

Ad hoc government payments impact on non-real estate farm debt

Non-real estate
farm debt

Charles Martinez, Christopher N. Boyer, Tun-Hsiang Yu and
S. Aaron Smith

*Department of Agricultural and Resource Economics, University of Tennessee,
Knoxville, Tennessee, USA, and*

Adam Rabinowitz

*Department of Agricultural Economics and Rural Sociology, College of Agriculture,
Auburn University, Auburn, Alabama, USA*

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Abstract

Purpose – The authors examined the impact of the Market Facilitation Program (MFP) and Coronavirus Food Assistance Program (CFAP) payments to United States agricultural producers on non-real estate agricultural loans.

Design/methodology/approach – The authors used quarterly, state-level commercial bank data from 2016–2020 to estimate dynamic panel models.

Findings – The authors found MFP and CFAP payments not associated with the percentage of non-real estate agricultural loans with payments over 90 days late. However, these payments associated with the percentage of non-real estate agricultural loans with payments between 30 and 89 days late. The available data utilized cannot consider when producers received the actual payment and what they specifically did with those funds.

Originality/value – The contribution of this study is for US policymakers and agricultural lenders. The findings could be helpful in designing and implementing future ad hoc payment programs and provide an understanding of potential shortcomings of the current safety net for agricultural producers in the Farm Bill. Additionally, findings can assist agricultural lenders in predicting the impact of ad hoc payments on their distressed loan portfolios.

Keywords Agricultural finance, Debt, Dynamic panel, Policy

Paper type Research paper

Introduction

Prior to 2018, there were growing concerns about the financial health of the United States (US) agricultural sector (Dinterman and Katchova, 2021; Dinterman *et al.*, 2018; Key *et al.*, 2019; Prager *et al.*, 2018; Zhang and Tidgen, 2018). Farm net cash income was falling, land price appreciation was slowed, and farm sector debt was increasing. Then, in the first quarter of 2018, several US trade partners including China, Canada, Mexico, and European Union imposed retaliatory tariffs on US products. US agriculture was disproportionality targeted, which caused further financial challenges for agricultural producers (Glauber, 2021; Janzen and Hendricks, 2020; Li *et al.*, 2018; Paulson *et al.*, 2020; Sabala and Devadoss, 2019; Zheng *et al.*, 2018; Wu and Turvey, 2021).

JEL Classification — Q14, Q18

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The US Department of Agriculture (USDA) responded to the trade dispute by initiating the Market Facilitation Program (MFP) in 2018, with the purpose of providing direct payments to producers who had been adversely affected by retaliatory tariffs during the trade disputes. There were two tranches for the 2018 MFP payments occurring in September and December 2018 that provided a maximum of \$9.6 billion. In 2019, MFP was expanded to include payments over three new tranches occurring in August 2019, November 2019, and February 2020, paying producers as much as \$14.5 billion. [Paulson et al. \(2020\)](#) used farm-level data from Illinois, Kansas, and Minnesota to determine how MFP payments impacted farm income. These payments were found to increase farm income, liquidity, and equity. Despite these positive effects of MFP on farm income, [Janzen and Hendricks \(2020\)](#) found MFP payments did not reestablish pre-2018 financial conditions.

Farmers were then confronted with even more economic chaos in 2020 with the COVID-19 pandemic. Negative impacts of COVID-19 on various parts of the agricultural sector are well documented to be widespread and large across the agricultural industry ([CAST Commentary, 2020](#); [Johansson et al., 2021](#)). The Coronavirus Food Assistance Program (CFAP) was developed in response to help producers who were adversely impacted by the pandemic. This included two rounds of payments in 2020, which paid out \$10.6 and \$13.1 billion dollars in direct payment assistance to producers. There were top-up payments and adjustments that increased the total disbursements through the CFAP program, however these payments were not included in this analysis ([USDA-FSA, 2021a, b](#)). Producers could sign up for the first round of CFAP payments from May through September 2020 (signup was extended to October 2020 in some areas), and the second round of CFAP payment applications were open September to December 2020. Cash receipts for commodity sales were down again in 2020, but CFAP assistance offset part of these losses ([Johansson et al., 2021](#)). CFAP payments to producers were forecasted to account for 36% of net farm income in 2020 ([Johansson et al., 2021](#)). Inflation adjusted net cash farm income in 2020 was estimated to be the highest net farm income level reported since 2014 ([Johansson et al., 2021](#)).

The MFP and CFAP ad hoc government programs aided US net and gross farm income; however, several important questions remain unanswered about the effects of these payments on other indicators of the financial health for agriculture, such as non-real estate agricultural debt. Producer's ability to repay debt, especially non-real estate agricultural debt, is an important indicator of farm financial stress ([Briggeman, 2011](#); [Escalante et al., 2016](#); [Featherstone et al., 2006](#); [Prager et al., 2018](#)). This paper attempts to provide insight into the association of MFP and CFAP payments on non-real estate agricultural debt. Specifically, we apply linear dynamic panel models to US commercial bank data to determine if there was a relationship between MFP and CFAP payments and non-real estate agricultural loans as well as non-real estate agricultural loans that had not been paid on time. While these data utilized do not consider when producers received the actual payment(s) nor what they specifically did with those payments, the study will provide insight into the relationship between MFP and CFAP payments and the financial health of the agricultural sector, as measured by non-real estate agricultural debt.

Non-real estate agricultural debt

[Patrick and Kuhns \(2016\)](#) showed when net farm income declined, non-real estate debt for farms increased. [Prager et al. \(2018\)](#) stated producers commonly take on more non-real estate debt to finance operational needs in periods of low commodity prices and incomes. When the actions of extending or growing debt to cover expenses is no longer viable, producers are often left with filing for bankruptcy ([Prager et al., 2018](#)).

Thus, non-real estate agricultural debt levels and ability to repay debt is an important early indicator of bankruptcy (Patrick and Kuhns, 2016; Prager *et al.*, 2018).

Chapter 12 bankruptcy, which is the bankruptcy chapter for farm families, is another important indicator of farm financial health (Dinterman and Katchova, 2021; Dinterman *et al.*, 2018; Dixon *et al.*, 2004; Harl, 2006; Stam and Dixon, 2004; Wu and Turvey, 2021). However, a challenge with bankruptcy data are the potential exclusions of farms not filing Chapter 12 bankruptcy (Dinterman and Katchova, 2021; Matthews *et al.*, 1992). Chapter 12 is not often utilized because farms do not meet debt or income requirements or they do not know about Chapter 12 bankruptcy (Dinterman and Katchova, 2021; Matthews *et al.*, 1992). Additionally, Chapter 12 filings remain well below the peak in the 1980s and average 490 total filings annually between 2008 and 2019, which is between two and three bankruptcies filings per year for every 10,000 US farms (Dinterman and Katchova, 2021; Dinterman *et al.*, 2018; Wu and Turvey, 2021). For example, Wu and Turvey (2021) estimated the impact of MFP payments on farm bankruptcy rate but state the impacts were difficult to measure at the time of the study. However, they stated that the trade dispute did increase bankruptcies by an estimated 25.7%. Non-real estate agricultural debt is an earlier indicator of financial problems and does not have as many data challenges as bankruptcy data, thus, making it an interesting variable to measure the impact of ad hoc payments on farm financial stress.

That said, non-real estate agricultural loans reached a new high in 2014 (\$162.8 billion) and stayed near record levels through 2018, which was \$161.1 billion (Cowley, 2018; Kauffman and Clark, 2017). The Kansas City Ag Credit Survey monitor tracks agricultural loans and the data indicates loan repayment rates have been declining and loan extensions increasing since 2013 (Cowley, 2018; Kauffman and Clark, 2017). This suggests producers were having increased difficulty servicing debt. These trends align with what Patrick and Kuhns (2016) and Prager *et al.* (2018) observed. Prager *et al.* (2018) imply that well-targeted government payments could mitigate financial stress (i.e. reducing producer need for more non-real estate agricultural debt).

While we know the MFP and CFAP payments reversed the trend on declining farm net income since 2018 (Paulson *et al.*, 2020; Johansson *et al.*, 2021; Wu and Turvey, 2021), questions remain about what impacts these payments have had on farm debt repayment? Farm debt continued to increase through 2018 and 2019, and by the end of 2019, delinquency rates hit a six-year peak on commercial agricultural loans (Kreitman, 2021). Then, for three consecutive quarters in 2020, total farm debt started to decline and most of this decline has been in non-real estate debt. From quarter two and three of 2020, non-real estate agricultural loans dropped 5% compared to previous year levels (Kreitman, 2021). In fact, total farm debt from quarter two of 2020 to quarter three of 2020 saw the largest decline for any quarter since the late 1980s (Kreitman, 2021). A report by the Kansas City Federal Reserve showed loan delinquency rates on non-real estate debt is starting to fall, indicating the loan repayment issues improved slightly (Cowley and Kreitman, 2021). The report suggested that continued government support and improving commodity prices may be contributing to a slower pace of lending (Cowley and Kreitman, 2021). This study offers a unique insight into important questions regarding the impact of the MFP and CFAP payments on the financial stress of the agricultural economy using non-real estate agricultural loans, which commonly increases during periods of financial stress.

Data

Agricultural loan data were collected from the Federal Financial Institution Examination Council Central (FFIEC) Data Repository (FFIEC, 2020), a public database that contains US

commercial banks quarterly performance reports. We chose to use commercial bank data because the most recent [USDA Agricultural Marketing Service \(2020\)](#) survey data showed that 47% of all agricultural lending volumes originated from commercial banks. [Turvey et al. \(2021\)](#) showed that Farm Credit Systems had higher real estate loan volume than commercial banks as of 2013, but commercial banks made up most of the non-real estate debt. They concluded commercial banks were more dominant than Farm Credit System banks in terms of short-term loans and operating lines of credit.

Data selected from this study was from the Call Reports in which commercial banks report on numerous operational positions. We utilized loans to finance agricultural production and other loans to farmers (RCON1590), agricultural production loans past due 30 through 89 days and still accruing (RCON1594), and loans past due 90 days or more and still accruing (RCON1597). Additionally, we also included data for farm real estate loans secured by farmland (RCON1420). These data were reported quarterly for individual US commercial banks and we utilize the period between 2016 and 2020. We chose these years of data because prior to 2016, farm incomes were coming off a historical high in 2012 and were still high relative to historical averages in 2013 and 2014 ([Key et al., 2019](#)). Also, ad hoc supplemental and disaster payments spiked in 2014 and 2015, but in 2016, 2017, and most of 2018, ad hoc payments were small ([Zulauf et al., 2020](#)). However, in 2019 and 2020, 84% of all agricultural payments were ad hoc ([Zulauf et al., 2020](#)).

Following [Prager et al. \(2018\)](#), these individual bank data were aggregated to the state-level for each quarter. We included all 48 contiguous states in the data. Therefore, our dataset included 20 time periods (4 quarters times 5 years) and 48 states per quarter, leading to a total of a balanced panel of 960 observations. A noted limitation of these data is the lack of clarity if this reported state is the location of the borrower. For example, a producer might borrow money from bank located or headquartered in a different state where the capital is being spent on the farm operation. [Figure 1](#) shows the average amounts of loans, by type, for the states included in the data with the timing of MFP and CFAP payments in the shaded regions. One interesting observation is loans that are 30–89 days overdue peaked in quarter one of each year. This could potentially be due to end of year (December 31) payments or operating lines of credit not being paid due to a lack of profitability or delayed sales by crop producers.

Non-performing (i.e. loans with late payments) loans were converted into ratios relative to the total non-real estate agricultural loans. The first was the non-real estate agricultural loans

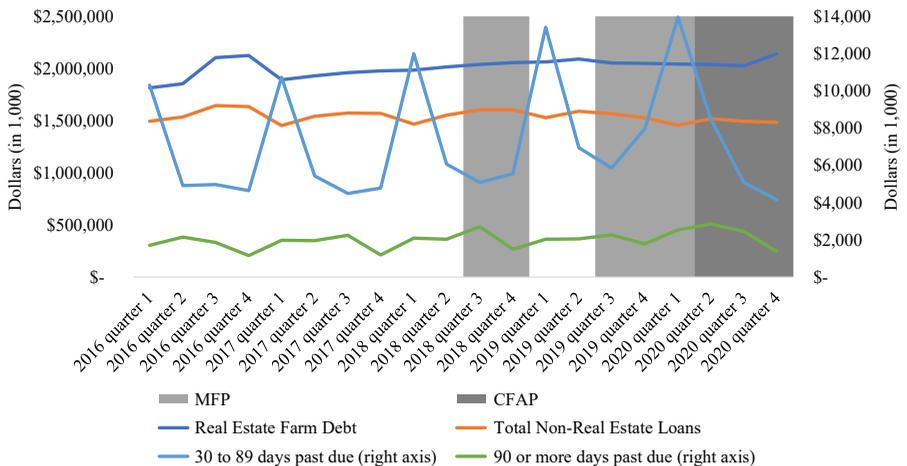


Figure 1.
Average quarterly loan amounts by type in the US during 2016–2020

past due 30 through 89 days and still accruing divided by the total non-real estate agricultural loans for each state (RCON1594/RCON1590). The second was the non-real estate agricultural loans past due 90 days or more and still accruing divided by the total non-real estate agricultural loans for each state (RCON1597/RCON1590). We multiplied these values by 100 to get a percentage of non-real estate agricultural loans with payments 30–90 days late (L1); and non-real estate agricultural loans with payments greater than 90 days late (L2). We convert these into ratios to show the percent of loan volume that were on time or with late payments. The absolute values of these loan volumes were also analyzed but if absolute debt volumes were only used, these estimates could not account for noise in changes of total non-real estate agricultural loans. Figure 2 shows these percentages or ratios over time. Percent of loans 30–89 days late fluctuated seasonally with the highest percentage occurring in quarter one of 2020 (0.96%) but declined 70% by quarter four of 2020 (0.28%). Similarly, non-real estate agricultural loans with payments that are 90 or more days late peaked in quarter two of 2020 (0.19%) but decreased by 47% by quarter four of 2020 (0.09%).

One unique component of this analysis is we kept these variables in separate late periods stages. Studies typically aggregate loans with late payments into delinquent or defaulted loans. Keeping these variables separate provides additional understanding on how these factors impact loans under two late periods. Furthermore, banks are required to report these loans in these classifications; thus, we chose to analyze them as individual loan volumes.

We also collected quarterly data for the same period on US bank prime loan rate, and state-level farm and non-farm net income. These variables were selected based on results of Prager *et al.* (2018) and Wu and Turvey (2021). US bank prime loan rates were collected (Board of Governors of the Federal Reserve System, 2021) and state-level farm income and non-farm income were included using Federal Reserve Bank of St. Louis proprietors farm income and non-farm income (US Bureau of Economic Analysis, 2021a, b). These are aggregate farm and non-farm incomes for each state by quarter. We anticipate a higher farm and non-farm income will lower the non-performing loans and total non-real estate agricultural loans (Prager *et al.*, 2018; Wu and Turvey, 2021). An increase in interest rate will likely increase the non-performing loan amounts and lower the total non-real estate loan volume (Prager *et al.*, 2018; Wu and Turvey, 2021). Table 1 shows the summary statistics of these variables as well as covariates included in the model.

Finally, we develop binary variables for year and quarter when MFP and CFAP payments were distributed. Therefore, a binary variable was equal to one during the third quarter of 2018 (September 2018), fourth quarter of 2018 (December 2018), quarter three of 2019 (August 2019), quarter four of 2019 (November 2019), and quarter one of 2020 (February 2020) [1].

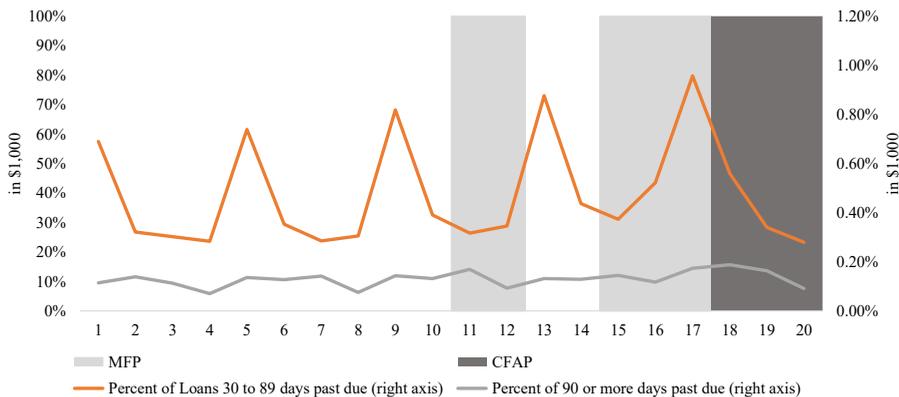


Figure 2. Percentage of loans by type in the US during 2016–2020

Table 1.
Summary statistics of
the dependent and
independent variables
from 2016–
2020 ($n = 959$)

Variable	Average	Standard deviation	Minimum	Maximum
Total Real Estate Farm Loans Secured by Farmland (in 1,000,000)	2,131.508	2,425.782	0	13872.99
Total Non-Real Estate Loans (in 1,000,000)	1,632.639	2,233.061	314	9497.996
Non-Real Estate Agricultural Loans Past Due 30 Through 89 Days and Still Accruing (in 1,000,000)	7.681	15.878	0	140.786
Non-Real Estate Agricultural Loans Past Due 90 Days or More and Non-Accruing (in 1,000,000)	2.112	4.873	0	50.864
Percent of Non-Real Estate Agricultural Loans 30–89 Days Late ^a	0.34	0.45	0.00	4.64
Percent of Non-Real Estate Agricultural Loans 90 or More Days Late ^b	0.08	0.14	0.00	1.71
Farm Income (in 1,000,000)	1.095	2.083	–0.659	19.706
Non-Farm Income (in 1,000,000)	31.50	43.42	2.40	251.19
Interest Rate	4.27	0.77	3.25	5.50

Note(s): ^aRCON1594 divided by RCON1590
^bRCON1597 divided by RCON1590

The CFAP payments were coded similarly with a binary variable equaling one in the second quarter of 2020 through fourth quarter of 2020. It is recognized that using binary variables have limitations in determining the effects of MFP and CFAP payments on agricultural debt. These data utilized cannot indicate a dollar amount change in agricultural debt from a dollar increase in ad hoc payments. However, it can provide some useful insight and using binary variables for MFP payments was how [Wu and Turvey \(2021\)](#) measured effects of MFP on bankruptcies. [Figure 1](#) also shows the time when these payments occurred in the shadowed regions.

Estimation

The panel data used in this analysis is a short- T dynamic panel, meaning it contains fewer time periods (T) than cross section units (N) ([Kripfganz, 2016](#)). For these short- T datasets, ordinary or generalized least-squares estimators can produce bias results ([Nickell, 1981](#)). This is a common problem for linear dynamic panel models and numerous studies have made modeling discoveries to circumvent issues with short- T panels. One early approach to address these issues was to use instrumental variable in generalized method of moments (GMM) estimations ([Arellano and Bover, 1995](#); [Blundell and Bond, 1998](#)). The GMM estimation provided flexibility and was easy to use. Quasi-maximum likelihood (QML) is a limited information maximum likelihood estimator that was also shown to avoid these issues with short- T panels by using an unconditional likelihood function ([Kripfganz, 2016](#)).

We employ QML estimation technique developed by [Kripfganz \(2016\)](#), which was based on [Bhargava and Sargan \(1983\)](#). This technique includes a lagged dependent variable in the model but minimizes its effect by correcting for the violation of the independence assumption. Otherwise, the lag dependent parameter estimate value would increase and other parameter estimate values would decrease. QML is a more efficient alternative in handling endogeneity issues with lagged dependent variable ([Kripfganz, 2016](#)).

Six linear dynamic panel models were estimated. First, we estimate two ratio models. Dependent variables for these models include: (1) the percentage of non-real estate agricultural loans past due 30 through 89 days (L1); and (2) the percentage of non-real estate agricultural loans past due 90 days (L2) using QML. Parameters reflect a change in the percent of loan payments that were not paid on time. Dependent variables for the other four

models were: (1) farm real estate loans secured by farmland (RCON1420); (2) non-real estimate agricultural loans with on time payments (RCON1590); (3) non-real estimate agricultural loans past due 30 through 89 days and still accruing (RCON1594); and (4) non-real estimate agricultural loans past due 90 days or more and still accruing (RCON1597). For the volume models, we scale these values by dividing by 1,000,000 to improve convergence speed.

Independent variables included the lag dependent variable, farm and non-farm income, interest rate, and binary variables or MFP and CFAP payments. We also included a year time trend variable and test for fixed or random effects for state. The models were generally defined as

$$y_{it} = \alpha + \beta_1 y_{it-1} + \beta_2 NF_{it} + \beta_3 F_{it} + \beta_4 I_t + \beta_5 MFP_t + \beta_6 CFAP_t + \sum_{t=1}^{T-1} \gamma_t d_t + s_n + \epsilon_{it} \quad (1)$$

where y_{it} is the dependent variables defined above in time t ($t = 1, \dots, T$) in state i ($i = 1, \dots, N$); y_{it-1} is the lag dependent variable, NF_{it} is non-farm income; F_{it} is farm income; I_t is the interest rate; MFP_t is a binary variable equation to one when MFP payments were made and zero otherwise; $CFAP_t$ is a binary variable equation to one when CFAP payments were made and zero otherwise; d_t is a binary variable for each year in the data; s_n is either random or fixed effects for each state the bank list on the call report; α , β 's, and γ are parameters to be estimated; and ϵ_{it} is the random error term.

Kripfganz (2016) developed the STATA command `xtpdqml` that implements QML estimators by Bhargava and Sargan (1983) and Hsiao *et al.* (2002) for random and fixed effects models, respectively. This command supports the use of the Hausman test to compare fixed or random effects models. Thus, we estimated both random and fixed effects models to determine the most appropriate specification. Rejecting the Hausman test will indicate the fixed effects model is preferred over random effects.

Results

Dynamic panel regression

Table 2 shows the estimated parameters for the linear dynamic panel ratio models. The Hausman test result is shown at the bottom of the table. We failed to reject the Hausman test

Variable	L1 ^a		L2 ^a	
	Parameter	Standard error	Parameter	Standard error
Intercept	0.9961***	0.1855	0.0699	0.0756
Lag Dependent	0.0163	0.0326	0.2083***	0.0727
Market Facilitation Program	-0.1618***	0.0331	0.0001	0.0136
Coronavirus Food Assistance Program	-0.7135***	0.0834	-0.0004	0.0397
Farm Income (in 1,000,000)	-0.0081	0.0149	-0.0017	0.0026
Non-Farm Income (in 1,000,000)	-0.0008	0.0010	-0.0002	0.0002
Interest Rate	-0.2150***	0.0504	-0.0034	0.0213
2017	0.2348***	0.0466	0.0208	0.0176
2018	0.5184***	0.0801	0.0264	0.0279
2019	0.6089***	0.0972	0.0192	0.0438
2020	0.7507***	0.0770	0.0205	0.0339
Hausman test (Prob > χ^2)	0.9885		0.5747	

Note(s): *, **, *** represent significance at the 10%, 5% and 1% levels respectively

^aL1 = percentage of loans with payments 30–90 days late; L2 = percentage of loans with payments greater than 90 days late

Table 2.
Parameter estimates
for dynamic panel ratio
models ($n = 959$)

for the models showing the percentage of non-real estate agricultural loans with payments that are 30–89 days late (L1) and over 90 days late (L2). Thus, the random effect effects models were used for the L1 and L2 models.

Table 3 shows the estimated parameters for the model with loan volumes were the dependent variables (farm real estate loans secured by farmland; non-real estate agricultural loans with on time payments; non-real estate agricultural loans past due 30 through 89 days and still accruing; and non-real estate agricultural loans past due 90 days or more and still accruing). The Hausman test result found a mix between random and fixed effects models. Random effects model was selected for the real estate loans and non-real estate agricultural loans past due 30 through 89-day models while fixed effects were used for the on-time loans and the non-real estate agricultural loans 90 days past due.

Several factors are associated with the percentage of non-real estate agricultural loans with payments that were 30–89 days late (L1). While state-level farm and state-level non-farm income were insignificant, parameter estimates for MFP and CFAP payments were significant and negative. This suggests that the percentage of non-real estate loans with payments between 30 and 89 days late declined in the same quarter these payments were distributed. We find from this model (L1) that the percentage of these late loans declined by 0.16% points when MFP was distributed and 0.71% points when CFAP was distributed. Parameter estimates in the volume models (Table 3) also show these loan volumes decline with the payments. Our estimates suggest these loans declined \$3.62 million with MFP and \$16.86 million with CFAP.

Additionally, the interest rate parameter estimate was negative and significant. We anticipated that a higher interest rate would lower non-real estate agricultural debt, which is the denominator of the dependent variable. However, a higher interest rate was found to increase these loan values and declined the loans with late payments. A possible explanation might be non-real estate agricultural debt is increasing because the cost of this money is higher. This unexpected interaction might be a topic of future research. Relative to 2016, the ratio of non-real estate agricultural loan amounts with payments between 30 and 89 days late relative to non-real estate agricultural loan amounts have increased. Table 3 shows the volume of loans with 30-to-89-day late payments were higher relative to 2016 but the total non-real estate agricultural loan volume was lower. This suggests that less non-real estate agricultural debt existed relative to 2016 but the volume of these loans with payments with 30–89 days late increased.

The percentage of non-real estate agricultural loans with payments that are over 90 days late (L2) were only impacted by the lag dependent variable. This suggests that MFP and CFAP did not change these loans. Table 3 shows similar results that these volumes did not change with MFP or CFAP payments. However, Table 3 does show that higher state-level farm income does lower these loan volumes.

Discussion

The literature indicates that well-target government payments could mitigate financial stress for producers and this study presents further evidence to support their findings (Prager *et al.*, 2018; Paulson *et al.*, 2020; Wu and Turvey, 2021). MFP and CFAP payments were associated with a decline in non-real estate agricultural loans with payments 30 and 89 days late, while the non-real estate agricultural loans with payments over 90 days late were not impacted. Paulson *et al.*'s (2020) farm-level model showed MFP payments reduced the likelihood of a farm defaulting on a loan, which they defined as a loan payment greater than 90 days late. The results from this analysis suggest loans that were close to defaulting (i.e. 30–89 days late on their payments) were negatively associated with these payments.

Long term structural issues such as several years of poor financial management or sudden disasters, such as loss of a primary operator, could explain loans with payments 90 or more

Variable	Total real estate farm loans ^a		On time payments ^a		Non-real estate agricultural loans Payments 30–89 days late ^a		Payments 90 plus days late ^a	
	Parameter	Standard error	Parameter	Standard error	Parameter	Standard error	Parameter	Standard error
Intercept	-283.79	325.80	439.78**	139.45	21.34***	5.54	4.11***	1.75
Lag Dependent	1.01***	0.00	0.61***	0.03	-0.03	0.03	0.24***	0.04
Market Facilitation Program	-20.76	60.07	35.24	24.60	-3.62***	0.94	0.04	0.28
Coronavirus Food Assistance Program	98.52	152.78	220.76*	61.97	-16.86***	2.37	-0.93	0.70
Farm Income (in \$1,000,000)	-9.00***	2.56	-66.44***	12.73	-0.31	0.47	-0.69***	0.14
Non-Farm Income (in \$1,000,000)	-0.10	0.09	-3.59*	1.93	-0.03	0.04	-0.02	0.02
Interest Rate	108.82	92.19	120.59***	37.51	-4.26***	1.43	-0.49	0.42
2017	-212.93	85.22	-130.12***	34.75	4.23***	1.33	0.54	0.39
2018	-230.69**	146.51	-211.34***	59.67	10.40***	2.28	1.17*	0.67
2019	-292.28	177.49	-258.22***	72.64	13.58***	2.77	1.45*	0.82
2020	-188.74	140.42	-231.66***	57.66	17.41***	2.19	1.69***	0.65
Hausman test (Prob > χ^2)		0.9580		0.000		0.6886		0.000

Note(s): *, **, *** represent significance at the 10%, 5% and 1% levels respectively
^aAll dependent variables were scaled by dividing them by 1,000,000. This was done to improve convergence speed

Table 3.
 Parameter estimates
 for dynamic panel
 models with volumes
 as dependent
 variables ($n = 959$)

days late. These loans may not benefit as much from ad hoc payments in the form of becoming current again or improving long term farm financial health because of these sudden changes or long-term management decisions. Additionally, loans that are 90 or more days late, could be in some form of remediation action (i.e. forced asset sale and or collection of security). Thus, if these types of proceedings have started, ad hoc payments may not be directed towards making those loans current. However, the findings of this study suggest these ad hoc might have varying impact for farms depending upon their financial health prior to a given ad hoc program payment being issued.

Conclusions

Starting in 2018 through 2020, the US government issued two sets of ad hoc payments to farms through the MFP and CFAP. The payments from MFP were about \$24 billion over three years and CFAP payments were slightly over \$23 billion issued in 2020. While these ad hoc government programs aided US net and gross farm income; little is known about the effects of these payments on other indicators of the financial health of agriculture. The objective of this paper was to provide insight into the effect of MFP and CFAP payments on non-real estate agricultural debt. Specifically, we estimate linear dynamic panel models to determine if MFP and CFAP payments impacted non-real estate agricultural loans, as well as non-real estate agricultural loans that had not been paid on time using US commercial bank data from 2016 to 2020.

Results suggest that MFP and CFAP payments were not associated with the percent of non-real estate agricultural loans with payments over 90 days late. However, these ad hoc payments were negatively correlated with the percent of non-real estate agricultural loans with payments between 30 and 89 days late. This study provides insight into how producers used MFP and CFAP payments and if they helped improve the financial health of the agricultural sector. Overall, these findings support [Paulson et al.'s \(2020\)](#) findings that the default rate would have likely increased without MFP and CFAP payments, which is something policy makers can consider when designing policies (i.e. ad hoc versus Farm Bill spending) to mitigate unforeseen events.

We recognize; however, this paper is not without limitation. The data utilized cannot consider when these producers received the actual payment and what they specifically did with those funds. A survey of producers asking them about their use of these payments is needed to better explain how these funds were used. Also, while the lag dependent model with year and state effects capture noise across space and time, several other factors that could be impacting the dependent variables are likely excluded. There is an omitted variable issue with this specification; however, the lack of applicable data makes this difficult to overcome.

Note

1. The [Appendix](#) shows an alternative specification where the MFP variable includes the first quarter of 2019. While a payment did not go out at this time, one tranche of MFP payments went out December 2018, which means impacts could likely be experienced in the first quarter of 2019. The results are similar demonstrating the variables robustness.

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Variable	L1 ^a		L2 ^a	
	Parameter	Standard error	Parameter	Standard error
Intercept	0.9563***	0.2078	0.0789	0.0710
Lag Dependent	0.0245	0.0343	0.2085***	0.0731
Market Facilitation Program	-0.0670***	0.0198	0.0077	0.0119
Coronavirus Food Assistance Program	-0.6061***	0.1195	0.0044	0.0354
Farm Income (in 1,000,000)	-0.0116	0.0087	-0.0019	0.0027
Non-Farm Income (in 1,000,000)	-0.0008	0.0008	-0.0002	0.0002
Interest Rate	-0.2038***	0.0534	-0.0059	0.0200
2017	0.2284***	0.0698	0.0223	0.0170
2018	0.4552***	0.1071	0.0262	0.0248
2019	0.5592***	0.1381	0.0181	0.0413
2020	0.6468***	0.1299	0.0153	0.0293
Hausman test (Prob > χ^2)	0.9865		0.5655	

Note(s): *, **, *** represent significance at the 10%, 5% and 1% levels respectively

^a L1 = percentage of loans with payments 30–90 days late; L2 = percentage of loans with payments greater than 90 days late

This table shows the results to the alternative model noted in the text. This specification includes a revised MFP variable where the first quarter of 2019 is also included. While a payment did not go out at this time, one tranche of MFP payments went out December 2018, which means impacts could likely be experienced in the first quarter of 2019. The significance and signs of variables are the exact same. Magnitude of effects change slightly

Table A1.
Parameter estimates
for dynamic panel ratio
models ($n = 959$)

Corresponding author

Charles Martinez can be contacted at: cmart113@utk.edu

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