Crop Insurance 1/0	0.130***	0.121	0.0305	0.0755***	
	(0.0326)	(0.0826)	(0.0365)	(0.0242)	
Individual Farms	-0.0231			0.200	
	(0.0867)			(0.134)	
Farm Investment	0.0279			0.0234	
	(0.0385)			(0.0372)	
Labor Cost	-0.00272			-0.0138***	
	(0.00668)			(0.00312)	
Gross Farm Income	0.00186	1.406***	0.864***	0.00216**	
	(0.00143)	(0.354)	(0.264)	(0.00101)	
Proportion of Production under Contracts	0.0526				
	(0.0312)				
Diversification Index	0.133**				
	(0.0559)				
Operator Age	-0.00537***	-0.00666***	-0.00362***	-0.00171	
	(0.00136)	(0.000631)	(0.000823)	(0.00189)	
Total Assets	0.00205			0.000627	0.00301
	(0.00147)			(0.000686)	(0.0119)
Receiving Crop Insurance 1/0=1 # Diversification Index	0.247*	0.321	0.121	0.469***	
	(0.132)	(0.297)	(0.198)	(0.0695)	
Crop Farm 1/0=1 # Gross Farm Income	-0.00922**				
	(0.00380)				
Crop Farm 1/0=1 # Acreage	0.00000388			0.000000722	
	(0.00000518)			(0.00000358)	
Crop Farm 1/0=1 # Diversification Index	0.0482		-0.0660	-0.157*	
	(0.0785)		(0.130)	(0.0789)	
some college # Gross Farm Income	0.0143**			0.0127**	
	(0.00649)			(0.00545)	
college degree # Gross Farm Income	0.00463*			0.00558*	
	(0.00231)			(0.00278)	
high school or GED # Total Off-Farm Income	0.0887				
	(0.0684)				

some college # Proportion of Production under Contracts	0.116** (0.0454)				
high school or GED # Ratio of Owned to Operated Land	-0.00961*** (0.00303)		-0.0162*** (0.00437)	-0.0292*** (0.00964)	
Ratio of Owned to Operated Land					0.00943 (0.0298)
Individual Farms=1 # Farm Investment	0.129** (0.0554)				
Individual Farms=1 # Gross Farm Income	0.0119** (0.00442)	0.366 (0.308)	0.108 (0.263)	0.00843*** (0.00259)	
Individual Farms=1 # Return on Assets	0.0262* (0.0149)				0.0457 (0.0710)
Individual Farms=1 # Acreage	0.0000118** (0.00000441)				
Individual Farms=1 # Operator Age	-0.000548 (0.00132)			-0.00305 (0.00217)	
Individual Farms=1 # Total Assets	0.00338 (0.00255)				
Land Sold=1 # Gross Farm Income	0.0418* (0.0214)				
Receiving Crop Insurance 1/0=1 # Gross Farm Income		-1.356*** (0.382)		-0.00213 (0.00243)	
Individual Farms=1 # Diversification Index			-0.0420 (0.0824)		
Operator Education (categorical)				-0.0294** (0.0120)	
Crop Farm 1/0=1 # Farm Investment				0.0437 (0.0416)	
college degree # Return on Assets				0.00428** (0.00198)	
Receiving Crop Insurance 1/0=1 # Operator Age					-0.00132 (0.000979)
some college # Labor Cost					0.0455 (0.0770)
Individual Farms=1 # Ratio of Owned to Operated Land					0.00337 (0.0283)
Constant	0.546*** (0.0890)	0.532*** (0.0426)	0.365*** (0.0588)	0.601*** (0.106)	0.971*** (0.0285)

Observations	25557	6541	9086	9930	617
Represented Farms	4014418	1987074	1590897	436447	83588
R^2	0.181	0.152	0.177	0.106	0.0417
Number of Double Selection Lasso Controls	6	6	8	19	6

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5. Post Double Selection Lasso OLS for Degree of Indebtedness

	All Farms	Small	Medium	Commercial	Vulnerable
Average Interest Rate Across all Loans	-0.00275 (0.00484)	-0.0123 (0.00820)	-0.00236 (0.00724)	0.0101 (0.00905)	-0.0652 (0.0393)
Total COVID government payments	-0.0328 (0.0969)	-2.132 (1.408)	-1.601 (1.086)	-0.124 (0.0818)	-0.0537 (0.579)
Observations	11619	1820	3110	6689	614
Represented Farms	1079268	422996	382423	273850	82849
R^2	0.0579	0.0813	0.0735	0.201	0.297
Number of Double Selection Lasso Controls	19	12	6	17	9

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. Post Double Selection Lasso OLS for Amount of Short-Term Credit

	All Farms	Small	Medium	Commercial	Vulnerable
Short-term credit interest rate	-0.0229***	0.00177	0.0117	0.0101**	-0.0327***
	(0.00166)	(0.00312)	(0.00799)	(0.00476)	(0.00967)
Total COVID government payments	0.930*	-1.630	-1.062	-0.0878	-2.085
	(0.456)	(1.369)	(1.150)	(0.110)	(2.378)
Observations	11619	1820	3110	6689	614
Represented Farms	1079268	422996	382423	273850	82849
R^2	0.299	0.0466	0.0433	0.0335	0.604
Number of Double Selection Lasso Controls	22	7	5	13	14

Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.