12-2022

# Loan Survival: Are Socially Disadvantaged Farmers More Likely to Default or Pay in Full?

Marie-Cécile Vekemans
*University of Arkansas, Fayetteville*

Loan Survival: Are Socially Disadvantaged Farmers More Likely to Default or Pay in Full?

A thesis submitted in partial fulfillment
of the requirements for the degree of
Master of Science in Agricultural Economics

by

Marie-Cécile Vekemans
Agrocampus Ouest,
Agronomy Engineer, 2021
Paris Saclay University,
Master in Agroecology and Social Science, 2022

December 2022
University of Arkansas

This thesis is approved for recommendation to the Graduate Council.

____________________________________
Bruce L. Ahrendsen, Ph.D.
Thesis Director

____________________________________
Stijn Speelman, Ph.D.
Committee Member

____________________________________
Charles B. Dodson, Ph.D..
Committee Member

____________________________________
Gianna Short, Ph.D.
Committee Member

## Abstract

This study aims at identifying racial and gender discrimination in the usage of credit for Socially Disadvantaged Farmers and Ranchers (SDFR) in the United States. Usage of credit is considered successful when a loan has been paid in full and a failure is considered when the borrower defaults. Identifying such a pathway would provide useful information to the Federal government United States Department of Agriculture (USDA) Farm Service Agency (FSA) to evaluate the effectiveness and equity of loan programs. This study uses data from the USDA FSA farm loan programs that mainly target socially disadvantaged farmers and other underserved groups. The analysis has been realized through a subdistributional Competing Risks model of survival analysis. The null hypothesis considers that SDFR status has no impact on loan outcome and length of time to loan outcome, where loan outcome is paid-in-full, default, or censored. The alternative hypothesis considers there is a difference in loan outcome regarding the SDFR status. The results obtained highlighted that Black and Hispanic farmers and ranchers had higher rates of delinquency and long-term delinquency and lower rates of payment in full than other groups. While these results are not a clear indicator of discrimination, they do not refute its absence.

## Acknowledgements

Thesis submitted in partial fulfilment of the requirements for the degree of Master of Science in Agricultural Economics issued by the University of Arkansas (United States of America) and the joint academic degree of International Master of Science in Rural Development from Ghent University (Belgium), Agrocampus Ouest (France), Humboldt University of Berlin (Germany), Slovak University of Agriculture in Nitra (Slovakia), University of Pisa (Italy) and University of Córdoba (Spain) in collaboration with Can Tho University (Vietnam), Escuela Superior Politécnica del Litoral (Ecuador), Nanjing Agricultural University (China), University of Agricultural Science Bengaluru (India), University of Pretoria (South-Africa) and University of Arkansas (United States of America).

This thesis was elaborated and defended at the University of Arkansas within the framework of the European Erasmus Mundus Joint Master Degree International Master of Science in Rural Development (Course N° 2019 - 1507 / 001 - 001) and the EU-US Cooperation Programme in Higher Education and Vocational Training (Transatlantic Degree Consortia Projects) nr. 2008-1745/001 – 001 CPT-USTRAN and the Fund for the Improvement of Postsecondary Education (EU-US Atlantis Program grant P116J080034, U.S. Department of Education). However, the contents of the thesis do not necessarily represent the policy of the supporting agencies, and you should not assume endorsement by the supporting agencies.

First, I would like to express my sincere gratitude to my advisor, Prof. Bruce L. Ahrendsen, for his continuous support of my studies and research. His guidance has helped me throughout the writing of this thesis. Without him, it would have been impossible for me to complete this thesis.

In addition to my advisor, special thanks go to Dr. Gianna Short and Dr. Charles B. Dodson, who gave me generous access to USDA data and reports, helped me find information, and model the program. This study could not have been accomplished without their help.

Many thanks to Prof. Stijn Speelman, my co-promoter at Ghent University, for his advice and kind support.

I would like to thank the other graduate students who supported me on this journey. I am very grateful for the chance to meet them and have this experience together.

I would like to express my sincere gratitude to all the Atlantis IMRD program staff who supported and helped me with the administrative work. I felt welcome at every place where I studied.

My sincere thanks go to Ms. Alicia Minden at the University of Arkansas for her help and support throughout my stay in the United States.

Last but not least, I am indebted to my family and friends. For the Atlantis program I had to move to different countries and study at different universities, which was not always easy. I would like to thank everyone who supported and encouraged me during this amazing journey.

**Table of Contents**

**Figures**

## Tables

**List of published Papers or Submitted Papers**

Vekemans, Marie-Cécile, Gianna Short, Charles B. Dodson, and Bruce L. Ahrendsen. "Loan Survival: Are Black Farmers More Likely to Default?". Submitted to the *Applied Economic Perspectives & Policy*, April 1, 2022.

# 1- Introduction

*1.1. Relevance of the topic*

Socially Disadvantaged Farmers and Ranchers (SDFRs) represent a valuable segment of agricultural producers[1] in the United States (U.S). According to the 2017 Census of Agriculture, 3.3% of all producers reported being Hispanic, Latino, or of Spanish origin, 1.7% identified as American Indian or Alaska Native, 0.6% identified as Asian, 1.3% identified as Black or African American and 0.1% as Native Hawaiian or other Pacific Islander. In addition, 0.8% of all producers reported more than one race. Women accounted for 36% of total U.S. producers.

These groups have historically experienced limited access to U.S. Department of Agriculture (USDA) programs and services, such as loan services and access to credit. The history of discrimination leads to a great deal of concern for the agricultural sector in the U.S. as evidenced by several studies (Orozco, Ward and Graddy-Lovelace, 2018; Leslie and White, 2018; Horst and Marion, 2019). Within USDA, some SDFR groups have historically experienced discrimination or disparate treatment in programs and services.[2] Specific instances of historical discrimination against SDFR groups have included denial of loans, credit services, limited access to legal protections against fraud, and outright violence and intimidation (Jett, 2011). The consequences are the loss of financial and other resources that prevent them from making the investments necessary for financial progress. This is evident in the loss of land and the income and wealth disparities between Black and White farmers (King et al., 2018; Coppess, 2021).

To address these patterns of discrimination, the 2501 program was incorporated into the 1990 Farm Bill. It includes conferences, workshops, and demonstrations on farming techniques and aims to connect underserved farmers and ranchers with local USDA officials to increase their awareness of USDA

[1] The term producer was used in the 2017 Census of Agriculture to describe the individual(s) involved in making decisions on a farm operation.
[2] The Sec, 355(e) of the Con Act defines SDFR to include Black or African American, American Indian or Alaska Native, Hispanic and Latino, Asian, and Native Hawaiian or other Pacific Islander. SDFR may also include women as in this study. However, only Blacks and American Indians have received any settlements.

programs. Since 2010, the 2501 program has awarded 563 grants totaling more than $158 million (U.S. Department of Agriculture Economic Research Service, 2022).

In addition, SDFRs have been eligible for targeted-benefits from a variety of Farm Act programs since the 1990s. SDFRs are particularly targeted by Titles I (Commodities), II (Conservation), V (Credit), VII (Research), XI (Crop Insurance) and XII (Miscellaneous) of the 2018 Farm Bill. The USDA Farm Agency Service (FSA) also provides loan guarantees to eligible SDFRs to purchase and operate farms and ranches. FSA reserves a portion of its direct and guaranteed Farm Ownership and Operating Loan funds for SDFRs. Recently, the 2018 Agriculture Improvement Act, also known as the Farm Bill, reauthorized and expanded support for SDFRs through a variety of USDA programs, such as farm credit programs, crop insurance conservation programs, and provisions. Finally, the American Rescue Plan Act of 2021 also sought to address discriminatory issues by providing debt relief to socially disadvantaged producers with direct and guaranteed FSA farm loans (U.S. Department of Agriculture Economic Research Service, 2022). In January 2021, President Biden issued an executive order directing agencies to assess the barriers underserved groups may face in accessing federal benefits (The White House, 2021).

This history remains an important issue because access to credit and success in credit are critical to sustaining farm operations. Credit helps farmers survive and grow by assisting them deal with income fluctuations. For disadvantaged groups, access to credit is crucial because it allows them to invest and acquire technology to increase the efficiency of their farming operations. Due to historical discrimination, SDFR may have poorer land resources and fewer assets. They may also suffer from poorer financial and technical education due to the underfunded education system in disadvantaged communities. All of this may hinder their ability to make financial progress even if they have access to credit.

Key et al. (2019) examined the importance of credit constraints for beginning farmers. Ahrendsen et al. (2022) showed that FSA appear to be crucial in enabling SDFR groups access loans. Thus, if discrimination exists in accessing these programs, unequal opportunities could lead to unequal chance of success, which would have a major impact on U.S. agriculture and rural communities. In fact, discrimination could impact access to resources such as land, capital, or markets, which could affect SDFR's progress in agriculture. Moreover, the effects of past discrimination could also affect the current progress of SDFR groups because they have fewer assets and acreage compared to non-SDFR, i.e., non-Hispanic White men.

### *1.2. Hypotheses and method*

The purpose of this study is to assess the performance of SDFRs under the USDA FSA direct operating loan program (DOL). As previously stated discrimination may affect SDFR's pathways of success by impacting the access to resources such as land, capital or markets. Identifying such pathways would also provide useful information to the Federal government and FSA offices to evaluate the effectiveness and equity of loan programs.

Recently, the study conducted by Dodson et al. (2022) found that delinquency rates tend to be higher among SDFR groups. Their approach relied on survival analysis to determine the probability of default. However, survival analysis only allows for one outcome. This study builds on that earlier work and estimates a competing risks model using FSA loan data to identify factors associated with two loan outcomes: Delinquency and Paid-in-full. The study examines differences in the likelihood of defaulting or paying in full by SDFR status and aims to explore the potential impact of a long history of discrimination on borrowers.

The study uses data from USDA FSA loan programs that primarily target SDFRs and other underserved groups. These include DOLs originated during 2011-2020. DOLs mainly target farmers by helping them start, maintain, and strengthen a farm or ranch. The analysis was realized using a Fine and Gray (1999), subdistributional competing risks model, in which competing risks are default and paid-in-full. The model includes financial, demographic, geographic, production specialty, and other factors. The null hypothesis states that SDFR status has no effect on type of loan outcome and length of time to loan outcome. The alternative hypothesis refutes this hypothesis, i.e., there is a difference in loan outcome related to SDFR status.

### *1.3. Organization*

The organization of this thesis is in six chapters. The first chapter is this introduction. The second chapter is used to provide background information about the study. It includes information about the SDFR as well as information about the loans they are eligible for. The following chapters present the data and the methodology used to conduct the study. The fifth chapter presents the results of the study. The final chapter provides a summary, some policy implications, and possible directions for further research.

## 2- Background

### *2.1. Profile of Socially Disadvantaged Famers*

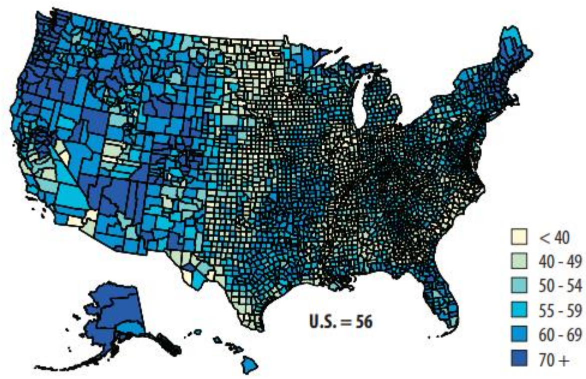
SDFR refers to groups that have been subject to racial or ethnic prejudice such as discrimination. SDFR include Blacks or African Americans, American Indians or Alaska Natives, Hispanics or Latinos, Asians, or Pacific Islanders as defined by USDA. Depending on the USDA program, such as the FSA farm loan program, SDFRs may also include women who are the primary decision maker (U.S. Department of Agriculture Economic Research Service, 2022). The following sections provide information on the status of these farmers.

#### *2.1.1. Women producers*

The Census of Agriculture (2017) found that 36% of all U.S. farm principal producers[3] were Women. In addition, the top states with female producers (as percent of total share of producers) were Arizona (49%), Alaska (47%), New Hampshire (46%), Oregon, Maine and Massachusetts (44%) and Washington,

[3] The 2017 Census of Agriculture reported up to four principal operators on each farm.

Nevada, Colorado and Vermont (42%). Thirty-eight percent of female producers were located in Texas, accounting for the state with the most female producers (U.S. Department of Agriculture National Agricultural Statistics Services, 2019c). The figure 1 displays the share of women operated farms as percent of total farms by county based on the census of agriculture in 2017.




Source: Congressional Research Service (2021); U.S. Department of Agriculture National Agricultural Statistics Services (2019c).

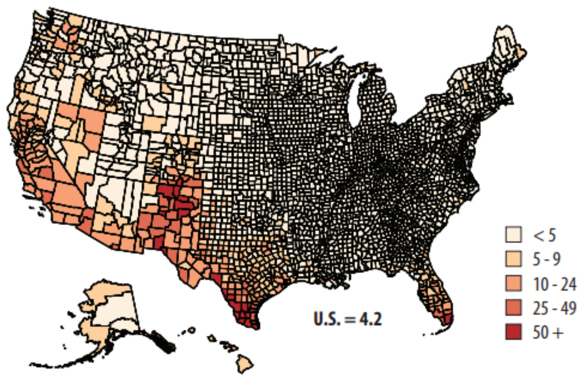
Figure 1. Share of Women Operated Farms by County (as percent of total farms), 2017

Female producers were, on average, slightly younger than male producers, and 30% of women were beginning farmers (Table 1), that is, farmers with 10 or fewer years of experience, compared to 25% for men. Farming was also not typically reported as a primary occupation.

Farms operated by women were mostly small-sized farms. They accounted for 38% of U.S. agricultural sales and 43% of farmland. They were mainly specialized in livestock and livestock products (51%). Fifty percent of these farms had sales and government payments under $5,000. Only 19% of them had sales and payments greater than $50,000 compared to 26% of male-operated farms (Table 1)(Congressional Research Service, 2021; U.S. Department of Agriculture National Agricultural Statistics Services, 2019c).

### *2.1.2. Hispanic, Latino and Spanish producers*

In 2017, 112,451 producers identified as Hispanic, Latino, or Spanish origin representing 3.3% of all U.S. producers with 60% of them located in Texas, California, New Mexico, Florida, Colorado, Washington, Oklahoma, Oregon, Arizona, Missouri, Idaho and Kansas (Figure 2) (U.S. Department of Agriculture National Agricultural Statistics Services, 2019d).




Source: U.S. Department of Agriculture National Agricultural Statistics Services (2019d)
Figure 2. Share of Hispanic Operated Farms by County (as percent of total farms), 2017

On average, Hispanic producers are younger than U.S. producers and more likely to be beginners (36% vs. 27% for all producers). They also tend to live off of the farm more than U.S. producers overall. In fact, 65% of them live on their farm, compared to 74% for U.S. producers overall (Table 1).

These farms also tend to be smaller, with 61% of these farmers having less than 50 acres. Hispanic-operated farms accounted for 32 million acres of farmland, or 3.6% of the U.S. total farm area. The average size of Hispanic-operated farms was 372 acres, and 78% of Hispanic-operated farmers owned the land they farmed.

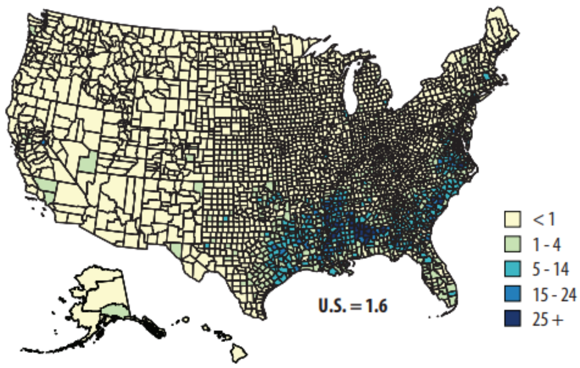
Their sales accounted for 5.6% of total U.S. agriculture sales, 59% of which were crop sales. Their farms also tended to be smaller in terms of annual sales, with 57% of farms having sales and government payments of less than $5,000 per year and only 16% of more than $50,000. In addition, 21% of farms operated by Hispanics specialized in the production of specialty crops such as fruits, nuts and berries, compared to 9% of all U.S. farms (Table 1) (Congressional Research Service, 2021).

### *2.1.3. Blacks/African American producers*

From 2012 to 2017, the number of farms with Black operators increased by 5%. Ninety percent of them lived in twelve southern states. Texas is the state with more Black producers than any other state, followed by Mississippi and Alabama. However, in terms of Black producers as a percentage of total producers, the most important states are Mississippi (13%), Louisiana (7%), South Carolina (7%), Alabama (6%) and Georgia (4%) (Figure 3). Most Black SDFRs tend to be older than U.S. producers overall. They are more likely to have served or to be serving in the U.S. military and greater proportion of them are men (Table 1) (U.S. Department of Agriculture National Agricultural Statistics Services, 2019b).

Farms operated by Black producers tend to be smaller than farms overall, with 85% of farms having less than 180 acres, compared to 70% of all farms operating less than 180 acres. This trend is underscored by the Orozco et al. (2018) study, which highlights the significance of land loss encountered by Black farmers over the past century. Farms operated by Black producers are also more likely to be smaller in terms of agricultural sales and government payments, with 93% having less than $50,000, while 75% of all farms had less than $50,000 (Table 1). Their farms accounted for 0.4% of total U.S. agricultural sales. In term of value, Black-operated farms sold $1.4 billion in agricultural products in 2017. Moreover, 48% of Black operated farms specialized in cattle and dairy production in 2017 versus 34% of all farms (U.S. Department of Agriculture National Agricultural Statistics Services, 2019b).

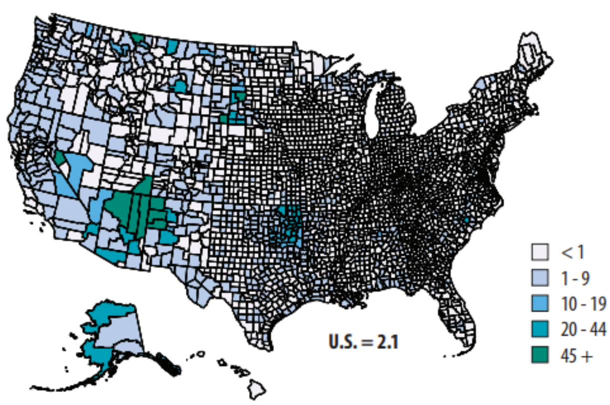
Black-operated farms accounted for 4.7 million acres of farmland, which constitutes a small proportion (0.5%) of the U.S. total. Sixty-seven percent of Black-operated farms were operated by the owners of the land, which is close to the U.S. average of 69% for all farmers (Table1) (U.S. Department of Agriculture National Agricultural Statistics Services, 2019b). Data on Black producers are retrieved in Table 1.




Source: Congressional Research Service (2021); U.S. Department of Agriculture National Agricultural Statistics Services (2019b)
Figure 3. Share of Black Operated Farms by County (as percent of total farms), 2017

### *2.1.4. American Indian/Alaska Native producers*

In 2017, 79,198 producers were identified as American Indian or Alaska Native, representing 2.3% of all U.S. producers. They operate primarily in Arizona, New Mexico and Oklahoma where they account for 59%, 22%, and 13% of each state's total producers, respectively (Figure 4) (U.S. Department of Agriculture National Agricultural Statistics Services,2019e).




Source: U.S. Department of Agriculture National Agricultural Statistics Services (2019e)
Figure 4. Share of American Indian/Alaska Native Operated Farms by County (as percent of total farms), 2017

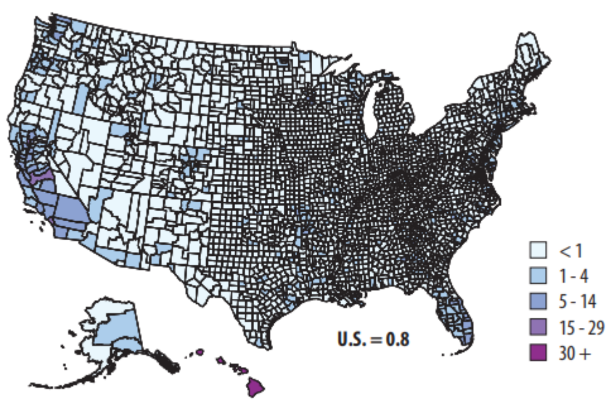
On average, American Indian/Alaska Native producers were younger and more likely to be female than U.S. producers overall (44% vs. 36%). American Indian/Alaska Native-operated farms accounted for 59 million acres of farmland. This represents 6.6% of the U.S. farmland.

In terms of sales, American Indian/Alaska Native-operated farms sold $3.5 billion worth of agricultural products in 2017, representing less than 1% of total U.S. agricultural sales. Sixty percent of this revenue was from the sale of livestock and livestock products. Farms mainly specialized on beef and cattle production and 63% of these farmers had sales and government payments under $5,000 per year (Table 1).

American Indian/Alaska Native–operated farms accounted for 59 million acres of land, which represents 6.5% of the U.S. total. The majority (73 percent) of these farms were less than 180 acres in size, the same as farms in the U.S. as a whole (Congressional Research Service 2021; U.S. Department of Agriculture National Agricultural Statistics Services 2019e).

#### *2.1.5. Asian producers*

The number of Asian producers were 25,310 in 2017, representing 0.7% of all U.S. producers. They were located primarily in California and Hawaii, where Asian producers accounted for 6% and 35% of producers in the two states, respectively (Figure 5) (U.S. Department of Agriculture National Agricultural Statistics Services 2019a).




Source: U.S. Department of Agriculture National Agricultural Statistics Services (2019a)
Figure 5. Share of Asian Operated Farms by County (as percent of total farms), 2017

Asian producers were younger and more likely to have started farming more recently than U.S. producers overall. Asian-operated farms accounted for 2.9 million acres of farmland, or 0.3% of the U.S. total farmland. They sold $7.5 billion worth of agricultural products in 2017, representing 1.9% of total U.S.

agricultural sales. Their activities were mainly focused on specialty crops such as fruits, nuts, and berries. Asian producers received $29 million in government payments in 2017, which accounts for less than one-half of one percent of all government payments. In 2017, 37% of these farms were smaller in size compared with all U.S. farms, with annual sales and payments of less than $5,000 per year.

Asian-operated farms accounted for 2.9 million acres of farmland, 0.3% of the U.S. total. Sixty-seven percent were smaller than 50 acres. The average size of Asian-operated farms was 160 acres, and 78% of Asian operators were owner of the land they farmed (Congressional Research Service, 2021). See Table 1 for the summary of SDFR farm information.

Table 1. Summary Statistics by SDFR Status for the 2017 Census of Agriculture

| **Producers** | **All U.S.** | **Women** | **Hispanic** | **Black** | **American Indian/Alaska Native** | **Asian** |
|---|---|---|---|---|---|---|
| Number count | 3,399,834 | 1,227,461 | 112,451 | 25,310 | 79,198 | 48,697 |
| *Sex (%)* | | | | | | |
| Men | 64 | / | 65 | 71 | 56 | 55 |
| Women | 36 | / | 35 | 29 | 44 | 45 |
| Average Age (Years) | 57.5 | 57.1 | 55.0 | 60.8 | 56.6 | 54.9 |
| *Years Of Farming (%)* | | | | | | |
| 10 or less | 27 | 30 | 36 | 29 | 28 | 40 |
| 11 or more | 73 | 70 | 64 | 71 | 72 | 60 |
| Lived On Their Farm (in %) | 74 | 79 | 65 | 61 | 80 | 61 |
| *Worked Off Farm (%)* | | | | | | |
| No days | 39 | 39 | 31 | 40 | 37 | 32 |
| 1 to 199 days | 21 | 22 | 28 | 25 | 24 | 30 |
| 200+ days | 40 | 39 | 41 | 35 | 39 | 38 |
| *Primary Occupation (%)* | | | | | | |
| Farming | 42 | 33 | 40 | 44 | 47 | 48 |
| Other | 58 | 67 | 60 | 56 | 53 | 52 |
| With Military Service (%) | 11 | 2 | 11 | 19 | 11 | 7 |
| Top States producers (as percent of total share producers) | / | Arizona (49%), Alaska (47%), New Hampshire (46%) | New Mexico (30%), California (12%), Texas (10%) | Mississipi (13%), Lousiana (7%), South Carolina (7%) | Arizona (59%), New Mexico (22%), Oklahoma (13%) | Hawaï (35%), California (6%) |
| *Economic Class of Farm (%)* | | | | | | |
| < $1,000 | 23 | 27 | 33 | 30 | 41 | 20 |
| $1,000 to $4,999 | 21 | 23 | 24 | 27 | 22 | 17 |
| $5,000 to $9,999 | 11 | 12 | 11 | 15 | 11 | 11 |
| $10,000 to $49,999 | 20 | 19 | 16 | 21 | 16 | 21 |
| $50,000+ | 25 | 19 | 16 | 7 | 10 | 31 |
| Principal type of operation | Cattle and dairy (34%) | Livestock and livestock products (51%) | Cattle and dairy (36%), specialty crops (21%) | Cattle and dairy (48%) | Cattle and dairy (42%) | Specialty crops (52%) |

Source: U.S. Department of Agriculture National Agricultural Statistics Services (2019e); U.S. Department of Agriculture National Agricultural Statistics Services (2019b); U.S. Department of Agriculture National Agricultural Statistics Services (2019d); U.S. Department of Agriculture National Agricultural Statistics Services ( 2019c); U.S. Department of Agriculture Economic Research Service (2022); U.S. Department of Agriculture National Agricultural Statistics Services (2019a)

### *2.2. Type of loans available to farmers*

#### *2.2.1. Variety of credit and lenders*

Farmers can access different types of credit to finance their operations and to recover from financial difficulties. Annual production loans can help farmers cover annual operating expenses, such as seed, fertilizer, or other inputs. Expenditures to finance non-real estate such as machinery, equipment, property improvements, or the purchase of breeding livestock are less common and usually financed over several years through intermediate term loans. Typically, the terms of intermediate loans range from 14 months to 7 years. Finally, real estate loans are used to finance land and buildings necessary for the business. Real estate loans tend to be larger and have longer terms. While terms can range from 5 to 40 years, 30 years is considered standard. It is very common for farms to accumulate multiple loans (Congressional Oversight Panel, 2009).

#### *2.2.2. Type of lenders*

According to the Congressional Oversight Panel (2009), there are several types of lenders from which farmers can apply for loans. In 2017, the USDA's Agricultural Resource Management Survey (ARMS) found that 22% of farmers borrowed from a single lender and 10% borrowed from at least two different lenders. Of all farmers' loan volume, 31% were issued by the Farm Credit System (FCS) and 4% came from FSA. In addition, commercial banks accounted for 47% of farmers' loan volume, and about 19% of farmers' loan volume was borrowed from other sources such as state and county government, savings and loan associations, life insurance companies, implement dealers, input suppliers, co-ops, credit cards, Federal Agricultural Mortgage Corporation (Farmer Mac), credit unions and other individuals or institutions (Key et al., 2019).

##### *2.2.2.1. Farm Service Agency (FSA)*

FSA is a government agency within the USDA. It has been referred to as a temporary lender of last resort for the agriculture sector. It offers direct loans to farmers and guaranties loans made and serviced by commercial lenders, such as the FCS or, commercial banks. The origin of FSA traces back to the Great

Depression. It has evolved over the years providing services such as lending, training, and commodity assistance programs for the rural population. FSA lending programs are mainly dedicated to family farmers. The operators are only eligible for FSA loans if they are unable to obtain credit at reasonable rates and terms elsewhere. The characteristics of loans made by the FSA farm loan program vary. DOLs include annual operating loans with a term of 1 year and intermediate term, which have a term of 7 years. FSA also provides long-term real estate farm ownership (FO) loans with terms of up to 40 years. Interest rates for direct loans are determined by the government's cost of borrowing. All FSA direct borrowers are required to furnish collateral and refinance their loans with a private lender, such as a commercial bank or the FCS, once their finances permit it.

FSA farm loan program, in addition to general direct and guaranteed OL and FO loans, offers loans to targeted groups or for particular purposes. For example, there are loans targeted to beginning or socially disadvantaged farmers and ranchers, youth, and Native American Tribes. There are microloans for OL and FO loans of $50,000 or less. There are conservation loans (CL) intended to promote conservation practices to protect natural resources. FSA also provides emergency (EM) loans to assist farmers recover from production and physical losses resulting from a natural disaster or emergency declared by the U.S. President (U.S. Department of Agriculture Farm Service Agency, 2021).

Before the mid-1980s, direct loan programs were the primary mechanism for providing credit assistance. Due to the high default and loss rates associated with direct loans combined with a smaller Federal budget there was a shift toward more guaranteed loans (Ahrendsen et al., 2005). The FSA guaranteed loans program saw its role increased with the Federal Agriculture Improvement and Reform (FAIR) Act in 1996 followed by the Farm Security and Rural Investment (FSRI) Act in 2002. The 2002 farm bill also implemented an interest assistance (IA) program for guaranteed operating loans which reduced rates paid by borrowers by 4 percentage points (Ahrendsen et al., 2004; Ahrendsen et al., 2011).

Moreover, in 2008, the Food, Conservation and Energy Act increased the limitation amount of direct OL and FO loans. These changes permitted more borrowers to access farm credit assistance from the government and the demand for guaranteed loans increased (U.S. Department of Agriculture Farm Service Agency, 2014). While the FSA lending programs are generally dedicated to serving family-size farms, specific sub-groups of family-size farms are targeted. Direct loan funds, in particular, are highly targeted toward historically underserved groups, which included young, beginning, veterans, as well as those farms operated by SDFR (USDA Natural Resources Conservation Service, 2018). Targeted groups of producers are only eligible for FSA loans if they meet all other eligibility criteria including the inability to obtain credit at reasonable rates and terms elsewhere despite being creditworthy (USDA FSA, 2021).

*2.2.2.2. Life Insurance Companies*

Life insurance companies can be an additional source of credit to farmers providing 6.7% of real estate credit (USDA Economic Research Service, 2022). They specialize in providing larger farm real estate loans (Congressional Oversight Panel, 2009).

*2.2.2.3. Commercial banks*

Commercial banks and the FCS are an important source of farm credit. However, since these are private entities, the characteristics of their farm loans are more difficult to identify than those of FSA. This is even more complicated because there is a wider variety of farm loans offered and a more diverse clientele of farmers served. Nevertheless, some characteristics can be distinguished from industry surveys and Call Reports. Farm loans have more in common with commercial loans than with residential mortgages (Congressional Oversight Panel, 2009). In addition, banks traditionally require an abundance of collateral when lending to farmers. They are generally reluctant to lend to those who do not have a relatively strong debt-to-equity position and perform a financial statement analysis (balance sheet, income statement, cash flows, owner equity) on most borrowers.

Farm loans at banks may also differ in terms of characteristics, such as: (a) Bank size: there are large differences in the size of commercial banks. Surprisingly, some of the largest farm lenders are not among the largest banks in the country. Small and community banks play a critical role in farm credit markets; (b) Farm size: the highly diverse U.S. agricultural sector results in widely varying credit needs. Also, certain banks may be targeted to the specific credit needs of a particular type of farm or farmer (Congressional Oversight Panel, 2009).

*2.2.2.4. Individuals and others*

Many small farms and family farms rely on financing from private lenders such as family and friends to finance either their operations or property purchase. In addition, some financial companies that qualify as non-traditional lenders, such as John Deere, provide loans to farmers to finance the purchase of their products or for other purposes. As such they compete with commercial banks and other sources of agricultural credit (Congressional Oversight Panel, 2009).

*2.2.2.5. The Farm Credit System (FCS)*

The FCS was established in 1916. Its purpose is to provide financing for agriculture and rural America. The FCS is considered a Government Sponsored Enterprise (GSE). However, it is not explicitly guaranteed by the government. While GSEs are considered quasi-government entities, they are not a lender of last resort, like FSA. The FCS competes directly with commercial banks. FCS currently consists of four funding banks and 65 lending associations owned cooperatively by borrowers (Farm Credit Administration, 2022). The FCS maintains its operations by selling systemwide debt securities in the capital markets. FCS Banks and lending associations are regulated by the Farm Credit Administration (FCA). The FCS offers a variety of loans: short-term production loans, intermediate term loans, and farm real estate loans. The purpose of loans and guidelines for the terms of FCS loans are defined by the Farm Credit Act of 1971. FCS loans are generally collateralized, which is expected for short-term operating loans. To manage credit risk, FCS institutions consider the borrower's integrity, credit history, cash flow, equity, collateral, and any off-farm income or obligations that could affect the borrower's ability to repay the farm loan. Moreover, each FCS institution must establish a credit limit, which is the maximum amount of credit that can be extended to the borrower (Congressional Oversight Panel, 2009).

*2.2.2.6. Other players in farm credit markets*

The Farmer Mac and the Federal Home Loan Banks also play an important role in enhancing the liquidity of major agricultural lenders through providing a secondary market for mortgage loans. Liquidity is important as increasing liquidity enables lenders to expand the amount that is provided. Farmer Mac was established by Congress with the passage of the Agricultural Credit Act of 1987. In 2008, the Food, Conservation and Energy Act expanded this mission to purchase and guarantee securities backed by loans from cooperative lenders to cooperative borrowers to finance rural electrification and telecommunications systems. Farmer Mac provides these services through three main programs: Farmer Mac I (non-USDA guaranteed loans), Farmer Mac II (USDA guaranteed loans), and Rural Utilities (rural utility loans). Farmer Mac is part of the FCS and is regulated by FCA.

The Federal Home Loan Bank (FHLB) system was created by Congress in 1932 through the FHLB Act. The FHLB system consists of 11 cooperative banks or Federal Home Loan Banks (FHLBs), each representing a district in the United States (FHLBANKS, 2022).. FHLBs provide liquidity to their member institutions by making short-term loans, or advances, using certain types of pledged assets for collateral. Previously, the pledged collateral had to be in the form of mortgage loans or government bonds. However, the Federal Home Loan Bank System Modernization Act of 1999 expanded the types of pledged collateral that small member institutions could offer to include agricultural, small business, and community development loans (Congressional Oversight Panel, 2009).

*2.2.3. Criteria affecting the probability of default*

Generally, a loan is delinquent if the borrower has not made the scheduled payment by the due date. However, the specific definition of delinquency can also vary by lending institution. For example, it may be defined as a percentage of total loans, percentage of total debt outstanding, or the total number of borrowers. It may also vary by the time delinquent. For FSA, the criterion for default is a payment that is 30 days or more past due. FSA reports delinquency rates in its Monthly Management Summary Reports both as a percentage of loan volume and as a percentage of loan count. The Monthly Management

Summary Report is an internal document produced monthly by Farm Service Agency Farm Loan Program division in Washington, DC, for USDA managers.

For commercial banks, a loan is considered delinquent if it is 30 days or more past due or nonperforming, as defined by the Chart 5 of the Commercial Bank report (Kauffman and Kreitman, 2021). It is also considered delinquent if interest is past due (nonaccrual status). This is a result as Generally Accepted Accounting Rules (GAAP) stipulate that a loan must be placed in nonaccrual status (which means that a commercial lender can no longer accrue interest income) after the loan has reached 90 days in default.

This study will consider default at 90 days delinquent to be consistent with industry standards since commercial lenders consider 90 days delinquent to be nonaccrual. Moreover, 90 days is more likely (than 30 days) to represent a serious repayment issue. Considering default at 30 days past due would lead to an increase in the number of delinquent loan observations. The study will also try to control for multiple factors that could impact delinquency or repayment rates. These factors are presented in the following parts.

*2.2.3.1. Type of loans*

First, the study conducted by Quaye et al. (2017) on farmers in the southeastern U.S. found that farmers with a single loan are less likely to default than others. They also highlighted the fact that farmers who take loans from commercial banks are more likely to default than the ones that do not.

As for the term of the loan, their study showed that the probability of defaulting decreases when the term is extended by one year. However, in terms of the value of the loan, it shows that an additional thousand dollars of credit increases the likelihood of default. The interest rate on the loan, or the prime rate, is also positively related to the likelihood that farmers will default (Quaye et al., 2017).

Finally, regarding the use of the loan, the study reveals that the particular use of the loan by the farmer can affect the likelihood of default. For example, a loan used to purchase forage for animals is more likely to be delinquent than a loan used to improve or rehabilitate the farm. However, a loan used to purchase livestock other than feed animals or for operating costs is less likely to be delinquent than a loan used for farm improvement or rehabilitation (Quaye et al., 2017).

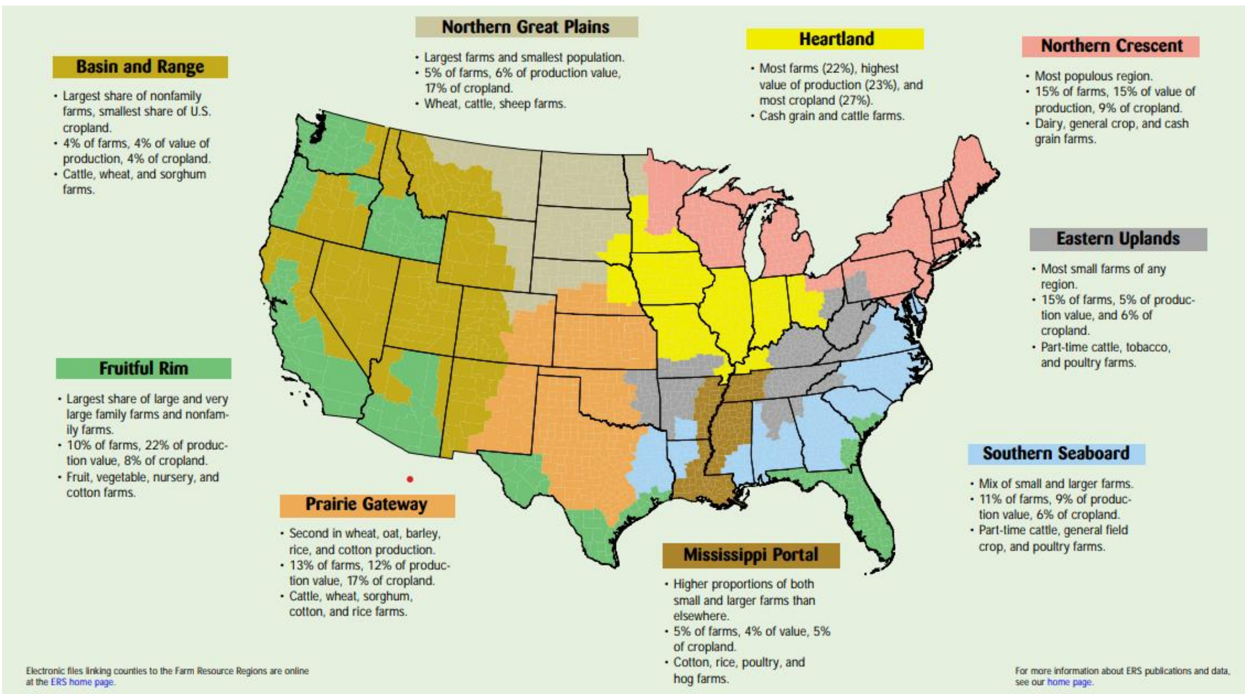
*2.2.3.2. Farm types*

Farm size can play an important role in delinquency rates. First, according to the report prepared by USDA based on census data (USDA-NASS, 2019), larger farms are much more likely to borrow than farms of other sizes. They highlighted that in 2017, 21% of farms with annual sales over $1 million had no debt, compared to 82% of farms with annual sales value under $10,000. In addition, larger farms are more likely to borrow from multiple sources. This could be due to their interest in having a wider choice of loan providers to finance their operations. Finally, larger farms also obtain a larger share of their debt from FCS than farms of other sizes (Key et al., 2019). Quaye et al. (2017) also reveal that as farm size increases, the likelihood of default decreases. In their study, larger farms correspond to higher-income farms. Their results appear to contradict recent findings from the USDA Economic Research Service (2019), which show that larger farms were more likely to be under financial stress than smaller farms in 2017. However, this difference can be explained by the definition of large farms used, as Quaye et al. (2017) define larger farms based on net income, while the USDA Economic Research Service (2019) defines those farms as having annual sales of at least $100,000.

The study conducted by Dodson et al. (2022) also suggests that farm financial characteristics can also affect delinquency rates. They showed that an increase in farm income was a factor tending to decrease the likelihood of becoming delinquent, while an increase in farm debt increases it. Also, farms with higher rates of return should have a lower probability of becoming delinquent. Farmers with higher net worth and farmers with a greater value of owned assets would be expected to have a lower probability of defaulting.

*2.2.3.3. Impact of region/state of operation*

In terms of regions of operation, Key et al. (2019) compares delinquency rates among four production regions in the U.S.: Fruitful Rim, Heartland, Northern Crescent, and Prairie Gateway. Farm resource regions are defined using farm production regions, land resource regions, crop reporting districts, and farm characteristics. The regions are designated at the county level and therefore do not generally follow State boundaries. There are nine regions defined by the USDA Economic Research Service (ERS): Basin and Range, Northern Great Plains, Heartland, Northern Crescent, Eastern Uplands, Southern Seaboard, Mississippi Portal, Prairie Gateway, and Fruitful Rim. The distribution of these regions is presented in Figure 6.

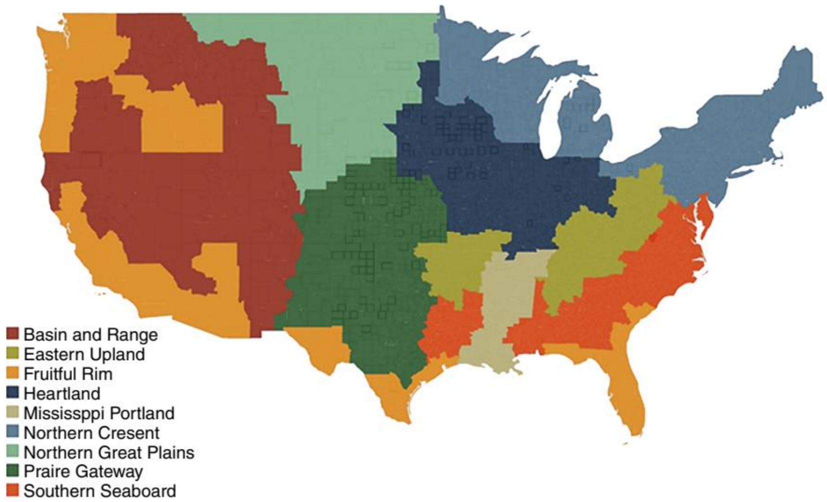



Source: USDA Economic Research Service (2000)

Figure 6. Farm Resource Regions

Basin and Range region records the largest share of nonfamily farms and the smallest share of U.S. cropland. It represents 4% of the farms, 4% of value of production and 4% of cropland. The principal types of operations in this region are cattle, wheat, and sorghum productions. Northern Great Plains is the region with the largest farms and smallest population. It contains 5% of farms, mainly specialized in wheat, cattle, and sheep production. It accounts for 6% of production value and 17% of cropland. The Heartland region accounts for most of the farms (22%), the highest value of production (23%) and most cropland (27%). Farms are mostly specialized in grain and cattle farming. The Northern Crescent accounts for 15% of the U.S. farms, 15% of value of production and 9% of cropland. The farm type is mainly about dairy, crop and cash grain. The Eastern Uplands region has a greater share of small farms than any other region. It accounts for 15% of the farms, 5% of the production value and 6% of cropland. Main operations in these regions are part-time cattle, tobacco, and poultry. The Southern Seaboard mixes small and large farms. It represents 11% of farms in the U.S., 9% of production and 6% of cropland. The main types of operations are part-time cattle, general field crop, and poultry farms. The Mississippi Portal is the region with both higher proportions of large and small farms mainly specialized in cotton, rice, poultry and hog production. It accounts for 5% of farms, 4% of value, and 5% of cropland. Prairie Gateway is the second region in terms of wheat, oat, barley, rice, and cotton production. It represents 13% of farms, 12% of production value, and 17% of cropland. The Fruitful Rim production region records the largest share of large farms. It represents 10% of U.S. farms, 22% of U.S. production value and 8% of cropland. The main type of operations in this region are fruit, vegetable, nursery, and cotton farm (USDA Economic Research Service, 2000).

Key et al. (2019) show that delinquency rates on real estate loans in the Fruitful Rim, Heartland, Northern Crescent, and Prairie Gateway regions follow a similar pattern. These regions have been chosen because they constitute the largest regions in terms of production value, and together represent 60% of all farms and 72% of the value of agricultural production. However, the magnitude of the rate varies widely. In the Northern Crescent and Fruitful Rim regions, delinquency rates increased more between 2008 and 2011 than in Heartland and Prairie Gateway (Figure 7) (Key et al., 2019).




Source: Key et al. (2019)

Figure 7. Economic Research Service Farm Resource Regions

In addition, the effects of temperature and precipitation have a small impact on loan delinquency, as highlighted by (Quaye et al., 2017). Therefore, climate may affect farmers differently as climatic conditions vary greatly by state.

*2.2.3.4. Farmer profile*

Another factor that can have a significant impact on the probability of delinquency is the profile of the farmer. Age was highlighted as an important factor. Studies reported that beginning farmers recorded lower default rates than other farmers. They explained those results because beginning farmers operate, on average, smaller farms and because their income is usually more diversified with a greater share of their total income from nonfarm sources than non-beginning farmers (Key et al., 2019).

Gender is also an important factor influencing probability to default.  Timely repayment appears more likely for women-led households which are less likely default than households headed by men (Cigsar and Unal, 2018).

*2.2.3.5. Insurance and involvement in other programs*

Farmers' involvement in insurance programs also affects their ability to repay their loans. The results of the study conducted on farms in the southeastern U.S. show that farmers who had a higher percentage of insurance expenditures were less likely to default than the others (Quaye et al., 2017). Agricultural insurance appears to reduce the likelihood of delinquencies. This is particularly true for crop insurance (Ifft et al., 2013).

### *2.3. Discrimination in access to loans for SDRFs*

#### *2.3.1. History of discrimination*

Horst and Marion (2019) have highlighted the long-term impact of structural discrimination on agriculture in the U.S. They link this historical background to the current disparities that exist in agriculture by race, ethnicity, and gender. White, non-Hispanic male farmers currently own more land and generate more farm revenue than SDFRs (U.S. Department of Agriculture National Agricultural Statistics Services 2019c; U.S. Department of Agriculture National Agricultural Statistics Services 2019b; U.S. Department of Agriculture National Agricultural Statistics Services 2019a; U.S. Department of Agriculture National Agricultural Statistics Services 2019d; U.S. Department of Agriculture National Agricultural Statistics Services 2019e). There are studies that display how cultural biases leads to structural racism that can perpetuate disparities between Whites and minorities. Minkoff-Zern and Sloat (2017) highlighted the negative impact on the Latina community resulting from USDA's inability to provide culturally relevant technical expertise. Calo and De Master (2016) provided examples of how the complexity of the paperwork involved in applying for USDA programs made the process even more difficult for non-English speakers.

Minkoff-Zern and Sloat (2017) recall the earlier history of the U.S. Prior to European arrival, more than 15 million Native Americans were organized into hundreds of tribes, each with its own food systems and land relations. In the 15$^{th}$ century, Europeans arrived and established a land tenure system for themselves, excluding the others. They established a system of record to buy and sell land. In this way, they dispossessed Native Americans of their land by force and manipulation. This resulted in Whites and wealthier individuals appropriating land at the expense of the poor, indigenous and people of marginalized racial and ethnic backgrounds. For example, the 1830 Indian Removal Act forcibly relocated Cherokee, Creeks, and other Indians from the east to west of the Mississippi River to make room for White settlers. The Homestead Acts in the latter half of the nineteenth and early twentieth centuries, redistributed the farmland that had been taken from Native Americans in the western United States to U.S. citizens at no or very low cost. By 1955, the Native American land was only slightly more than 2% of its original size. Today, it consists mainly of land that is considered to be poorly suited for agriculture.

Blacks have also been discriminated against through violence and exclusion. By 1860, plantation owners in the South had enslaved some 4 million people brought from Africa to work on tobacco, rice, and cotton farms. The wealth generated as a result was enormous (Robins, 2015). Yet, even after slavery was abolished in 1865, the descendants of slaves did not benefit from this wealth. Many former slaves had neither the land nor the resources to become independent farmers. They became sharecroppers or farmworkers and had to continue working under oppressive working conditions (Hannah-Jones, 2019). The land with the richest soils, such as the "Black Belt" between Georgia and Arkansas, was owned and operated by white and wealthy men using Black sharecroppers to perform the labor.

Asian farmers also faced structural discrimination in the U.S. In the 1800s, significant numbers of immigrants came from the Philippines, China, Japan, and South Asia to work on plantations, farms, mines, and railroads in Hawaii and the West Coast. Asian immigrants played a very important role in the development of agriculture in California. However, they faced anti-Asian hostility at various levels. For example, in the late nineteenth and early twentieth centuries, Federal and state governments enacted a series of exclusionary laws that prohibited Asians from owning land. These included the 1882 Chinese Exclusion Act, the 1913 California Alien Land Law, and later related laws that prohibited Japanese from owning land unless they were citizens.

In terms of gender, there were structural barriers to land ownership and agriculture for women of all races and ethnicities. Women were excluded from land ownership before the 1862 Homestead Act that enabled heads of households to claim land and then offered single women opportunities to own land. Nevertheless, even after this Act, women of color faced numerous structural barriers to engaging in agriculture due to both their race/ethnicity and gender and farmland ownership remained largely dominated by White men at the end of nineteenth century.

This exclusion was followed into the 1900s as federal farm policies tended to encourage consolidation of farms and agribusinesses.  This accelerated the concentration of land ownership and led to a decline in the number of farmers of all races, ethnicities, and gender between 1930 and 1950. More recently, the Farm Bill subsidies and access to international markets have benefited the largest farms growing wheat, corn, or soybeans which were more likely to be owned and operated by white males. The institutionalization of commodity price support has also reduced opportunities for small-scale farmers to enter farming, which has particularly hurt SDFRs, which tend to receive less government support (Bekkerman et al., 2019).

In the 1930s, after the onset of the Great Depression, measures were taken to offset the economic downturn in the agricultural sector. The Agricultural Adjustment Administration (AAA) was created and established county committees throughout the country to oversee the local administration of USDA farm programs. SDFRs, however, were often excluded from these committees. The receipt of fewer Government benefits delivered to SDFR farmers relative to white farmers created an appearance of discrimination by the local committees. For example, local committees may have contributed to a lower SDFR participation by not making SDFRs more aware of the availability of many government farm programs. In 1964, the Civil Rights Act aimed to address this problem, but was unable to completely eradicate it (Gilbert, Sharp and Felin, 2001; Ko, 2021).

The increasing size of farms forced farm owners to hire additional workers. The U.S. government implemented the Mexican Farm Labor Program, also known as the Bracero Program, to facilitate their research. The program included a series of laws between 1942 and 1964 that convinced millions of Mexicans to work legally on U.S. farms and railroads. The program was discontinued because of its controversial aspect. Yet, U.S. agriculture still relies heavily on non-U.S. born workers. Thirteen percent of farmworkers interviewed in 2017–2018 were migrants. Among them, nearly half were domestic migrants (24% domestic follow-the-crop and 23% domestic shuttle migrants), more than a third were international migrants (3% international follow-the-crop and 39% international shuttle migrants), and 11% were newcomers who had been in the U.S. less than a year (U.S. Department of Labor Employment and Training and Administration, 2021). Farm workers are among the most economically disadvantaged and socially vulnerable groups in the U.S. They typically earn low wages and have fewer legal protections than other workers and are less likely to become farm operators or owners of farmland in the U.S.

One important form of discrimination affecting minority farmers and Women relates to lending. The USDA Farmers Home Administration (FmHA), which operated from 1946 through 1994, faced accusations of disparaging treatment of minority and women farmers. In 1999, the USDA was sued for discrimination against Black farmers. The suit alleged that the agency had discriminated against Black farmers on the basis of race and failed to investigate or adequately respond to complaints from 1983 to 1997[4]. This episode is known as the Pigford cases (Cowan and Feder, 2012). As a result, significant changes were made to reduce disparities in access to government assistance for Black farmers. In 2010, the Pigford v. Glickman class action lawsuit resulted in a $1.25 billion settlement to be paid out to class members. The agency also faced and settled lawsuits from Hispanic and Latino (Garcia v. Vilsack), Native American (Keepseagle v. Vilsack) and female farmers (Love v. Vilsack) for significant discrimination in lending practices (Horst and Marion, 2019). However, only Blacks and American Indians received any settlements. The USDA, however, did not admit to discrimination in any of these settlements (Roesch et al., 2005).

Prior to filing of the Pigford case inequities in access to government assistance for minority farmers had already been recognized and actions taken. Specifically, the county boards, composed of local producers elected to three-year terms, were barred from influencing any farmer’s eligibility for farm loans (USDA

[4] The authority for farm lending shifted to the Farm Service Agency in 1994.

Reorganization Act of 1994).[5] Also, FSA had begun providing a portion of the credit funds to minority farmers in 1992 (Agricultural Credit Improvement Act of 1992). USDA's 2501 program was created under the 1990 Farm Bill to assist socially disadvantaged farmers, ranchers, and foresters, who historically had limited access to USDA programs and services.[6] To address the concerns of SDFR groups, the 2008 Farm Bill established the Office of Advocacy and Outreach, whose major program areas include SDFR. Although FSA has targeted loans to individual SDFR, as of 2018, the Office of Advocacy and Outreach awarded funds to various organizations to conduct outreach initiatives and training to assist SDFR and veteran farmers and ranchers in owning and operating farms and ranches and increasing their participation in USDA programs and services. The 2008 Farm Bill established the Advisory Committee on Minority Farmers to ensure that SDFR have equal access to USDA programs. FSA established a microloan program that targets new and small farmers and ranchers, many of whom may be SDFR. USDA also requires that minority representatives serve Farm Service Agency district committees (Horst and Marion, 2019).

However, in examining the consequences of this history, Horst and Marion (2019) conclude that the changes have not been comprehensive. According to their study, racial, ethnic, and gender disparities have not changed from the past. SDFRs continue to face discrimination in access to credit, seeds, and other assistance. In fact, farmers typically take short-term loans to cover their operating costs and their family's living expenses. They also usually borrow for one year to cover annual expenses, which they repay after harvest. This practice is more difficult for SDFRs because they struggle to compete with White farmers because of less access to federal relief, fewer industry connections, less access to credit and smaller farms. These conditions prevent them from improving or upgrading their machinery, which would allow them to generate more revenue. Particularly with FSA loans, Blacks' participation rates in government programs permitting farmers to borrow money, obtain better commodity prices, and improve land are low (Gilbert et al., 2001). The recent review of participation rates in loan programs by Black

[5] The county committees were non-Federal employees who were elected by farmers within the county or jurisdiction served by the local office. The committee had the authority to verify the eligibility of any loan applicant. They also had the authority to approve the loan applicant's business plan.
[6] https://www.usda.gov/sites/default/files/documents/2501-factsheet-2022.pdf

farmers in Georgia by Asare-Baah et al. (2018) identified reasons for non-application and non-participation for all the programs. The reasons were lack of knowledge, negative perceptions, and complications with program requirements and financial issues. These pathways of discrimination are highly problematic for social, economic and environmental issues throughout the United States (Fagundes et al., 2020).

### *2.3.2. Characteristics of SDFR borrowers*

As highlighted in part one, the 2017 Census of Agriculture has shown differences between SDFR borrowers and other farm borrowers (U.S. Department of Agriculture National Agricultural Statistics Services 2019c; U.S. Department of Agriculture National Agricultural Statistics Services 2019b; US Department of Agriculture National Agricultural Statistics Services 2019a; U.S. Department of Agriculture National Agricultural Statistics Services 2019d; U.S. Department of Agriculture National Agricultural Statistics Services 2019e). First, they typically manage smaller farms and are more likely to specialize in specialty crops or livestock production (mainly dairy, beef and cash grain). They also tend to be more financially strained and have less capital than other groups of farmers. Geographically, they are found primarily in economically impoverished regions (Dodson, 2013).

These differences have implications for the type of borrowers they embody, and their likelihood of default as previously developed. In fact, default probabilities vary significantly by loan, borrower, and location. Higher default rates appear to be associated with higher loan-to-value ratios, lower incomes and home values, and smaller loan amounts. In addition, Berkovec et al. (1996) show that minority borrowers of housing loans are more likely to have loans with risky characteristics contributing to higher default rates.

Berkovec et al. (1996) also showed that Black borrowers have the highest default rates, while Asian borrowers exhibit the lowest default rates for home loan mortgages. These findings are explained by noting that Black and Hispanic borrowers are more likely to have a loan with a prepayment penalty, a balloon payment, and a scheduled payment provision in the first 48 months of a loan's life. Black and Hispanic borrowers also practice more risk layering, which stands for multiple high-risk features included in the same loan, than other minorities and their unemployment rates are significantly higher than Asians and Whites. Finally, the Berkovec et al. (1996) study notes that Black borrowers are more likely to have a low or no documentation loan. All of these characteristics are shown to impact the type of loan and the probability of loan default for Black borrowers.

McDonald et al. (2022) show that the differences in operation and household characteristics of the average SDFR and non-SDFR are associated with a lower likelihood of credit usage by an SDFR than a non-SDFR. Finally, Asare-Baah et al. (2018) reveal for select counties in Georgia that more Black farmers applied for OL than FO loans. Therefore, this study will focus on USDA FSA DOL loans that were originated during 2011-2020.

### *2.4. Study of discrimination in economics*

In economics, discrimination is defined as when members of a minority group are treated differently, often less favorably than members of a majority group with identical productive characteristics. There are two types of models for analysing discrimination: competitive models and collective models. However, competitive models are more prevalent in economics than collective models, which are more commonly used in sociology (Autor, 2009). Competitive models assume that individuals may have a discriminatory behaviour. They can be further divided into prejudice or "taste-based" models and statistical models.

#### *2.4.1. Prejudice model*

The prejudice or taste-based model was introduced by Becker's theory of discrimination (Becker, 1957). The theory was first elaborated to explain how individual employers and employees behave in the market. It develops the idea that some workers, employers, or customers do not want to work with or come into contact with members of other racial groups or with women. This prejudice is made because of a "taste" or preference against people from disadvantaged groups. This taste can be examined as a preference between goods and services. This initial theory was extended to credit in the second edition of the *Economics of Discrimination* (Becker, 1971). In terms of credit, the theory translates the fact that lenders would have a "taste for discrimination" and would be less likely to lend money to minorities. Therefore, SDFR would have to meet higher credit requirements to receive an equivalent loan (Berkovec et al., 1996).

However, this approach has been criticized by Yinger (1996), who shows that if credit characteristics not observed by the lender are correlated with minority status, or if Whites are treated more favorably than minorities in foreclosure proceedings, or if minority default losses are lower than those of Whites, then higher default rates could be observed for minorities even if lenders discriminate.

*2.4.2. Statistical Discrimination Model*

Statistical discrimination was first developed by Phelps (1972). It is based on the proposition that there is a lack of information or imperfect information about the abilities or behaviors of the members of the minority group. Therefore, firms are more likely to use all observable characteristics to statistically discriminate against workers if those characteristics are correlated with performance. This creates an incentive to use demographic characteristics such as race and gender to assign credit (Balvanz et al., 2011). Two different approaches are commonly used in statistical discrimination.

The first concerns the role of self-confirming stereotypes. This model was developed by Coate and Loury (1993). It examines the effect of affirmative action on discrimination. Affirmative action represents a set of policies and practices adopted by the government to integrate minorities in areas where they are underrepresented. According to their model, affirmative actions can lead to two outcomes. First, they can lead employers to want to hire minorities regardless of the policy because they improve the perception of minorities. Second, affirmative action can reduce investment in minority skills by reducing incentives for minorities and subsequently lead to a situation where employers rightly believe that minorities are less productive than the majority. Therefore, this second outcome will result in a continued need for affirmative action to achieve parity.

The second outcome refers to higher uncertainty in measuring the productivity of a group of individuals, related to cultural differences, for example. In the example of a labor market, this can lead to misallocation of workers to their tasks, resulting in underinvestment in skill acquisition.

Several models have been used to study discrimination. One of these is the Oaxaca-Blinder decomposition. The model was developed in parallel by Blinder (1973) and Kitagawa (1955). The idea of the model is to decompose a dependent variable studied between two groups into two components: explained and unexplained. The decomposition allows explaining the difference in the means of the dependent variable between the two groups by first decomposing the gap into the part due to the differences in the means of the independent variable and by also decomposing the group differences in the effects of the independent variable.

Finally, some other approaches use a paired tests procedure with random surveys of borrowers conducted at the application stage. This approach can be used to determine whether loan rates, and terms differ between racial and non-racial minority groups. Another approach is also to examine loan application data to test for discrimination in the loan approval process (Dodson, 2013).

## 3. Data and Descriptive Analysis

### *3.1. Data*

The data are issued by USDA's FSA Farm Loan Programs. The data set used to estimate the competing risks model comes from various sources within FSA. They include borrower demographic information such as race, ethnicity, gender, marital status, year started farming, if they have previously been USDA borrowers, and loan performance. Also included is farm information including type of farm, total acreage, crop acres, location by state, and financials, such as total liabilities and equity, total assets, current liabilities, working capital, value of farm production, gross revenue, debt-to-asset ratio, margin after debt service, discretionary income, term debt coverage ratio, asset turnover ratio, government program payments, loan to collateral, net farm income, and net income.

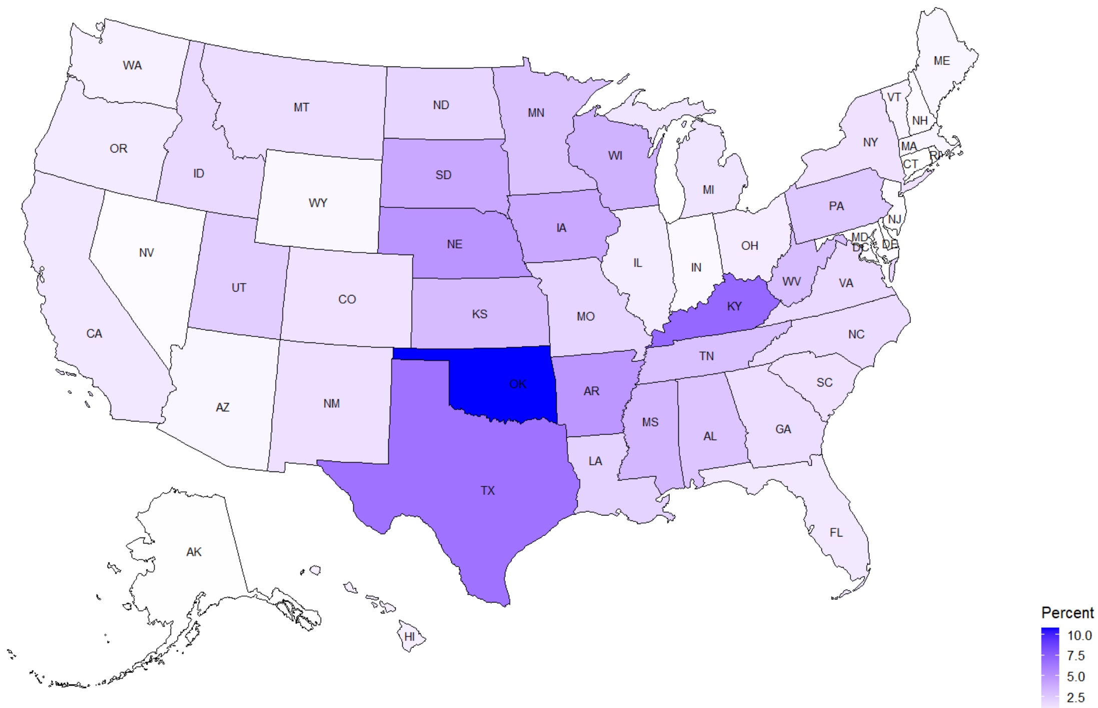
FSA data refer to the loan level but also include borrower characteristics. To collect all information on loans and borrowers, several sources of FSA were used. The observations are DOL with seven-year maturities (7-DOL) obligated during calendar years 2011- 2020. The aggregate data includes information on the type of loan, the date it was obligated, loan status and demographic and financial data. A single borrower could have received multiple loans in the sample period. In fact, the data set consists of 69,331 loans, made to 46,474 borrowers (Appendix 1). Because multiple loan borrowers and single loan borrowers may have different types of operations and different repayment capacities, as highlighted earlier in the literature, integrating multiple times one type of borrower in the sample could lead to potential bias. Therefore, to eliminate this potential bias among borrowers with multiple 7-DOLs, the total number of 7-DOL obligated during the time period are sampled using a sampling weight, following a Poisson process. The Poisson process was used because observation of the data showed a Poisson type of distribution (Appendix 1). The sampling weight for each 7-DOL observation is based on the number of loans each borrower had for the sample period. The Poisson sampling process stands on an independent Bernoulli trial that determines if the element will be part of the sample or not. A Poisson process is a model for a series of discrete events where the average time between events is known, but the exact timing of the events is random. The occurrence of an event is independent of the previous event. Therefore, there is only one indication of the average time between events. Three criteria must be met to run a Poisson process: (1) the events are independent, (2) the average rate (events per time period) is constant, (3) two events cannot occur simultaneously. The Poisson distribution probability is the probability of observing k events in a time period given the length of the time period and the average events per time and is expressed as: $P(k\ events\ in\ the\ time\ period) = e^{-\lambda}\frac{\lambda^k}{k!}$ where $\lambda = \frac{events}{time} * time\ period$ is the rate parameter. The final sample obtained with this process and used for analysis consists of 46,161 loans.

Before implementing the model, it was necessary to determine the different outcomes that occurred for these loans during this period. To determine the outcome of each loan, a column “outcome” was created that integrated four outcomes: Delinquent (the loan was not paid before 90 days after the payment due date), Long-Term Delinquent (the loan was not paid before 6 months after the payment due date), Paid in Full, and Censored (no outcome has occurred during the period). Censored would also include loans that were not delinquent nor paid-off through the end of the period. To determine the delinquency or long-term delinquency of each loan, the first step was to declare if the loan was delinquent or not following the definitions presented before. However, some outcomes occurred during the period of analysis that were not paid or delinquent. Therefore, in these cases it was necessary to identify the outcomes looking at the "DEBT_STL_CD" column, which stands for the code of the debt settlement. This code permitted to classify the outcomes as each code stands for a specific outcome (Appendix 2) when the loan was not identified as already delinquent or long-term delinquent or censored using the duration. Using the outcome column, the code for the competing risks model permitted to consider three outcomes: Paid in Full when the value of the outcome column equaled "Paid in Full", Delinquent when the value of the outcome column equaled "Delinquent" or "LongTermDelinquent" and Censored when the value of the column equaled "Censored".

### *3.2. Descriptive*

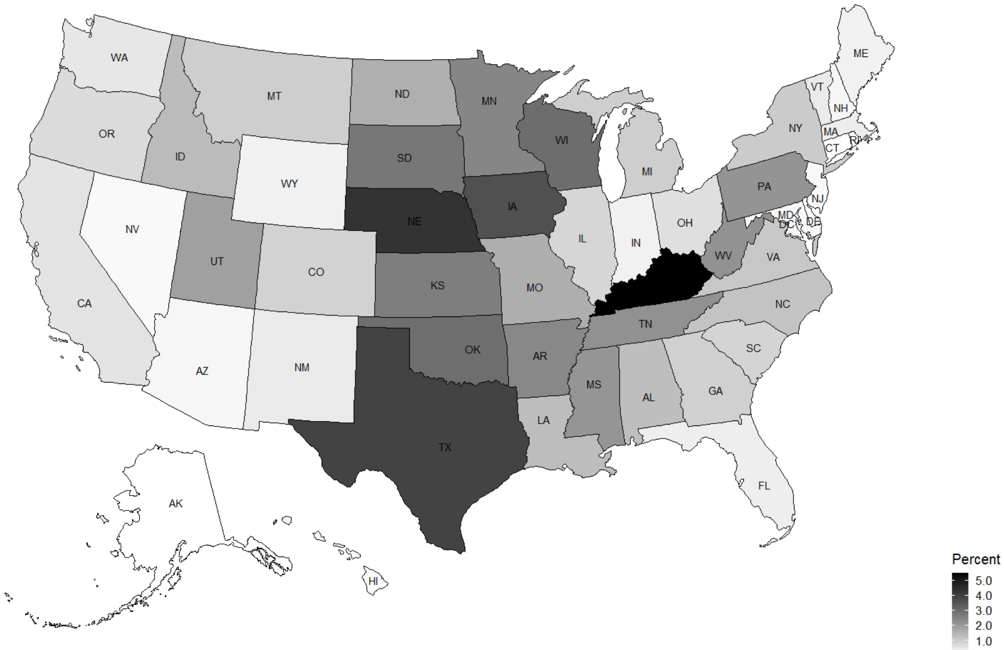
The next part of the study aims to perform some empirical analysis of the data before estimating the competing risks model. This provides a better understanding of the data. It also provides information on the differences that can be observed among the types of lenders. It also provides insight into the possible outcomes that may be observed with the model.

Overall, 68.8% of the loans in the sample are attributed to non-Hispanic White men borrowers, 13.2% are to Women, 3.6% are to Hispanics, 3.9% are to borrowers who identify themselves as Black, 12.3% as American Indian, 0.8% as Asian and 0.3% as Native Hawaiian or other Pacific Islander. The initial analysis looked at the distribution of these loans. These were heavily concentrated in specific regions such as Oklahoma, Kentucky, Texas, Nebraska and Arkansas, which accounted for 10.0%, 7.0%, 6.5%, 5.0%, and 4.7% of the loans, respectively (Figure 8).



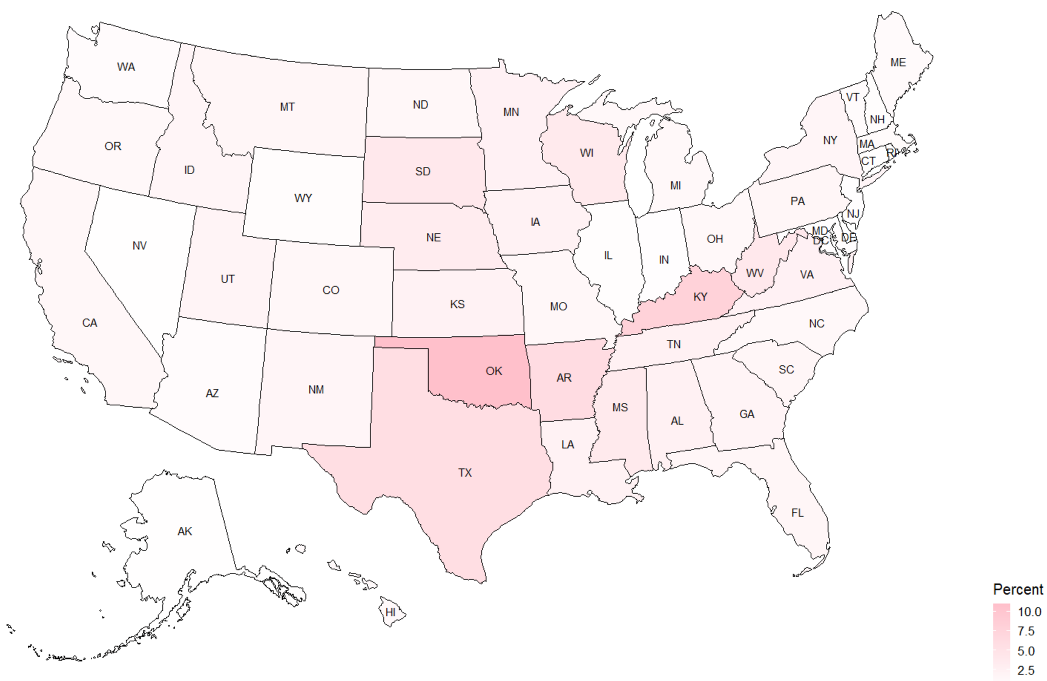

n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
0.62%, 0.02% and 0.05% of the loans are respectively located in Puerto Rico, Virgin Islands and Western Pacific
Source: Farm Service Agency Farm Loan Program and calculations
Figure 8. Distribution of Seven-year Direct Operating Loans to All Borrowers in the Sample, 2011-2020

This distribution was different for loans to minorities, although loans to non-Hispanic White men and Women had similar distributions (Figures 9 and 10).




n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
0.02%, 0.0% and 0.0% of the loans are respectively located in Puerto Rico, Virgin Islands and Western Pacific
Source: Farm Service Agency Farm Loan Program and calculations

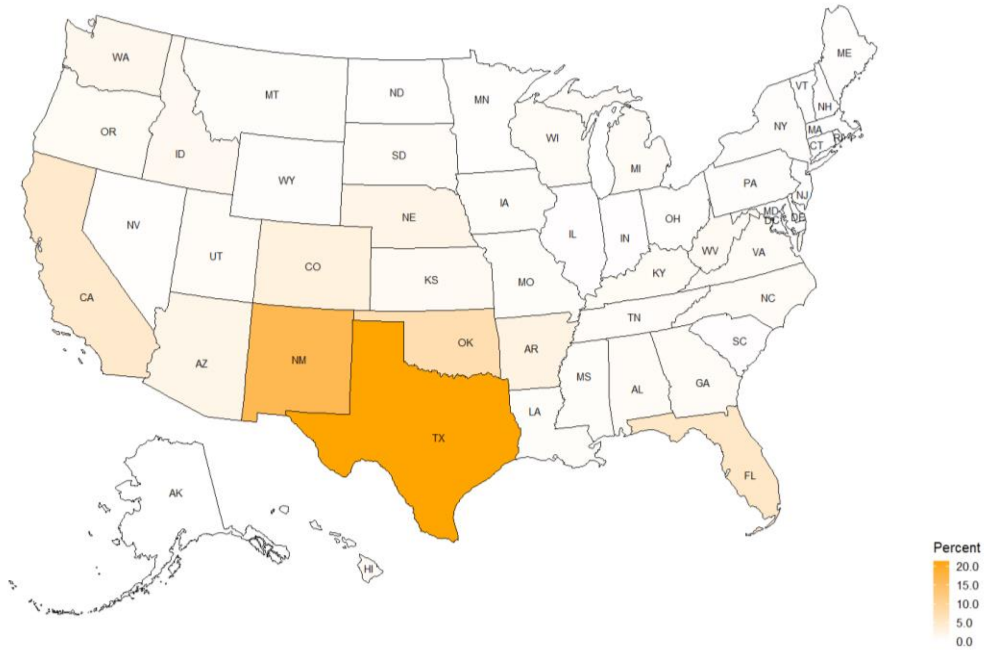
Figure 9. Distribution of Seven-year Direct Operating Loans to Non-Hispanic White men in the Sample, 2011-2020




n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
0.50%, 0.02% and 0.05% of the loans are respectively located in Puerto Rico, Virgin Islands and Western Pacific
Source: Farm Service Agency Farm Loan Program and calculations

Figure 10. Distribution of Seven-year Direct Operating Loans to Women in the Sample, 2011-2020

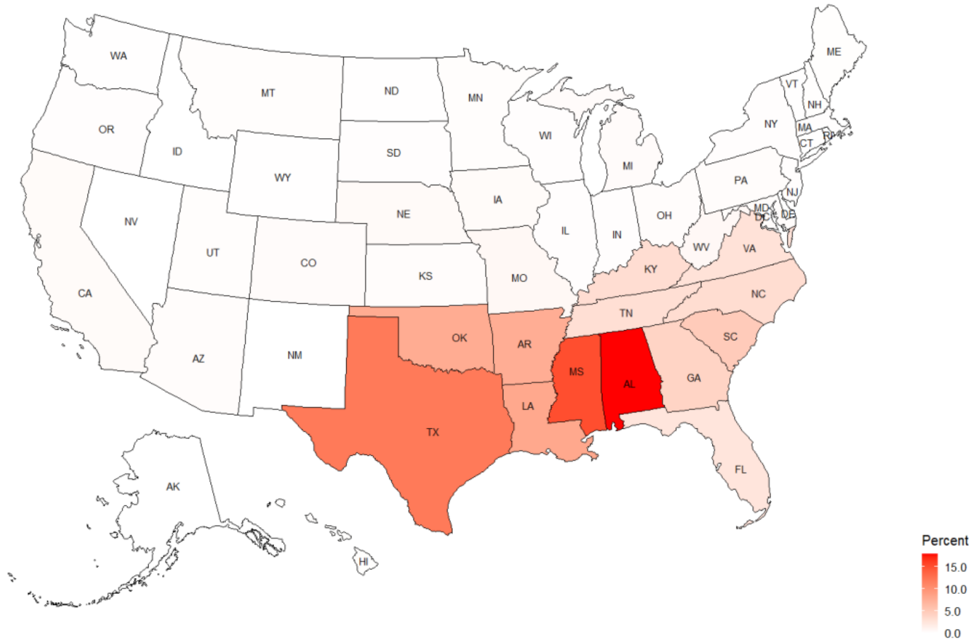
The distribution of the SDFR loans vary by race and ethnicity. Hispanic loans principally targeted some states such as Texas (21.4%), New Mexico (16.5%) and Puerto Rico (15.0%) (Figure 11).




n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
15.0%, 0.0% and 0.0% of the loans are respectively located in Puerto Rico, Virgin Islands and Western Pacific
Source: Farm Service Agency Farm Loan Program and calculations

Figure 11. Distribution of Seven-year Direct Operating Loans to Hispanic Borrowers in the Sample, 2011-2020

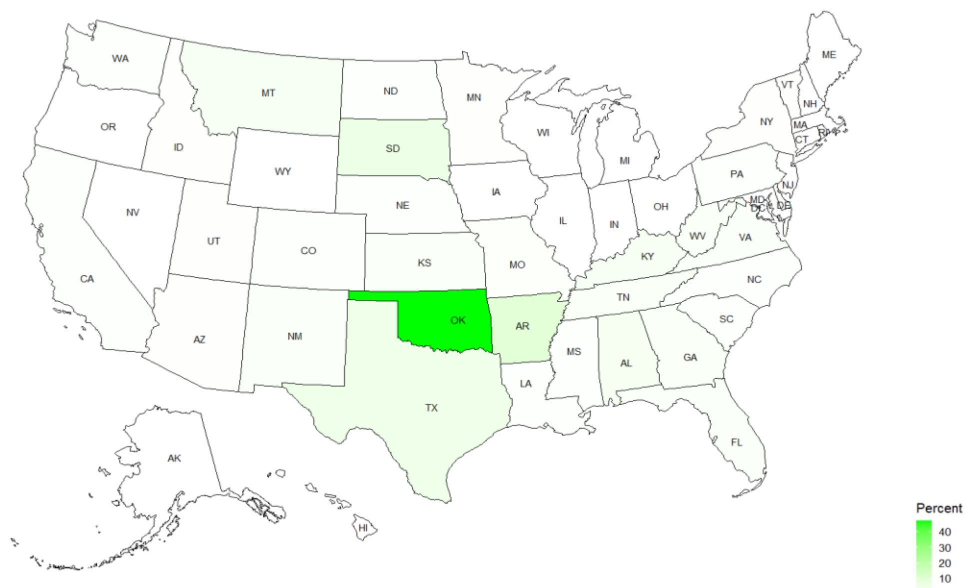
Loans to Black farmers were mainly encountered in Alabama, Mississippi, Texas, Louisiana, and Arkansas, which respectively accounted for 18.8%, 15.3%, 12.2%, 8.0% and 7.8% of the loans to Black farmers (Figure 12).




n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
0.34%, 0.39% and 0.0% of the loans are respectively located in Puerto Rico, Virgin Islands and Western Pacific
Source: Farm Service Agency Farm Loan Program and calculations

Figure 12. Distribution of Seven-year Direct Operating Loans to Black Borrowers in the Sample, 2011-2020

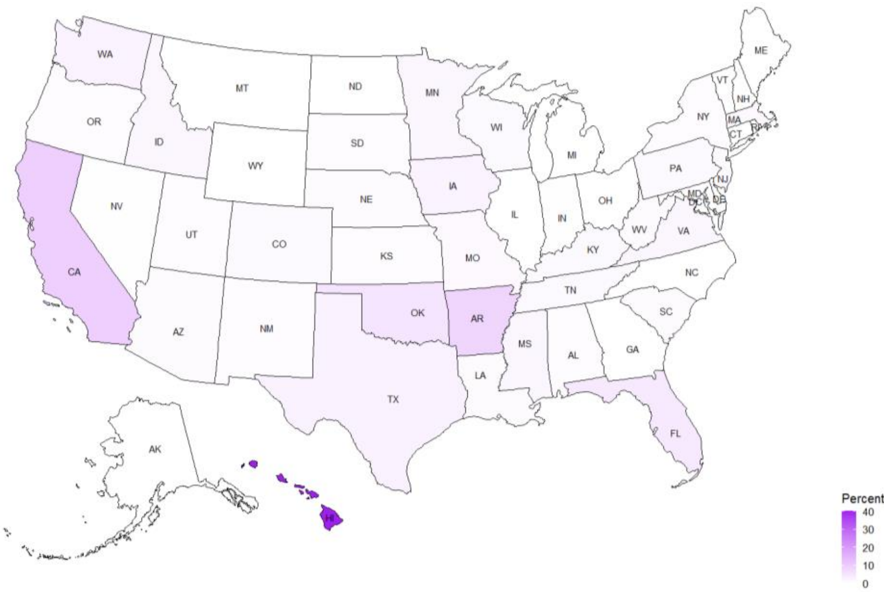
American Indian loans mainly occurred in Oklahoma (46.7%), Arkansas (5.8%) and South Dakota (5.2%) (Figure 13).




n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
0.03%, 0.02% and 0.0% of the loans are respectively located in Puerto Rico, Virgin Islands and Western Pacific
Source: Farm Service Agency Farm Loan Program and calculations

Figure 13. Distribution of Seven-year Direct Operating Loans to American Indian Borrowers in the Sample, 2011-2020

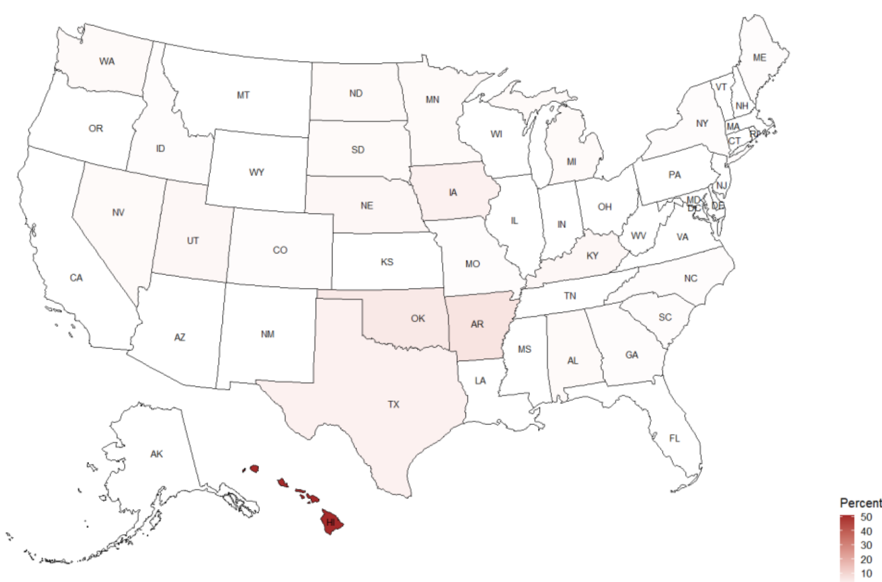
Asian loans borrowers were mainly found in Hawaii (40.3%) and California (9.6%) (Figure 14).




n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
0.0%, 0.0% and 1.04% of the loans are respectively located in Puerto Rico, Virgin Islands and Western Pacific
Source: Farm Service Agency Farm Loan Program and calculations

Figure 14. Distribution of Seven-year Direct Operating Loans to Asian Borrowers in the Sample, 2011-2020

Finally, Pacific Islander loans were principally located in Hawaii (51.0%) and Western Pacific (10.3%) (Figure 15).

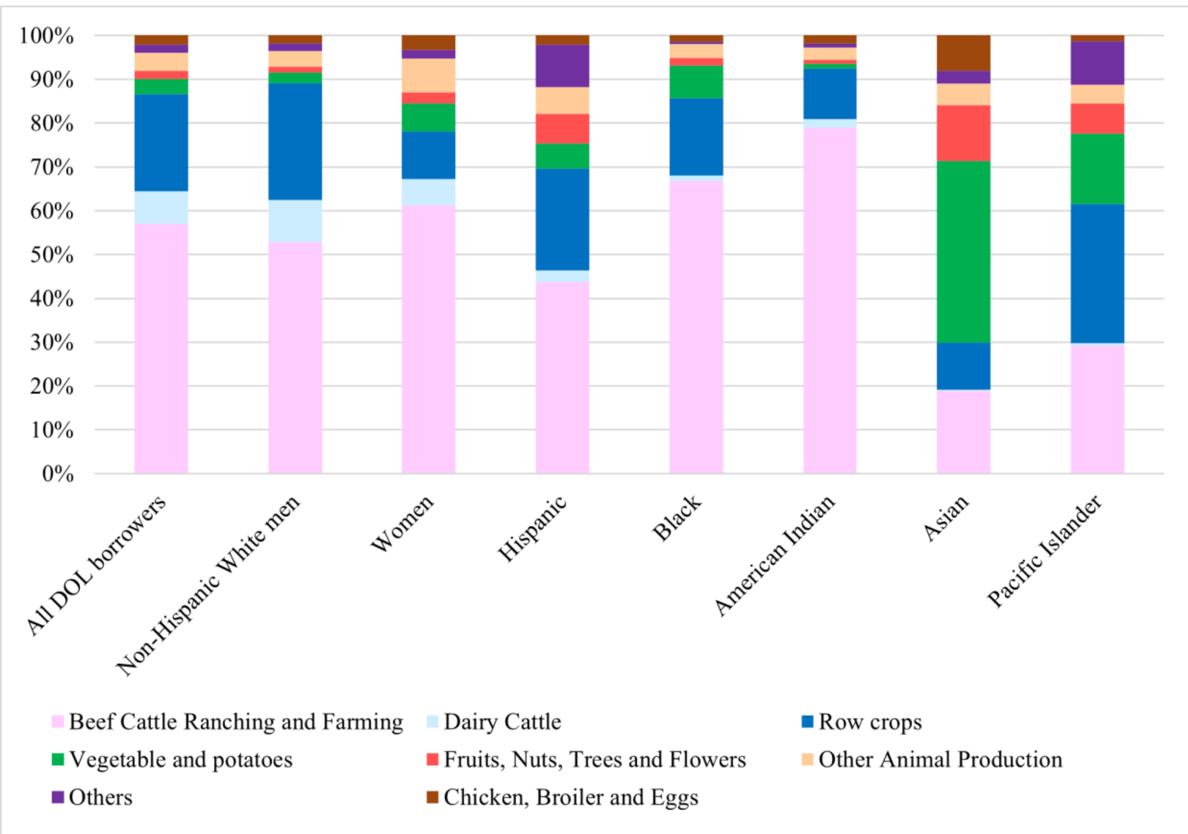



n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
0.65%, 0.0% and 10.3% of the loans are respectively located in Puerto Rico, Virgin Islands and Western Pacific
Source: Farm Service Agency Farm Loan Program and calculations

Figure 15. Distribution of Seven-year Direct Operating Loans to Pacific Islander Borrowers in the Sample, 2011-2020

The distribution of these loans by ethnicity and race was similar to the distribution of farmers previously described by the U.S. Department of Agriculture National Agricultural Statistics Services.

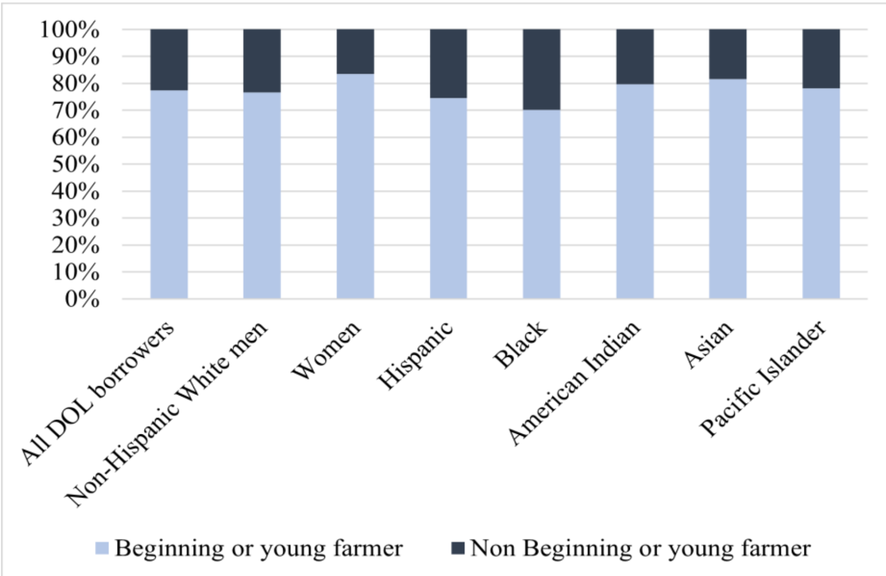
In term of farm type, the majority of all loans were in beef cattle farming (56.4%) followed by row crops (22.6%) and dairy farming (7.6%) (Figure 16). This observation was still quite accurate for each group with no regards to its ethnicity and gender. However, Asian and Pacific Islander loans were much more likely to be associated with vegetable and crops production than the other groups. For Asian loans, 41.5% were listed as vegetable production and 31.6% of the Pacific Islander loans were dedicated to crops. Asian loans also register relatively high proportion of broiler activity compared with the others. Dairy farming was a sector that did not appear a lot for SDFR groups, while it was the third most predominant farm type for loans to non-Hispanic White men, accounting for 9.5% of their loans (Figure 16).



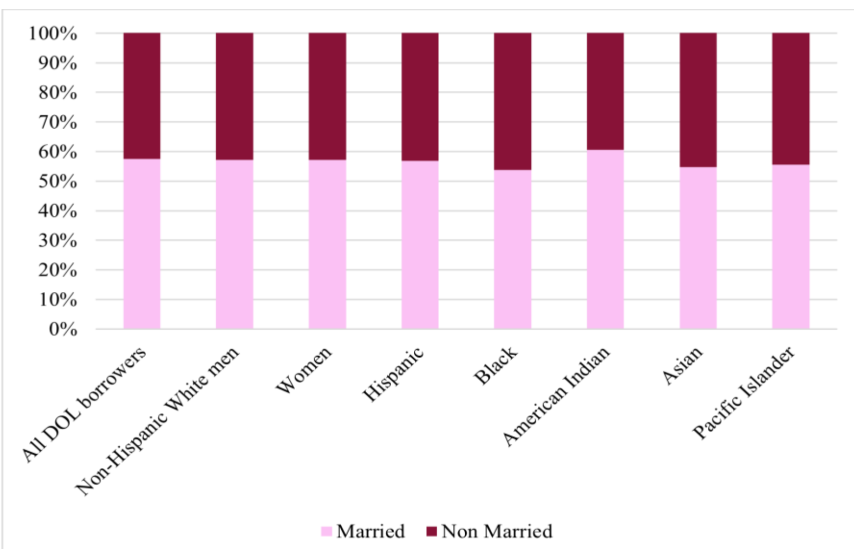

n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
Source: Farm Service Agency Farm Loan Program and calculations
Figure 16. Percent of Seven-year Direct Operating Loans by Farm Type, by SDFR Status, 2011-2020

Finally, the comparison of farmer beginning or young, and marital statuses showed no large differences between the gender or race/ethnicity groups (Figures 17 and 18).

As described in the previous sections, differences among SDFR groups may have implications for the potential outcomes of delinquency, which are described in the following part.

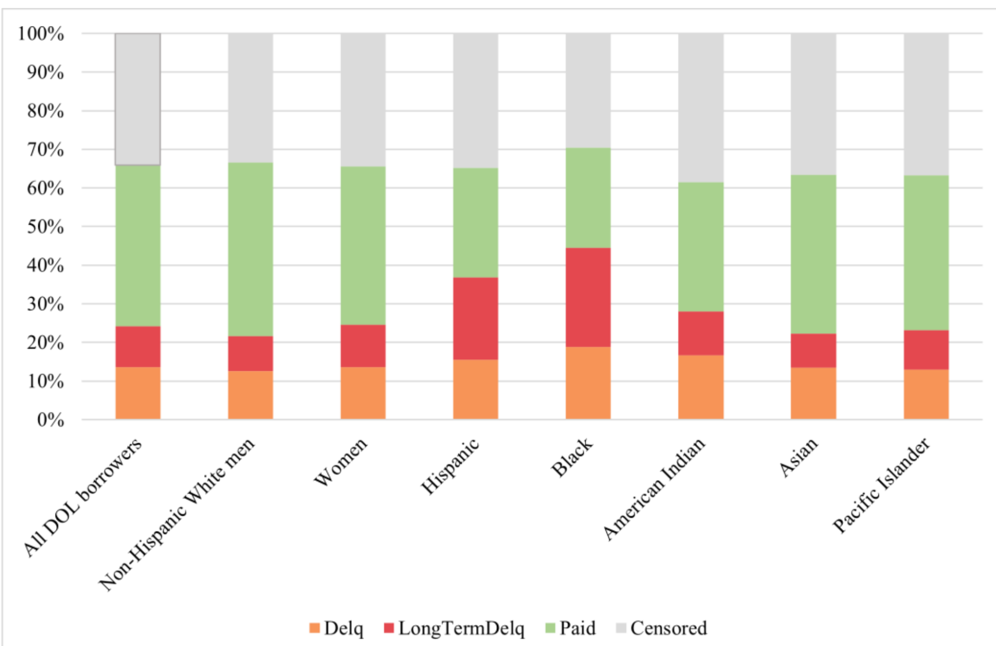



n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
Source: Farm Service Agency Farm Loan Program and calculations
Figure 17. Percent of Seven-year Direct Operating Loans by Beginning or Young Status, by SDFR Status, 2011-2020




n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
Source: Farm Service Agency Farm Loan Program and calculations
Figure 18. Percent of Seven-year Direct Operating Loans by Marital Status, by SDFR Status, 2011-2020

The second part of the descriptive analysis aims to provide information on the potential differences in loan outcomes among different groups. Here, four outcomes are defined: delinquency, long-term delinquency, paid in full and censored. Observations clearly show disparities across race, ethnicity, and gender (Figure 19). Hispanics and Blacks accounted for a higher percentage of delinquent and long-term delinquent loans than other groups. Among loans to Blacks and Hispanics, 44.5% and 36.9% were delinquent or long-term delinquent compared to 21.7% for Non-Hispanic White men. Results for Asian, Pacific Islander, and women were fairly similar, and their share of delinquent and long-term delinquent loans was lower than for the other groups, except for non-Hispanic White men. Loans for Non-Hispanic White men were mainly paid in full, and the proportion of delinquent groups was lower for this group than in the SDFR groups. These observations give clues to the potential outcomes for the model. However, as noted earlier, the effects of other characteristics may confound the results. It is therefore necessary to control for the potential effects of these characteristics, which was done by using a competing risks model.




n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
Source: Farm Service Agency Farm Loan Program and calculations

Figure 19. Percent of Seven-year Direct Operating Loans by Outcome, by SDFR Status, 2011-2020

To control for the significance of these differences, some t-tests have been used. The results are presented in Appendix 3.

# 4. Methodology

## *4.1. Methods in literature*

### *4.1.1. Survival models*

Credit risk and specifically survival models have been used to assess loan access discrimination in lending. They make it possible to estimate the probability that a borrower will default on a loan. They determine the probability of default of borrowers or a group of borrowers.

Survival models can be decomposed into two elements. The first element is the baseline hazard function h(t), which describes the risk of an event per unit time that changes over time given the baseline levels of the covariate. It considers the instantaneous potential per unit time for an outcome to occur if the loan has not experienced an outcome at time t. It is expressed as $h(t) = \lim_{\triangle t \to 0} \left\{ \frac{P(t \leq T < t + \Delta t | T \geq t)}{\triangle t} \right\}$. T refers to the continuous random variable for the survival time of a loan. The second element is the effect parameters, which describe the variation in the hazard function in response to the explanatory covariates.

The survival function is defined as S(t) = $P(T > t) = \exp(-\Delta(t))$ (Kleinbaum and Klein, 2012). It gives the probability that the time T of the event will occur after the time t.

$F(t) = 1 - S(t) = P(T \leq t)$ is called the distribution or cumulative incidence function (CIF). It can also be expressed as $\Delta(t) = \int_0^t h(z)dz$. Finally, the risk set is the group of individuals that have not yet experienced the event at time t and who have not yet been censored at time t. This is not a static set as the individuals at risk may change over time.

In medical studies, Cumulative Incidence Functions (CIF) have been used to measure the occurrence of new cases of infection or disease in a population over a given period of time. The Incidence Proportion (IP) is also expressed as $IP\ (t) = 1 - e^{-IR(t).D}$ where IR is the Incidence Rate (IR) and D is the duration of exposure (Zhang, Zhang and Scheike, 2008).

CIF indicates the probability that an event occurs before time t. If no event has occurred before the time t, the observation is considered as censored. Conventional methods for survival data assume that the censoring distribution and the event time distribution are independent. This means that the censored observations can be represented by the uncensored ones. This is commonly referred to as non-informative censoring.

A common proportional hazard model is the Cox model (Cox, 1997). It assumes that all individuals in the data set experience the same baseline hazard rate and that the regression variables and coefficients do not change with time. This would be expressed as: $\log \lambda_i(t) = \beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki}$, where $\lambda_i(t)$ refers to the instantaneous hazard of the event for the subject i at time t, $\lambda_0(t)$ is the baseline hazard function and $\beta_j$ refers to the log-hazard ratio for the j covariate. In its multiplicative form, it is $\lambda_i(t) = \lambda_0(t)\, e^{\beta_1 X_{1i} + \beta_2 X_{2i} + \cdots + \beta_k X_{ki}}$, where $\exp(\beta_j)$ is the hazard ratio for the jth covariate i.e. the relative change in the hazard of the event for a one unit increase in $X_j$. It is the relative magnitude of the effect of the covariate on the hazard of the outcome and it remains constant over time. In this type of model, there are no assumptions made about the shape of the hazard function or the distribution of the time of occurrence of the outcome (Kleinbaum and Klein, 2012). Also, in this model, it is important to differentiate the rate, which refers to the number of events per unit of time to the risk that refers to the probability of an event occurring.

Previous work used a Cox proportional hazards survival model to estimate the time to default for seven-year term DOL (Dodson et al., 2022) but did not differentiate between types of outcome, i.e., paid-in-full. The current study addresses this shortcoming by implementing a competing risks model of survival analysis with competing risks being default and paid-in-full. Moreover, using a competing risks model would permit us to control for the other characteristics that may impact the likelihood to default as shown by Donoghoe and Gebski (2017). They demonstrated that models specifying censoring distribution performed better by giving lower bias and variance in the estimate of the subdistribution hazard ratio.

### *4.1.2. Competing Risks models*

In the presence of competing risks, survival analysis presents an additional challenge because the hazard function does not have a one-to-one link to the cumulative incidence function describing the risk (Wolbers et al., 2014). Unlike survival models, where you wait long enough to observe the outcome for everyone, in competing risks, the occurrence of a competing event precludes the occurrence of the primary event of interest. This means that the event of interest, in this case delinquency, may not occur for all subjects. Indeed, another outcome for studies of loans would be that these loans are paid in full.

Another advantage of competing risks models is that they integrate time-varying covariates. These refer to covariates whose values can change over the duration. Two types of time-varying covariates were defined by Kalbfleisch and Prentice (1980): external and internal time-varying covariates. External time-varying covariates can be defined before the study for all subjects and time points or can result of a random process external to the subject. Internal time-varying covariates are measured on the subject as long as it remains uncensored.

Finally, competing risks models use the proportional hazards assumption. This refers to the fact that the ratio of hazard functions is fixed over the time. This is expressed as $\frac{\lambda(t)}{\lambda_0(t)} = \frac{\lambda_0(t)e^{\beta}}{\lambda_0(t)} = e^{\beta}$. Nevertheless, it is still possible to incorporate non-proportional hazards in the models.

Competing risks models can be used to identify factors associated with the incidence of one outcome or to estimate the incidence of an outcome over time. The first objective can be achieved by using a cause-specific hazard function. However, for the second objective, a subdistribution hazard ratio model would be more appropriate.

First, in competing risks models, the classical form of the Kaplan Meier cumulative incidence function can be corrected by including the type of event in the function. This gives a cause-specific hazard function defined by $h_i(t|X) = \lim_{\triangle t \to 0}\left\{\frac{P(t \le T < t+\Delta t, D=i | T \ge t)}{\triangle t}\right\}$, where i refers the type of event. The survival function is then given by $S(t) = \exp\left(-\sum_{k=1}^{K} \Delta_k(t)\right)$ (Prentice et al., 1978). This type of model, such as the Cox proportional hazard model, allows identification of factors associated with the rate of occurrence of the outcome. It treats competing outcomes as censoring, as was done by Dixon et al. (2011). However, the use of the classic Cox proportional hazard method does not permit to identify the direction of the effect of the variables on the incidence of the event of interest. This is because, in the presence of competing risks, the relationship between a regression coefficient and the incidence of the event of interest depends on the effect of the covariate on cause i, the effect of the covariate on all other causes, and the baseline hazards of all other causes.

To address this problem, Fine and Gray introduced a subdistribution hazard function that gives the instantaneous ratio of the occurrence of an event of type i, when the observation (loan) has not yet experienced the outcome (delinquency) at time t or has experienced a competing event (paid in full) before t (Fine and Gray, 1999). The hazard function is then defined by $h_i(t|X) = \lim_{\triangle t \to 0} \left\{ \frac{P(t \leq T < t + \Delta t, D = i | T \geq t \text{ } or \text{ } (T < t \text{ } and \text{ } D \neq i), X)}{\triangle t} \right\}$. Subdistribution hazard model permits to recover the ability to interpret the direction of the effect of the covariate on the incidence of the outcome through subdistribution hazard ratios. This highlights the relation between subdistribution hazard ratios, and the cumulative incidence function expressed as $\left(1 - CIF(t)\right) = (1 - CIF_0(t))^{\exp(\beta^T x)}$. $\exp(\beta)$ is defined as the ratio of the hazard function of an event and the baseline hazard function and is fixed over time. Unlike the Cox function, the coefficients here can be interpreted as a measure of association with the Cumulative Incidence Function. A Hazard Ratio (HR) = 1 would mean that there is no association between the covariate and the corresponding CIF. A HR > 1 implies that an increase in the value of the covariate is associated with an increasing risk or incidence. A HR < 1 implies that an increase in the covariate value is associated with a lower risk or incidence. The further HR is from one, the larger the estimated effect on the CIF. Finally, comparing two $HR_1$ and $HR_2$ with $HR_2 > HR_1$, (both greater than one), implies that a one-unit change in $X_2$ has a greater effect on the incidence than a similar change in $X_1$. However, it cannot explicitly quantify this effect (Austin, 2019).

### *4.2. Description of the model designed for the study*

#### *4.2.1. Description of the model*

The competing risks model implemented in this study considers 2 possible outcomes: (1) Paid in Full, (2) Default. A valid hazard model is defined by a non-informative random censoring. As it was defined earlier, this means that individuals who are censored can be represented by those for which we know the information, and that there is no loss of information. In this study, the data suggests that there is no reason to believe that censoring is informative as the censored data show similar characteristics as the non-censored data (Appendix 4) (Cox and Oakes, 1984).

The variable studied is the loan duration until a loan outcome (Paid in Full, Delinquency) occurs. Loan duration is measured in days. The explicative variables are those that can affect the duration of the loan and the outcome of the loan. The characteristics that may affect loan duration and outcome were described in the previous sections. In this study, independent variables included demographic characteristics such as status groups (Women, Hispanic, Black, American Indian, Asian, Pacific Islander and non-Hispanic White men), young or beginning and marital status. They also included financial information on farm financials such as low coverage, illiquidity, solvency, discretionary income, gross receipts, farm type, and current and intermediate point-of-sale financing. These variables, with the exception of discretionary income, were computed as binary variables, 1 coded for the presence of the characteristic and 0 for its absence. For example, the intermediate point-of-sale was coded as 1 if the DOL borrower had intermediate term loans outstanding and 0 otherwise.

In addition to the race/ethnicity/gender variables, the model included numerous control variables that are expected to affect borrower risk (Dodson and Ahrendsen, 2018; Dodson et al., 2022). Greater creditworthiness is expected to decrease the probability of default and lengthen its duration. A higher solvency, repayment capacity, more liquidity and additional discretionary income would also decrease the probability of default and decrease the rate of delinquency. Moreover, married borrowers are expected to be less likely to default as they possibly benefit from greater off-farm incomes. Young or beginning farmers may have fewer financial resources and are expected to have higher rates of delinquency. Finally, point of sale financing have been shown to be positively related to the incidence of default (Dodson et al., 2022). Table 2 presents the variables implemented in the model and their potential expected effects on outcomes and duration. The expected effects referred to the criteria impacting default presented earlier in the background section.

Table 2. Description of the Variables Implemented for the Subdistributional Hazard Competing Risks Model

| **VARIABLES STUDIED** | | | | |
|---|---|---|---|---|
| **Variable** | **Description** | **Definition** | | |
| Duration | Days from obligation to outcome. | Default occurs when the borrower becomes 90 days delinquent on the given or any other outstanding direct operating loan | | |
| Loan Outcome | Outcome of the loan | Censored<br>Paid in Full<br>Delinquent + LongTermDelinquent | | |
| **EXPLICATIVE VARIABLES** | | | | |
| **Variable** | **Description** | **Definition** | **Expected effect on likelihood to pay in full** | **Expected effect on likelihood to default** |
| WM | Non-Hispanic White Men | 1 if loan borrower is not identified in one of the other categories, else 0 | Baseline | Baseline |
| WO | Women | 1 if loan borrower identifies as a Woman, else 0 | + | - |
| HI | Hispanic | 1 if loan borrower identifies as Hispanic, else 0 | - | + |
| AA | Black | 1 if loan borrower identifies as Black or African American, else 0 | - | + |
| AI | American Indian | 1 if loan borrower identifies as American Indian or Alaskan Native, else 0 | - | + |
| A | Asian | 1 if loan borrower identifies as Asian, else 0 | + | - |
| PI | Pacific Islander | 1 if loan borrower identifies as Native Hawaiian or other Pacific Islander, else 0 | + | - |
| New_Beg | Beginning or young farmer | 1 if beginning farmer (10 or fewer years of farming experience) or $<35$ years of age at time of application, else 0 | - | + |
| Married | Marital status | 1 if borrower is married, 0 else | + | - |
| Low Coverage | Low debt coverage | 1 if term debt coverage ratio $\leq 1$, else 0 | - | + |
| Solvency | Low solvency | 1 if debt-asset ratio $\geq 0.70$, else 0 | - | + |
| | Medium solvency | 1 if debt-asset ratio $\geq 0.40$ and $<0.70$, else 0 | Baseline | Baseline |

| | | | | |
|---|---|---|---|---|
| | High solvency | 1 if debt-asset ratio <0.40, else 0 | + | - |
| Illiquidity | No liquidity | 1 if liquidity ratio <1.0 or working capital <$0, else 0 | - | + |
| Discretionary_Inc | Total discretionary income | Net income + nonfarm income – family living expense (in $10,000s) | + | - |
| Gross_Revenue | Small farm | 1 if gross revenue <$100,000, else 0 | +/- | +/- |
| | Mid-size farm | 1 if $100,000≤gross revenue<$350,000 | Baseline | Baseline |
| | Large farm | 1 if gross revenue ≥$100,000, else 0 | +/- | +/- |
| Farm Type | Beef cattle farm | 1 if beef cattle farm, else 0 | Baseline | Baseline |
| | Row crop farm | 1 if specialized in corn, soybeans, cotton, wheat, rice or other row crop, else 0 | - | + |
| | Dairy farm | 1 if specialized as a dairy farm, else 0 | + | - |
| | Specialty crop | 1 if specialized in vegetables, potatoes, fruits or nursery, else 0 | + | - |
| | Poultry, other livestock | 1 if specialized in poultry, other or livestock enterprises besides beef or dairy, else 0 | - | + |
| POS_Finance_Cur | Binary for current term point-of-sale loans | 1 if borrower used current point-of sale financing, else 0 | - | + |
| POS_Int_Balances | Categorical indicator for intermediate point-of-sale balance | POS_Balance $0 | Baseline | Baseline |
| | | POS_Balance $1-10K | - | + |
| | | POS_Balance $10-50K | - | + |
| | | POS_Balance $50K+ | - | + |

n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.

### *4.2.2. Summary Statistics*

This part aims at controlling for possible outliers that may induce biased estimation results for the model. The summary statistics are presented in Table 3. The mean for each variable by SDFR status are presented in Appendix 3. No outliers are identified, such that would need to be removed from the analysis.

Table 3. Descriptive Statistics Implemented in the Competing Risks Model for Seven-year Direct Operating Loans by SDFR Status, 2011-2020

| | | | | |
|---|---|---|---|---|
| **DEPENDENT** | | | | |
| **Variable Description** | **Mean** | **Standard deviation** | **Min** | **Max** |
| Duration | 1,205.2 | 737.5 | 12 | 3,763 |
| *Loan Outcome* | | | | |
| Censored | 0.340 | 0.474 | 0 | 1 |
| Paid in Full | 0.422 | 0.494 | 0 | 1 |
| Delinquent + LongTermDelinquent | 0.238 | 0.426 | 0 | 1 |
| **INDEPENDENT** | | | | |
| **Variable Description** | **Mean** | **Standard deviation** | **Min** | **Max** |
| Non-Hispanic White men | 0.688 | 0.463 | 0 | 1 |
| Women | 0.138 | 0.345 | 0 | 1 |
| Hispanic | 0.036 | 0.186 | 0 | 1 |
| Black | 0.039 | 0.192 | 0 | 1 |
| American Indian | 0.128 | 0.334 | 0 | 1 |
| Asian | 0.008 | 0.090 | 0 | 1 |
| Pacific Islander | 0.003 | 0.058 | 0 | 1 |
| Beginning or young farmer | 0.773 | 0.419 | 0 | 1 |
| Marital status | 0.575 | 0.494 | 0 | 1 |
| Low debt coverage | 0.287 | 0.452 | 0 | 1 |
| Low solvency | 0.407 | 0.491 | 0 | 1 |
| Medium solvency | 0.302 | 0.459 | 0 | 1 |
| High solvency | 0.292 | 0.545 | 0 | 1 |
| Illiquidity | 0.609 | 0.488 | 0 | 1 |
| Total discretionary income | 3.383 | 5.769 | -96.732 | 300.144 |
| *Gross Revenue* | | | | |
| Small farm | 0.621 | 0.485 | 0 | 1 |
| Mid-size farm | 0.256 | 0.436 | 0 | 1 |
| Large farm | 0.123 | 0.329 | 0 | 1 |
| *Farm Type* | | | | |
| Beef cattle farm | 0.564 | 0.496 | 0 | 1 |
| Row crop farm | 0.226 | 0.419 | 0 | 1 |
| Dairy farm | 0.076 | 0.265 | 0 | 1 |
| Specialty crop | 0.048 | 0.214 | 0 | 1 |
| Poultry, other livestock | 0.084 | 0.278 | 0 | 1 |
| Binary for current term point-of-sale loans | 0.053 | 0.224 | 0 | 1 |
| *Categorical indicator for intermediate point-of-sale balance* | | | | |
| POS_Balances $0 | 0.789 | 0.408 | 0 | 1 |
| POS_Balances $1-10K | 0.051 | 0.220 | 0 | 1 |
| POS_Balances $10-50K | 0.102 | 0.303 | 0 | 1 |
| POS_Balances $50K+ | 0.058 | 0.233 | 0 | 1 |

n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
Source: Farm Service Agency Farm Loan Program and calculations

*4.2.3. Implementation of the model*

*4.2.3.1. Packages*

To implement a CIF model in R, the variables must be prepared and constructed so that they can be implemented in the function coding for the CIF. The specific functions used in this study are listed in Appendix 6.

*4.2.3.2. Code*

*4.2.3.2.1. Creation of the sample*

The first part of the code uploaded the full data from an Excel spreadsheet and generate the sample used for the analysis in R. As mentioned earlier, Poisson sampling was then performed to generate the final sample of 46,161 observations that was used for the analysis. Poisson sampling was generated using the UPpoisson function based on a vector of probabilities. This vector was calculated based on the number of loans in the variable called "multipleloans". For example, an observation with a "multipleloans" variable value of 5 receives a probability of 1/5 to be included in the sample. The code for the sampling procedure is shown in Figure 20.

```
# ############################## Create sample  ################################

# create variable if multiple loans
dol_surv1 <- subset(dol_surv, dol_surv$loans != 0)
dol_surv$multipleloans <- ifelse(dol_surv$loans!=1,1/dol_surv$loans,1)
table(dol_surv$multipleloans, useNA = "ifany")
summary(dol_surv$multipleloans)

#Poisson sampling
library(sampling)
s <- UPpoisson(dol_surv$multipleloans)
sampled.dol_surv <- getdata(dol_surv, s)
print(sampled.dol_surv)
```

Figure 20. Code Implemented for the Sampling Process

*4.2.3.2.2. Preparation of the variables*

The second step of the coding process created the variables used in the model. The first variables were related to the race of the borrower. They were coded as binary values. For example, for Black borrowers, the AA variable was equal to 1 if the borrower was identified as Black, 0 if not (Figure 21).

```
##################### Data prep - create binaries ############################

#AA - Black
sampled.dol_surv$AA <- ifelse(sampled.dol_surv$RACE_BLK_IND=="1",1,0)
sampled.dol_surv$AA[is.na(sampled.dol_surv$AA)] <- 0
table(sampled.dol_surv$AA, useNA = "ifany")

#AI - American Indian
sampled.dol_surv$AI <- ifelse(sampled.dol_surv$RACE_AMER_IND_AK_IND=="1",1,0)
sampled.dol_surv$AI[is.na(sampled.dol_surv$AI)] <- 0
table(sampled.dol_surv$AI, useNA = "ifany")

#A - Asian
sampled.dol_surv$A <- ifelse(sampled.dol_surv$RACE_ASIA_IND=="1",1,0)
sampled.dol_surv$A[is.na(sampled.dol_surv$A)] <- 0
table(sampled.dol_surv$A, useNA = "ifany")

#PI - Pacific Islander
sampled.dol_surv$PI <- ifelse(sampled.dol_surv$RACE_HI_PAC_ISL_IND=="1",1,0)
sampled.dol_surv$PI[is.na(sampled.dol_surv$PI)] <- 0
table(sampled.dol_surv$PI, useNA = "ifany")

#Hi - Hispanic
sampled.dol_surv$HI <- ifelse(sampled.dol_surv$ethnc_cd=="1",1,0)
sampled.dol_surv$HI[is.na(sampled.dol_surv$HI)] <- 0
table(sampled.dol_surv$HI, useNA = "ifany")

#WO - Women
sampled.dol_surv$GNDR_SHRT_NM[sampled.dol_surv$GNDR_SHRT_NM == "Org/Other"] <- "Org/Male"
sampled.dol_surv$WO <- ifelse(sampled.dol_surv$GNDR_SHRT_NM == "Org/Female", 1,
                    ifelse(sampled.dol_surv$GNDR_SHRT_NM == "Female", 1, 0))
sampled.dol_surv$WO[is.na(sampled.dol_surv$WO)] <- 0
table(sampled.dol_surv$WO, useNA = "ifany")
```

Figure 21. Code Implemented for Race Binaries

Then the same procedure was used to generate the binary marital status. For the Beginning or Young farmer binary, the variable equals 1 if the years of farming are less than 11 years or if the borrower's age is under 35 years old (Figure 22).

```
# create marriage binary
sampled.dol_surv$married <- ifelse(is.na(sampled.dol_surv$Marital_Status), 0,
                           ifelse(sampled.dol_surv$Marital_Status == "Married",1,0))
table(sampled.dol_surv$married, useNA = "ifany")

# beginning or young - binary
sampled.dol_surv$years_farming <- sampled.dol_surv$year - as.numeric(sampled.dol_surv$Year_Start)
sampled.dol_surv$new_beg <- ifelse(sampled.dol_surv$years_farming < 11, 1,
                    ifelse(sampled.dol_surv$age_at_obl < 35, 1,  0))
sampled.dol_surv$new_beg[is.na(sampled.dol_surv$new_beg)] <- 0
table(sampled.dol_surv$new_beg, useNA = "ifany")
```

Figure 22. Code Implemented for Married and Beginner or Young Status Binaries

The farm type variable was created as a factor that considered 5 outcomes: Beef cattle, Dairy cattle, Row crops, Specialty crops and Poultry, Other livestock, Other/Unknown (Figure 23).

The point of sales variables were binary variables equal to 1 when a point of sales current or intermediary existed. The pos_balances variable was implemented in the model as a factor of four levels: "no_int_pos", "1-10k", "10-50", and "50k+".

```r
# farm type
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Beef Cattle Ranching and Farming"] <- "Beef Cattle"

sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Dairy Cattle"] <- "Dairy Cattle"

sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Corn Farming"] <- "Row Crops"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Soybean Farming"] <- "Row Crops"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="All Other Grain Oilseed Farming"] <- "Row Crops"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Wheat Farming"] <- "Row Crops"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Cotton Farming"] <- "Row Crops"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Peanut Farming"] <- "Row Crops"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Rice Farming"] <- "Row Crops"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Sugar Crops"] <- "Row Crops"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Tobacco Farming"] <- "Row Crops"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="All Other Miscellaneous Crop Farming"] <- "Row Crops"

sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Berry Farming"]                          <- "Specialty Crops"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Grapes"]                                 <- "Specialty Crops"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Greenhouse, Nursery, and Floriculture Production"] <- "Specialty Crops"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Potato Farming"]                         <- "Specialty Crops"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Tree Fruits & Nuts"]                     <- "Specialty Crops"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Vegetable (except Potato) and Melon Farming"] <- "Specialty Crops"

sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Broiler Production"]      <- "Poultry, Other livestock, Unknown"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Chicken Egg Production"]  <- "Poultry, Other livestock, Unknown"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Turkey Production"]       <- "Poultry, Other livestock, Unknown"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Apiculture"]              <- "Poultry, Other livestock, Unknown"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Aquaculture"]             <- "Poultry, Other livestock, Unknown"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Goat Farming"]            <- "Poultry, Other livestock, Unknown"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Hog and Pig Farming"]     <- "Poultry, Other livestock, Unknown"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Other Animal Production"] <- "Poultry, Other livestock, Unknown"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label =="Sheep Farming"]           <- "Poultry, Other livestock, Unknown"
sampled.dol_surv$farm_type[is.na(sampled.dol_surv$naics_label)]                      <- "Poultry, Other livestock, Unknown"
sampled.dol_surv$farm_type[sampled.dol_surv$naics_label == "0"]                      <- "Poultry, Other livestock, Unknown"

sampled.dol_surv$farm_type <- factor(sampled.dol_surv$farm_type,
                                     levels = c("Beef Cattle","Row Crops","Dairy Cattle",
                                                "Specialty Crops","Poultry, Other livestock, Unknown"))

table(sampled.dol_surv$farm_type, useNA = "ifany")
```

Figure 23. Code Implemented for Farm Type Binaries

The code for the implementation of these variables is presented in figure 24. Only the pos_cur_count and the pos_int_bal were used in the competing risks model.

```r
# Point of sales
sampled.dol_surv$pos_cur_count[is.na(sampled.dol_surv$pos_cur_count)] <- 0
sampled.dol_surv$pos_finance_cur <- ifelse(sampled.dol_surv$pos_cur_count > 0, 1, 0)
table(sampled.dol_surv$pos_finance_cur)
prop.table(table(sampled.dol_surv$pos_finance_cur))

sampled.dol_surv$pos_int_count[is.na(sampled.dol_surv$pos_int_count)] <- 0
sampled.dol_surv$pos_finance_int <- ifelse(sampled.dol_surv$pos_int_count > 0, 1, 0)
table(sampled.dol_surv$pos_finance_int)
prop.table(table(sampled.dol_surv$pos_finance_int))



sampled.dol_surv$pos_int_balances[is.na(sampled.dol_surv$pos_int_balances)] <- 0
sampled.dol_surv$pos_int_bal <- cut(sampled.dol_surv$pos_int_balances,
                                    c(min(sampled.dol_surv$pos_int_balances),
                                      1,10000,50000,
                                       max(sampled.dol_surv$pos_int_balances)),
                                     include.lowest = TRUE,
                                     labels = c("no_int_pos", "1-10k", "10-50k", "50k+"))
table(sampled.dol_surv$pos_int_bal)
```

Figure 24. Code Implemented for Point of Sales Variables

The next step was to prepare the financial data. The datum where financial information was missing were removed. The first variable considered was the solvency. This was calculated based on the debt to asset ratio and was generated as a variable integrating 3 levels: "under 0.4", "0.4-0.7" and "0.7+". The second financial variable, low_coverage, dealt with the borrower's ability to repay. It used the debt_coverage_ratio. Low coverage was defined with a term_debt_coverage_ratio less than or equal to 1.1, which attributes a value of 1 to the binary variable low_coverage. Then, the liquidity of the borrower was also added to the model. A binary variable called illiquidity was created and equals to 1 when the liquidity_ratio was less than 1. The discretionary_income of the borrower was added to the model as well as the gross revenue. The gross_revenue was implemented as a factor with 3 levels: "small", "midsize" and "large" farms. Figure 25 illustrates the code used to implement these financial variables.

```
# #################### Data prep - financials section ########################

# remove observations without financial info
sampled.dol_surv <- sampled.dol_surv[!is.na(sampled.dol_surv$debt_to_assets_ratio),]

# solvency - lower ratio is better
sampled.dol_surv$solvency <-cut(sampled.dol_surv$debt_to_assets_ratio,
                    c(min(sampled.dol_surv$debt_to_assets_ratio),
                      40,70,
                      max(sampled.dol_surv$debt_to_assets_ratio)),
                    include.lowest = TRUE,
                    labels = c("under 0.4", "0.4-0.7"," 0.7+"))
sampled.dol_surv$solvency <- factor(sampled.dol_surv$solvency, levels = c("0.4-0.7","under 0.4"," 0.7+"))
table(sampled.dol_surv$solvency, useNA = "ifany")

# repayment ability -
sampled.dol_surv$low_coverage <- 0
sampled.dol_surv$low_coverage[sampled.dol_surv$term_debt_coverage_ratio <= 1.1 ] <- 1
sampled.dol_surv$low_coverage[sampled.dol_surv$term_debt_coverage_ratio > 1.1 ] <- 0
table(sampled.dol_surv$low_coverage, useNA = "ifany")

# liquidity - higher ratio is better (if lr <1 or working capital <0 then 1 else 0)
sampled.dol_surv$illiquidity <- 0
sampled.dol_surv$illiquidity[sampled.dol_surv$liquidity_ratio < 1 ] <- 1
sampled.dol_surv$illiquidity[sampled.dol_surv$working_capital < 0 ] <- 1
table(sampled.dol_surv$illiquidity, useNA = "ifany")

# discretionary income: net income + non-farm income  - family living expense
sampled.dol_surv <- sampled.dol_surv[!is.na(sampled.dol_surv$discretionary_income),]

sampled.dol_surv$discretionary_inc <- sampled.dol_surv$discretionary_income / 10000

summary(sampled.dol_surv$discretionary_inc)


# gross revenue (farm production, measure of farm using $)
sampled.dol_surv$gross_revenue <- cut(sampled.dol_surv$gross_rev,
                          c(min(sampled.dol_surv$gross_rev),
                            100000,350000,
                            max(sampled.dol_surv$gross_rev)),
                          include.lowest = TRUE,
                          labels = c("small","midsize", "large"))
sampled.dol_surv$gross_revenue <- factor(sampled.dol_surv$gross_revenue, levels = c("midsize","small","large"))
table(sampled.dol_surv$gross_revenue, useNA = "ifany")
```

Figure 25. Code Implemented for Financial Variables Preparation

#### *4.2.3.2.3. Cumulative Incidence Functions model*

Once the variables were created, the first step of the study was to observe the differences in outcomes for each SDFR status. This was accomplished by plotting the CIFs. The cuminc function enabled the creation of the CIFs. It required the creation of an outcome factor integrating the four options: Paid in full, Delinquent, LongtermDelinquent and Censored, as well as a RaceStatus factor that allowed the function to plot for each group. The option multiple_panels = TRUE allowed multiple charts to be obtained for each group. The code is presented in Figure 26.

```
# Racestatus
sampled.dol_surv$RaceStatus <- ifelse (sampled.dol_surv$WO == 1, "Women",
                               ifelse(sampled.dol_surv$HI ==1, "Hispanic",
                                      ifelse(sampled.dol_surv$PI==1,"PacificIslander",
                                             ifelse(sampled.dol_surv$A==1,"Asian",
                                                    ifelse(sampled.dol_surv$AI==1, "AmericanIndian",
                                                           ifelse(sampled.dol_surv$AA==1, "Black","Whitemale"))))))
# Cumuincidence function
outcome <- as.factor(sampled.dol_surv$outcome)
summary(outcome)
Race <- as.factor(sampled.dol_surv$RaceStatus)

fit <- cuminc(sampled.dol_surv$duration, outcome, group = Race)
fit2 <- ggcompetingrisks(fit,multiple_panels = TRUE)
print(fit2)
```

Figure 26. Code Implemented for the Cumulative Incidence Functions

#### *4.2.3.2.4. Subdistributional Hazard Competing risks model*

To run the Subdistributional Hazard Competing risks model, the crr function from the cpmrsk package in R was used. This function fits the ’proportional subdistribution hazards’ regression model described by Fine and Gray (1999). The model directly assesses the effect of covariates on the subdistribution of a particular type of failure (Paid in Full and Delinquency) in a competing risks model.

To implement the function, one of the arguments is the matrix of covariates examined in the model. This matrix is created by using the model.matrix function. The final [,-1] removes the constant term from the output of model.matrix. The code for implementing the matrix is shown in Figure 27.

```
# #### Competing Risk Modelling ##################################################
install.packages("cmprsk") # Only need to do this once
library(cmprsk)

sampled.dol_surv<-sampled.dol_surv[complete.cases(sampled.dol_surv$farm_type),]  ## farm_type has 44 NA values

# Explanatory variables must be in a model matrix: creation of the matrix
X = cbind(AA)
X = model.matrix(Status ~ AA + AI + A + PI + HI + WO +  new_beg +  married + low_coverage + solvency + illiquidity +
                   discretionary_inc + gross_revenue + farm_type + pos_finance_int + pos_finance_cur, data = sampled.dol_surv)
head(X)
X = X[,-1]; head(X)
```

Figure 27.  Code Implemented for the Matrix of Covariate

Once the matrix is created, the crr function can be used, as shown in Figure 28, to run the competing risks model for both outcomes: Delinquency (failcode=2) and Paid in Full (failcode=1). The variable cencode determines the code for the censored variables.

```
crr <- crr(sampled.dol_surv$duration, fstatus=sampled.dol_surv$Status, cov1=X, failcode="2", cencode="0")
summary(crr)

crr1 <- crr(sampled.dol_surv$duration, fstatus=sampled.dol_surv$Status, cov1=X, failcode="1", cencode="0")
summary(crr1)
```

Figure 28. Code Implemented to Run the Competing Risks Model

## 5. Results

### *5.1. Cumulative Incidence Functions*

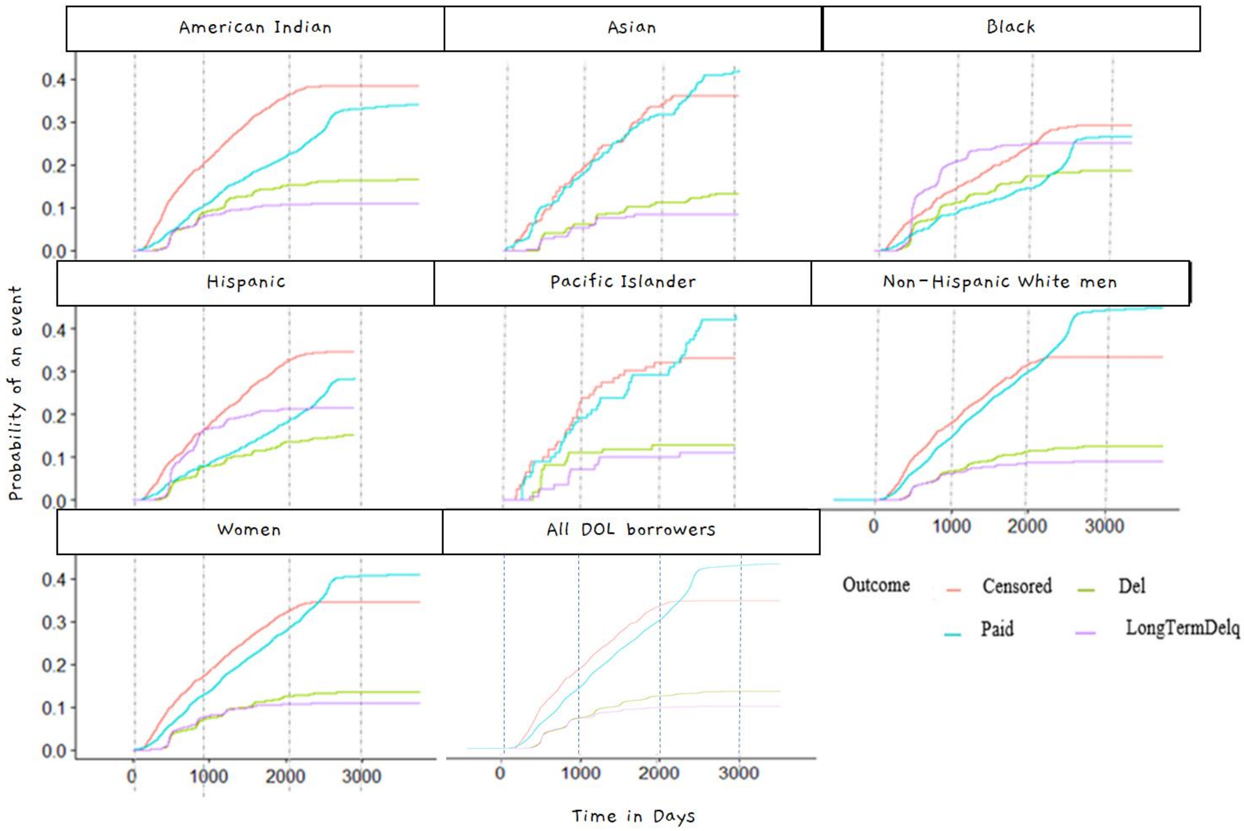
The Cumulative Incidence Function for use with competing risks allows estimation of the incidence of competing risks. A visual representation of the results of the cumulative incidence functions shows differences between Black farmers and other farmers (Figure 29).  Seven years (the maturity of the loans) is 2555 days, so several of the CIF's plateau around this time. Overall, we observed differences between the groups. We also find that the likelihood of Black and Hispanic farmers' loans being paid in full (blue lines) is lower for the 1000-, 2000-, and 3000-day reference maturities than for other loans (8%, 15% and 27% for Black farmers and 9%, 18% for Hispanics farmers versus 15%, 30% and 44% for non-Hispanic White men, 14%, 28%, 41% for Women and 11%, 22%, 33% for American Indian. Pacific Islander and Asian loans were more likely to be paid in full with higher paid in full probabilities than other groups globally with 19%, 29% and 42% for Pacific Islander loans and 18%, 32% and 42% for Asian (Table 4).

The LongTerm Delinquency (purple lines) on this type of loan is also much higher for Blacks and Hispanics than for the other groups especially after the first year, where a large jump is observed. At 1,000 days, the probability of LongTerm Delinquency is 21% for Blacks and 17% for Hispanics versus 7% for Non-Hispanic White men and Pacific Islanders, 8% for women and American Indian and 5% for Asian. For additional comparison, the probabilities of each event at the three different benchmark durations by SDFR status are shown in Figure 29 and are displayed in Table 4. These differences across groups can be considered to be significant with regards to the *p*-values attributed to each outcome that were under 0.05 (Table 4). However, the Gray's test does not permit to differentiate significantly each group compared to another.

Table 4. Results and Significance of the Cumulative Incidence Function for Seven-year Direct Operating Loans, 2011-2020

| **Outcomes** | **SDFR status** | **Days** | | | **$X^2$ (Gray's test for equality across groups)** | ***p*-value (* if significant: < 0.05)** |
|---|---|---|---|---|---|---|
| | | **1,000** | **2,000** | **3,000** | | |
| Paid In Full | Non-Hispanic White men | 0.147 | 0.299 | 0.443 | 420.76 | 0.000* |
| | Women | 0.137 | 0.278 | 0.407 | | |
| | Hispanic | 0.086 | 0.180 | NA | | |
| | Black | 0.085 | 0.146 | 0.266 | | |
| | American Indian | 0.112 | 0.219 | 0.332 | | |
| | Asian | 0.177 | 0.318 | 0.419 | | |
| | Pacific Islander | 0.193 | 0.294 | 0.422 | | |
| Delinquent | Non-Hispanic White men | 0.067 | 0.114 | 0.126 | 98.55 | 0.000* |
| | Women | 0.075 | 0.125 | 0.136 | | |
| | Hispanic | 0.079 | 0.135 | NA | | |
| | Black | 0.110 | 0.180 | 0.190 | | |
| | American Indian | 0.092 | 0.152 | 0.165 | | |
| | Asian | 0.061 | 0.112 | 0.133 | | |
| | Pacific Islander | 0.110 | 0.128 | 0.128 | | |
| Long Term Delinquent | Non-Hispanic White men | 0.063 | 0.087 | 0.090 | 617.68 | 0.000* |
| | Women | 0.079 | 0.107 | 0.109 | | |
| | Hispanic | 0.166 | 0.213 | NA | | |
| | Black | 0.204 | 0.250 | 0.252 | | |
| | American Indian | 0.082 | 0.108 | 0.110 | | |
| | Asian | 0.054 | 0.083 | 0.083 | | |
| | Pacific Islander | 0.073 | 0.101 | 0.110 | | |
| Censored | Non-Hispanic White men | 0.180 | 0.316 | 0.335 | 69.54 | 0.000* |
| | Women | 0.184 | 0.320 | 0.345 | | |
| | Hispanic | 0.176 | 0.320 | NA | | |
| | Black | 0.139 | 0.240 | 0.291 | | |
| | American Indian | 0.216 | 0.360 | 0.384 | | |
| | Asian | 0.184 | 0.336 | 0.361 | | |
| | Pacific Islander | 0.229 | 0.321 | 0.330 | | |

n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
Source: Farm Service Agency Farm Loan Program and calculations




[a] Del: Delinquent, LongTermDelq: Long Term Delinquent, Paid: Paid In Full, and Censored
n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021; nAmerican Indian: 5,907; nAsian: 385; nBlack: 1,776; nHispanic: 1,656; nPacific Islander: 155; nWomen: 6,362; nNon-Hispanic White men: 31,767
Source: Farm Service Agency Farm Loan Program and calculations
Figure 29. Cumulative Incidence Functions for Seven-year Direct Operating Loans in Sample by Outcome[a], by SDFR status, 2011-2021

Specifically looking at each SDFR groups in comparison with the overall sample, it is observable that non-Hispanic White men and women do not differ from the overall sample for each outcome.  This could relate to the fact that loans to Women and non-Hispanic White men represent about 83% of the total loans in the sample.

Hispanic and Black borrowers display similar trends. They were more likely to be LongTermDelinquent after the first year. American Indian cumulative incidence functions illustrated a light tendency to be delinquent faster than the overall sample. Finally, Asian and Pacific Islander showed similar trends in term of defaulting or paying in full. These groups were not highly different from the overall sample (Figure 29).

### *5.2. Competing Risks model*

As presented earlier, the HR corresponds to the exponentiated coefficient obtained with the model. When HR<1, it implies that an increase in the covariate value is associated with decreased rate of the event occurring. If HR>1, it implies that an increase in the covariate value is associated with an increased rate of the event occurring. The further away HR is from 1, the larger the estimated effect size. However, a quantitative magnitude of the HR cannot be interpreted (Gardiner, 2016; Austin and Fine, 2017). The coefficients and *p*-values are presented in Table 5.

The results reveal that being a Black borrower was associated with a significant increase in the incidence of delinquency and a significant decrease in the incidence of paying in full. This trend was also observed for Hispanic and American Indian borrowers. Affiliation with Pacific Islander and Asian groups showed no significant association with the incidence of delinquency or paying in full. Being a woman borrower was not significantly related to the incidence of full repayment, although a woman borrow was significantly related to incidence of default, but a lower level of significance. Being a beginning or young and being married tended to increase the incidence of paying in full, while slightly, decreasing the incidence of delinquency.

The study controlled for as many other relevant variables as was possible given the data to eliminate possible biases that might prevent us from observing differences in loan outcomes by SDFR status. The results were generally consistent with expectations based on prior work and financial expectations (Table 5). A low solvency (debt-asset ratio > 0.7) was associated with a significant increase in the incidence of delinquency, while it was associated with a decrease in the incidence of paying in full. However, a high solvency (debt-asset ratio < 0.4) was not significantly associated with either outcome. The HR also shows that low debt coverage or illiquidity was associated with a small increase in the incidence of delinquency and with a small decrease in the incidence of paying in full. Discretionary income was not significantly associated with the incidence of defaulting or paying in full. Regarding use of non-traditional credit by borrowers, having an intermediate-term point-of-sale balance over $50,000 and having a current-term point-of-sale loan were both significantly associated with an increase in the incidence of delinquency and a decrease in the incidence of paying in full.

Small farms (as measured by gross revenue) were actually associated with a decrease in delinquencies compared to medium farms, but small farms were not associated with a decrease in the incidence of paying in full compared to mid-size farms. The type of farm or type of operation was significantly associated with the incidence of delinquency. Compared with the baseline of beef cattle farming, loans related farms with row crops, specialty crops, poultry and other livestock were associated with an increase of the incidence of delinquency, while loans to dairy cattle operations were associated with a decrease of this incidence. For the pay in full outcome, loans to dairy cattle operations were associated with an increase of the incidence of paying in full while it was associated with a decrease of this incidence for specialty crops operations.

Table 5. Results of the Competing Risks Model for Seven-Year Direct Operating Loans by SDFR Status, 2011-2020

| **Outcome** | **Delinquent** | | **Paid in Full** | |
|---|---|---|---|---|
| **Variable** | **Exp(coef)** | ***p*-value** | **Exp(coef)** | ***p*-value** |
| Women | 1.074 | 0.011* | 0.981 | 0.350 |
| Hispanic | 1.847 | 0.000*** | 0.558 | 0.000*** |
| Black | 2.399 | 0.000*** | 0.462 | 0.000*** |
| American Indian | 1.396 | 0.000*** | 0.733 | 0.000*** |
| Asian | 0.852 | 0.150 | 1.021 | 0.800 |
| Pacific Islander | 0.957 | 0.800 | 1.099 | 0.460 |
| Young or beginning | 0.864 | 0.000*** | 1.107 | 0.000*** |
| Married | 0.823 | 0.000*** | 1.097 | 0.000*** |
| Low solvency | 1.257 | 0.000*** | 0.903 | 0.000*** |
| High solvency | 0.964 | 0.170 | 1.001 | 0.950 |
| Low debt coverage | 1.072 | 0.001** | 0.957 | 0.005** |
| Illiquidity | 1.251 | 0.000*** | 0.896 | 0.000*** |
| Discretionary Income | 1.002 | 0.180 | 1.000 | 0.830 |
| Intermediate point-of-sale balance $1-10k | 0.988 | 0.780 | 1.001 | 0.990 |
| Intermediate point-of-sale balance $10-50k | 0.971 | 0.380 | 0.996 | 0.870 |
| Intermediate point-of-sale balance $50k+ | 1.114 | 0.015* | 0.907 | 0.006** |
| Current point-of-sale binary | 1.197 | 0.000*** | 0.865 | 0.000*** |
| Small farm | 0.816 | 0.000*** | 1.012 | 0.520 |
| Large farm | 0.979 | 0.550 | 0.985 | 0.570 |
| Row crops | 1.167 | 0.000*** | 0.970 | 0.099 |
| Dairy cattle | 0.709 | 0.000*** | 1.269 | 0.000*** |
| Speciality crops | 1.371 | 0.000*** | 0.900 | 0.003** |
| Poultry, other livestock | 1.151 | 0.000*** | 0.955 | 0.093 |

n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
* $p$-value<0.05; ** $p$-value<0.01; *** $p$-value<0.001.
Source: Farm Service Agency Farm Loan Program and calculations

### *5.3. Robustness of the analysis*

To analyze the robustness of the results, the model has been estimated with five different samples created with the Poisson sampling procedure, including the sample already presented. The results are presented in Table 6. The results of the CIF for each sample are presented in Appendix 6. As expected, the different samples have similar results. This supports the results and conclusions based on the first sample.

Table 6. Descriptive Statistics, Cumulative Incidence Functions and Competing Risks Model Results for Seven-Year Direct Operating Loans by SDFR Status for Five Randomly Generated Samples, 2011-2020

| | **Sample 1 (studied)** | **Sample 2** | **Sample 3** | **Sample 4** | **Sample 5** |
|---|---|---|---|---|---|
| Number of observations | 46,161 | 46,160 | 46,163 | 46,225 | 46,099 |
| **Descriptive statistics** | | | | | |
| Non-Hispanic White men | 0.688 | 0.687 | 0.688 | 0.686 | 0.689 |
| Women | 0.138 | 0.139 | 0.132 | 0.134 | 0.139 |
| Hispanic | 0.036 | 0.035 | 0.034 | 0.034 | 0.035 |
| Black | 0.039 | 0.038 | 0.037 | 0.036 | 0.038 |
| American Indian | 0.128 | 0.127 | 0.121 | 0.122 | 0.126 |
| Asian | 0.008 | 0.008 | 0.008 | 0.008 | 0.008 |
| Pacific islander | 0.003 | 0.004 | 0.003 | 0.003 | 0.003 |
| Beginning or young farmer | 0.773 | 0.770 | 0.735 | 0.735 | 0.767 |
| Married | 0.575 | 0.572 | 0.549 | 0.547 | 0.570 |
| Low debt coverage | 0.287 | 0.283 | 0.271 | 0.271 | 0.284 |
| Low Solvency | 0.407 | 0.400 | 0.386 | 0.384 | 0.400 |
| Medium Solvency | 0.302 | 0.300 | 0.286 | 0.288 | 0.301 |
| High Solvency | 0.292 | 0.287 | 0.275 | 0.275 | 0.286 |
| Illiquidity | 0.609 | 0.602 | 0.577 | 0.579 | 0.603 |
| Total discretionary income | 3.383 | 3.455 | 3.407 | 3.384 | 3.385 |
| Small Gross revenue farm | 0.621 | 0.612 | 0.588 | 0.589 | 0.612 |
| Mid-size Gross revenue farm | 0.256 | 0.252 | 0.241 | 0.240 | 0.253 |
| Large Gross revenue farm | 0.123 | 0.122 | 0.118 | 0.117 | 0.122 |
| Beef cattle farm | 0.564 | 0.555 | 0.535 | 0.536 | 0.559 |
| Row crop farm | 0.226 | 0.225 | 0.216 | 0.215 | 0.227 |
| Dairy farm | 0.076 | 0.075 | 0.073 | 0.073 | 0.076 |
| Specialty crop | 0.048 | 0.047 | 0.047 | 0.046 | 0.048 |
| Poultry, other livestock | 0.084 | 0.084 | 0.087 | 0.088 | 0.090 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Binary for current term point-of-sale loans | 0.053 | | | 0.052 | | | 0.050 | | | 0.049 | | | 0.052 | | |
| POS_Balance $0 | 0.789 | | | 0.793 | | | 0.760 | | | 0.759 | | | 0.793 | | |
| POS_Balance $1-10K | 0.051 | | | 0.050 | | | 0.049 | | | 0.049 | | | 0.050 | | |
| POS_Balance $10-50K | 0.102 | | | 0.100 | | | 0.095 | | | 0.096 | | | 0.100 | | |
| POS_Balance $50K+ | 0.058 | | | 0.057 | | | 0.055 | | | 0.055 | | | 0.057 | | |
| Duration | 1,205 | | | 1,207 | | | 1,206 | | | 1209 | | | 1206 | | |
| Loan Outcome-Censored | 0.340 | | | 0.334 | | | 0.320 | | | 0.320 | | | 0.336 | | |
| Loan Outcome-Paid in Full | 0.422 | | | 0.418 | | | 0.400 | | | 0.401 | | | 0.416 | | |
| Loan Outcome-Delinquent and Long-Term Delinquent | 0.238 | | | 0.234 | | | 0.228 | | | 0.226 | | | 0.235 | | |
| **Cumulative Incidence Functions-Results** | | | | | | | | | | | | | | | |
| | Days | | | Days | | | Days | | | Days | | | Days | | |
| Loan outcomes | 1,000 | 2,000 | 3,000 | 1,000 | 2,000 | 3,000 | 1,000 | 2,000 | 3,000 | 1,000 | 2,000 | 3,000 | 1,000 | 2,000 | 3,000 |
| *Paid in Full* | | | | | | | | | | | | | | | |
| Non-Hispanic White men | 0.147 | 0.299 | 0.443 | 0.148 | 0.302 | 0.446 | 0.147 | 0.300 | 0.442 | 0.148 | 0.301 | 0.444 | 0.148 | 0.302 | 0.445 |
| Women | 0.137 | 0.278 | 0.407 | 0.135 | 0.276 | 0.409 | 0.137 | 0.280 | 0.411 | 0.136 | 0.279 | 0.412 | 0.134 | 0.274 | 0.407 |
| Hispanic | 0.086 | 0.180 | NA | 0.090 | 0.188 | NA | 0.088 | 0.183 | NA | 0.097 | 0.195 | NA | 0.091 | 0.185 | NA |
| Black | 0.085 | 0.146 | 0.266 | 0.089 | 0.151 | 0.268 | 0.090 | 0.147 | 0.272 | 0.089 | 0.151 | 0.269 | 0.087 | 0.147 | 0.268 |
| American Indian | 0.112 | 0.219 | 0.332 | 0.109 | 0.223 | 0.334 | 0.111 | 0.223 | 0.335 | 0.112 | 0.221 | 0.336 | 0.109 | 0.217 | 0.328 |
| Asian | 0.177 | 0.318 | 0.419 | 0.162 | 0.285 | 0.386 | 0.171 | 0.300 | 0.395 | 0.151 | 0.281 | 0.381 | 0.158 | 0.294 | 0.393 |
| Pacific islander | 0.193 | 0.294 | 0.422 | 0.191 | 0.296 | 0.443 | 0.219 | 0.333 | 0.467 | 0.183 | 0.312 | 0.477 | 0.181 | 0.310 | 0.448 |
| *Delinquent* | | | | | | | | | | | | | | | |
| Non-Hispanic White men | 0.067 | 0.114 | 0.126 | 0.067 | 0.113 | 0.125 | 0.068 | 0.115 | 0.128 | 0.666 | 0.114 | 0.126 | 0.067 | 0.113 | 0.125 |
| Women | 0.075 | 0.125 | 0.136 | 0.076 | 0.128 | 0.140 | 0.075 | 0.126 | 0.137 | 0.074 | 0.125 | 0.137 | 0.746 | 0.126 | 0.121 |
| Hispanic | 0.079 | 0.135 | NA | 0.085 | 0.143 | NA | 0.090 | 0.146 | NA | 0.086 | 0.142 | NA | 0.077 | 0135 | NA |
| Black | 0.110 | 0.180 | 0.190 | 0.114 | 0.176 | 0.190 | 0.109 | 0.171 | 0.187 | 0.114 | 0.175 | 0.190 | 0.110 | 0.173 | 0.186 |

| | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| American Indian | 0.092 | 0.152 | 0.165 | 0.095 | 0.157 | 0.169 | 0.096 | 0.155 | 0.170 | 0.092 | 0.154 | 0.169 | 0.093 | 0.158 | 0.711 |
| Asian | 0.061 | 0.112 | 0.133 | 0.058 | 0.108 | 0.126 | 0.075 | 0.128 | 0.149 | 0.058 | 0.108 | 0.133 | 0.059 | 0.099 | 0.121 |
| Pacific islander | 0.110 | 0.128 | 0.128 | 0.096 | 0.113 | 0.113 | 0.076 | 0.095 | 0.095 | 0.101 | 0.119 | 0.119 | 0.103 | 0.121 | 0.121 |
| *Long Term Delinquent* | | | | | | | | | | | | | | | |
| Non-Hispanic White men | 0.063 | 0.087 | 0.090 | 0.062 | 0.086 | 0.089 | 0.063 | 0.087 | 0.091 | 0.063 | 0.087 | 0.090 | 0.062 | 0.086 | 0.089 |
| Women | 0.079 | 0.107 | 0.109 | 0.077 | 0.103 | 0.105 | 0.079 | 0.105 | 0.108 | 0.080 | 0.105 | 0.108 | 0.080 | 0.106 | 0.108 |
| Hispanic | 0.166 | 0.213 | NA | 0.162 | 0.215 | NA | 0.163 | 0.214 | NA | 0.165 | 0.211 | NA | 0.168 | 0.211 | NA |
| Black | 0.204 | 0.250 | 0.252 | 0.205 | 0.251 | 0.255 | 0.198 | 0.242 | 0.244 | 0.201 | 0.246 | 0.250 | 0.208 | 0.254 | 0.258 |
| American Indian | 0.082 | 0.108 | 0.110 | 0.080 | 0.106 | 0.109 | 0.081 | 0.107 | 0.110 | 0.080 | 0.106 | 0.108 | 0.080 | 0.106 | 0.109 |
| Asian | 0.054 | 0.083 | 0.083 | 0.058 | 0.087 | 0.087 | 0.057 | 0.082 | 0.082 | 0.061 | 0.090 | 0.090 | 0.0515 | 0.081 | 0.081 |
| Pacific islander | 0.073 | 0.101 | 0.110 | 0.061 | 0.078 | 0.090 | 0.076 | 0.105 | 0.114 | 0.064 | 0.083 | 0.092 | 0.070 | 0.086 | 0.095 |
| **Competing risks model-Results-Hazard Rates (HR)** | | | | | | | | | | | | | | | |
| *if significant *p*-value<0.05; ** if significant *p*-value<0.01; *** if significant *p*-value<0.001. | | | | | | | | | | | | | | | |
| HR<1 implies that an increase in the covariate value is associated with a decreased rate of the event occurring. | | | | | | | | | | | | | | | |
| HR>1 implies that an increase in the covariate value is associated with an increased rate of the event occurring. | | | | | | | | | | | | | | | |
| The further away HR is from 1, the larger the estimated effect size. | | | | | | | | | | | | | | | |
| *Delinquent* | | | | | | | | | | | | | | | |
| Women | 1.074* | | | 1.083* | | | 1.063* | | | 1.069* | | | 1.089* | | |
| Hispanic | 1.847*** | | | 1.890*** | | | 1.916*** | | | 1.902*** | | | 1.895*** | | |
| Black | 2.399*** | | | 2.460*** | | | 2.374*** | | | 2.420*** | | | 2.430*** | | |
| American Indian | 1.396*** | | | 1.394*** | | | 1.413*** | | | 1.391*** | | | 1.418*** | | |
| Asian | 0.852 | | | 0.839 | | | 0.837 | | | 0.839 | | | 0.783 | | |
| Pacific islander | 0.957 | | | 0.744 | | | 0.730 | | | 0.809 | | | 0.829 | | |
| *Paid in Full* | | | | | | | | | | | | | | | |
| Women | 0.981 | | | 0.968 | | | 0.990 | | | 0.983 | | | 0.969 | | |
| Hispanic | 0.558*** | | | 0.564*** | | | 0.540*** | | | 0.580*** | | | 0.554*** | | |
| Black | 0.462*** | | | 0.459*** | | | 0.471*** | | | 0.464*** | | | 0.457*** | | |
| American Indian | 0.733*** | | | 0.733*** | | | 0.732*** | | | 0.735*** | | | 0.719*** | | |
| Asian | 1.021 | | | 0.959 | | | 1.005 | | | 0.958 | | | 0.989 | | |
| Pacific islander | 1.099 | | | 1.196 | | | 1.297 | | | 1.183 | | | 1.180 | | |

n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
Source: Farm Service Agency Farm Loan Program and calculations

## 6. Conclusions

### *6.1. Conclusions*

The observed results permit an understanding of the factors associated with whether an FSA borrower defaults or pays in full. While the CIF does not provide an estimate of the magnitude of this impact, it does provide insight into the relative importance for the two potential outcomes. The results found for Black, Hispanic and American Indian farmers indicated a higher incidence of default and a lower incidence of paid-in-full relative to non-Hispanic White men.

While the results presented here are not conclusive about the presence or absence of historical or current discrimination, they are consistent with certain conditions. First, the results are inconsistent with the existence of Becker's taste-based discrimination that was described previously. This refers to the fact that discriminated groups would have lower default rates and higher paid-in-full rates. Second, the poorer relative loan performance of Black, Hispanic, and American Indian borrowers could be related to a cumulative effect due to historical discrimination. These groups of farmers tend to operate smaller, less efficient farms, have fewer financial resources, and specialize in low return enterprises. However, these are all factors for which the analysis attempted to control. This finding would be consistent with the presence of systemic racism over time and may explain the disparities still seen today in the success of loans to these SDFR statuses. The U.S. Government Accountability Office (2019) report shows that SDFR primary producers remain less likely to have outstanding farm debt than all other farmers and ranchers. However, USDA FSA has increased the number of guaranteed loans for SDFR by 69.6% from 2014 to 2018.

These results also raise questions about how effective loan programs alone are in helping SDFRs make financial progress. The lack of technical and financial resources for SDFRs is a major barrier to their financial success. To be successful, credit programs may need to be combined with broader financial and technical assistance programs such as that provided through USDA's 2501 Program which provides some funding for outreach to SDFRs. While extension can reduce the technical deficits of SDFRs, it will have minimal impact on wealth. Reducing the financial gap for SDFRs will require policies which are more expensive, such as higher loan subsidies, targeted government payments, or financial grants.

### *6.2. Implication for further studies*

Due to data limitations, it was not possible to consider some other factors that may be associated with a higher incidence of delinquency and a lower incidence of paying in full such as Internet access or participation in other programs such as crop insurance, mentioned previously. This could be an area for further study to examine these other factors.

Moreover, it is important to note that in the loan repayment cycle, default is not an outcome which FSA necessarily has a direct influence over. The borrower determines whether they pay the loan or not. However, FSA may have an indirect influence on this decision through providing technical assistance, management advice, and financial training.

Default also does not necessarily mean that the borrower's tenure is over. Once a loan has been unpaid for over 90 days, it goes into a servicing phase which has many regulations where FSA works with the borrower, often to restructure the FSA loan or other FSA loans the borrower has. This has not been investigated in this research but is important as found by Dodson and Ahrendsen (2018) for subsequent loan default and may be of interest for future research.

Also, the modelling of competing risks did not allow for the inclusion of more than two outcomes: Paid in full and Delinquent. However, in the Cumulative Incidence Functions, it was noticeable that some of the SDFRs loans, specifically loans to Blacks and Hispanics had more LongTermDelinquent loans than others. Thus, it would be of interest to analyze these outcomes separately. Other studies may investigate this by using another type of modelling such as multi-state models that are commonly used in medical research.

Finally, these results may be of interest of researchers, lenders, and policymakers to question the still remaining impact of the history of past discrimination and to adjust SDRF access to and the use of credit.

## References


Ahrendsen, B.L., B.L. Dixon, L.A. Settlage, S.R. Koenig, and C.B. Dodson. 2011. "A triple hurdle model of U.S. commercial bank use of guaranteed operating loans and interest assistance." *Agricultural Finance Review* 71(3):310–328.

Ahrendsen, B.L., C.B. Dodson, B.L. Dixon, and S.R. Koenig. 2005. "Research on USDA farm credit programs: past, present, and future." *Agricultural Finance Review* 65(2):165–181.

Ahrendsen, B.L., C.B. Dodson, G. Short, R.L. Rainey, and H.A. Snell. 2022. "Beginning farmer and rancher credit usage by socially disadvantaged status." *Agricultural Finance Review* 82(3):464–485.

Ahrendsen, B.L., S.R. Koenig, B.L. Dixon, C.B. Dodson, and L.A. Settlage. 2004. "Analysis of Borrower and Lender Use of Interest Assistance on FSA Guaranteed Farm Loans." *Staff Paper* SP 02 2004.

Asare-Baah, L., R. Zabawa, and H. Findlay. 2018. "Participation in Selected USDA Programs by Socially Disadvantaged Farmers in Selected Black Belt Counties in Georgia." *Journal of Rural Social Sciences* 33(1):2. Available at: https://egrove.olemiss.edu/cgi/viewcontent.cgi?article=1029&context=jrss.

Austin, P.C., and J.P. Fine. 2017. "Practical Recommendations for Reporting Fine-Gray Model Analyses for Competing Risk Data." *Statistics in Medicine* 36(27):4391–4400.

Autor, D. 2009. "Lecture Note: The Economics of Discrimination I." Available at: https://economics.mit.edu/files/4095.

Balvanz, P., M.L. Barlow, L.M. Lewis, K. Samuel, W. Owens, D.L. Parker, M. De Marco, R. Crowder, Y. Williams, D. Barker, A. Lightfoot, and A. Ammerman. 2011. "'The next generation, that's why we continue to do what we do': African American farmers speak about experiences with land ownership and loss in North Carolina." *Journal of Agriculture, Food Systems, and Community Development* 1(3):67–88. Available at: https://www.foodsystemsjournal.org/index.php/fsj/article/view/41/40.

Becker, G.S. 1957. *The Economics of Discrimination* University of Chicago Press.

Becker, G.S. 1971. *The Economics of Discrimination*. Second Edition. University of Chicago Press.

Bekkerman, A., E.J. Belasco, V.H. Smith, and C. McIntosh. 2019. "Does Farm Size Matter? Distribution of Crop Insurance Subsidies and Government Program Payments across U.S. Farms." *Applied Economic Perspectives and Policy* 41(3):498–518.

Berkovec, J.A., G.B. Canner, and S.A. Gabriel. 1996. "Mortgage Discrimination and FHA Loan Performance." *Cityscape: A journal of Policy Development and Research* 2(1):9–24.

Blinder, A.S. 1973. "Wage Discrimination: Reduced Form and Structural Estimates." *The Journal of Human Resources* 8(4):436–455. Available at:

https://www.jstor.org/stable/pdf/144855.pdf?refreqid=excelsior%3A2caf70ca2981065af648f45dde0a2a0b&ab_segments=&origin=.

Calo, A., and K. Teigen De Master. 2016. "After the incubator: Factors impeding land access along the path from farmworker to proprietor." *Journal of Agriculture, Food Systems, and Community Development* 6(2):111–127. Available at: https://foodsystemsjournal.org/index.php/fsj/article/view/451/431.

Cigsar, B., and D. Unal. 2018. "The effect of gender and gender-dependent factors on the default risk." *Revista de Cercetare si Interventie Sociala* 63(December):28–41.

Coate, S., and G. Loury. 1993. "Will affirmative-action policies eliminate negative stereotypes?" *American economic review* 83(5):1220–1240. Available at: https://inequality.stanford.edu/sites/default/files/media/_media/pdf/Reference Media/Coate and Loury_1993_Discrimination and Prejudice.pdf.

Congressional oversight panel. 2009. "Farm Loan Restructuring."

Congressional Research Service. 2021. "Defining a Socially Disadvantaged Farmer or Rancher (SDFR): In Brief." Available at: https://crsreports.congress.gov/product/pdf/R/R46727/7.

Coppess, J. 2021. "The History and Development of USDA Farm Loan Programs, Part 3: 1946 to 1961." In U. of I. at U.-C. Department of Agricultural and Consumer Economics, ed. *farmdoc daily*. Available at: https://farmdocdaily.illinois.edu/2021/03/the-history-and-development-of-usda-farm-loan-programs-part-3-1946-to-1961.html.

Cowan, T., and J. Feder. 2012. "The pigford cases: USDA settlement of discrimination suits by black farmers." *Black Farmers in America: Historical Perspective, Cooperatives and the Pigford Cases*:46–59. Available at: https://www.clearinghouse.net/chDocs/resources/caseStudy_TadlockCowenJodyFeder_1361971920.pdf.

Cox, D.R. 1997. "Some Remarks on the Analysis of Survival Data." In D. . Lin and T. . Fleming, eds. *Proceedings of the First Seattle Symposium in Biostatistics*. Springer, New York, NY.

Cox, D.R., and D. Oakes. 1984. *Analysis of Survival Data*. London: Chapman and Hall.

Dixon, B.L., B.L. Ahrendsen, B.R. Mcfadden, D.M. Danforth, M. Foianini, and S.J. Hamm. 2011. "Competing risks models of Farm Service Agency seven-year direct operating loans." *Agricultural Finance Review* 71(1):5–24.

Dodson, C.B. 2013. "Racial/Ethnic Discrimination in USDA's Direct Farm Lending Programs By Charles B. Dodson." In *Agricultural and Applied Economics Association (AAEA) Conferences, 2013 Annual Meeting, August 4-6, 2013, Washington, D.C.* pp. 1–17.

Dodson, C.B., and B.L. Ahrendsen. 2018. "Characteristics of borrowers likely to benefit from loan modifications." *Agricultural Finance Review* 78(4):425–440. Available at: https://www.emerald.com/insight/content/doi/10.1108/AFR-08-2017-0072/full/pdf?title=characteristics-of-borrowers-likely-to-benefit-from-loan-modifications.

Dodson, C.B., B.L. Ahrendsen, and G. Short. 2022. "Does use of nontraditional credit increase risk?" *Agricultural Finance Review* 82(2):359–378. Available at:

https://www.emerald.com/insight/content/doi/10.1108/AFR-06-2021-0085/full/pdf.

Donoghoe, M.W., and V. Gebski. 2017. “The importance of censoring in competing risks analysis of the subdistribution hazard.” *BMC Medical Research Methodology* 17(52). https://doi.org/https://doi.org/10.1186/s12874-017-0327-3.

Fagundes, C., L. Picciano, W. Tillman, J. Mleczko, S. Schwier, G. Graddy-Lovelace, F. Hall, and T. Watson. 2020. “Ecological costs of discrimination: Racism, red cedar and resilience in farm bill conservation policy in Oklahoma.” *Renewable Agriculture and Food Systems* 35(4):420–434.

FHLBANKS. 2022. “FHLBANKS A Nation of Local Lenders: About Us.” Available at: https://fhlbanks.com/about-us/.

Fine, J.P., and R.J. Gray. 1999. “A Proportional Hazards Model for the Subdistribution of a Competing Risk.” *American Statistical Association* 94:496–509.

Gardiner, J.C. 2016. “Competing Risks Analyses: Overview of Regression Models.” In *Proceedings of the SAS Global Forum 2016 Conference*. Cary, NC: SAS Institute Inc.

Gilbert, J., G. Sharp, and M.S. Felin. 2001. “The Decline ( and Revival ?) of Black Farmers and Rural Landowners : A Review of the Research Literature.” Available at: https://minds.wisconsin.edu/bitstream/handle/1793/21927/31_wp44.pdf?sequence=1&isAllowed=y.

Hannah-Jones, Nikole. 2021. The 1619 Project: A New Origin Story. Edited by The New York Times Magazine, 1st ed., WH Allen.

Horst, M., and A. Marion. 2019. “Racial, ethnic and gender inequities in farmland ownership and farming in the U.S.” *Agriculture and Human Values* 36:1–16. Available at: https://link.springer.com/content/pdf/10.1007/s10460-018-9883-3.pdf.

Ifft, J., T. Kuethe, and M. Morehart. 2013. “Debt Use by Farms with Crop Insurance.” *Choices* 28(3):1–5.

Jett, T. 2011. “The Justice that Justice Denied: The Problematic Case of the Black Farmers Civil Rights Settlement with the Department of Agriculture.” *APSA 2011 Annual Meeting Paper*. Available at: https://ssrn.com/abstract=1901373.

Kalbfleisch, J.D., and R.L. Prentice. 1980. *The statistical analysis of failure time data* N. Y. John Wiley and Sons, ed.

Kauffman, N., and T. Kreitman. 2021. “Farm Debt Declines Further and Credit Stress Eases.” *Federal Reserve Bank ok Kansas City*. Available at: https://www.kansascityfed.org/agriculture/agfinance-updates/farm-debt-declines-further-credit-stress-eases/.

Key, N., C. Burns, and G. Lyons. 2019. “Financial conditions in the U.S. agricultural sector : Historical comparisons.” *Economic Information Bulletin - USDA Economic Research Service* (211):30. Available at: https://www.ers.usda.gov/webdocs/publications/95238/eib-211.pdf?v=8745.1.

King, K.Q., S.D. Wood, J. Gilbert, and M. Sinkewicz. 2018. “Black Agrarianism: The Significance of African American Landownership in the Rural South.” *Rural Sociology* 83:677–699.

Kitagawa, E.M. 1955. “Components of a Difference Between Two Rates.” *Journal of the American Statistical Association* 50(272):1168–1194. Available at: https://www.jstor.org/stable/2281213.

Kleinbaum, D.G., and M. Klein. 2012. *Survival Analysis: A Self-Learning Text* M. Gail, K. Krickeberg, J. M. Samet, A. Tsiatis, and W. Wong, eds. Springer Science+Business Media. Available at: file:///C:/Users/cecil/Downloads/Survival_Analysis_A_Self_Learning_Text_T.pdf.

Ko, J.-Y. 2021. "An Examination of Socially Disadvantaged Farmers and Ranchers Program on Black Farmers in the United States." *Academic Journal* 8(01):502–513.

Leslie, I.S., and M.M.White. 2018. "Race and Food: Agricultural Resistance in U.S. History." In P. Batur and J. Feagin, eds. *Handbook of the Sociology of Racial and Ethnic Relations*. Springer, Cham, pp. 347–364.

McDonald, T.M., J. Law, A.K. Giri, and D. Subedi. 2021. "The role of nontraditional lending for socially disadvantaged and financially stressed farmers." *Agricultural Finance Review*. Available at: https://www.emerald.com/insight/content/doi/10.1108/AFR-06-2021-0072/full/html?skipTracking=true.

Minkoff-Zern, L.-A., and S. Sloat. 2017. "A new era of civil rights? Latino immigrant farmers and exclusion at the United States Department of Agriculture." *Agriculture and Human Values* 34:631–643. Available at: https://link.springer.com/article/10.1007/s10460-016-9756-6#citeas.

Orozco, A.A., A. Ward, and G. Graddy-Lovelace. 2018. "Documenting USDA Discrimination: Community-Partnered Research on Farm Policy for Land Justice." *ACME: An International Journal for Critical Geographies* 17(4):999–1023. Available at: https://acme-journal.org/index.php/acme/article/view/1514.

Phelps, E.. 1972. "The Statistical Theory of Racism and Sexism." *American Economic Review* 62(4):659–661.

Prentice, R.L., J.D. Kalbfleisch, N. Peterson, J.A. V. Flournoy, V.T. Farewell, and N.E. Breslow. 1978. "The Analysis of Failure Times in the Presence of Competing Risks." *Biometrics* 34:541–554.

Quaye, F.M., D. Nadolnyak, and V. Hartarska. 2017. "Factors Affecting Farm Loan Delinquency in the Southeast." *Research in Applied Economics* 9(4):75.

Robins, Jonathan E. 2015. "Sven Beckert. Empire of Cotton: A Global History." Review, *Enterprise & Society* 16(4): 991–93. doi:10.1017/eso.2015.50.

Roesch, M., M.G. Doherr, and J.W. Blum. 2005. "Farmland Values, Land Ownership, and Returns to Farmland, 2000-2016." Available at: http://linkinghub.elsevier.com/retrieve/pii/S0022030205729246.

The White House. 2021. "Presidential Actions." https://www.whitehouse.gov/briefing-room/presidential-actions/.

U.S. Department of Agriculture Economic Research Service. 2000. "Economic Research Service Farm Resources Regions." *Agricultural Information Bulletin* 760: 2. https://www.ers.usda.gov/webdocs/publications/42298/32489_aib-760_002.pdf?v=42487.

U.S. Department of Agriculture Economic Research Service. 2019. "Larger Farms and Younger Farmers Are More Vulnerable to Financial Stress." *Amber Waves, Farm Economy*. Available at: https://www.ers.usda.gov/amber-waves/2019/october/larger-farms-and-younger-farmers-are-more-vulnerable-to-financial-stress/ [Accessed October 9, 2021].

U.S. Department of Agriculture Economic Research Service. 2022. “Socially Disadvantaged, Beginning, Limited Resource, and Female Farmers and Ranchers.” Available at: https://www.ers.usda.gov/topics/farm-economy/socially-disadvantaged-beginning-limited-resource-and-female-farmers-and-ranchers/.

U.S. Department of Agriculture Farm Service Agency. 2014. “Farm loan programs – guaranteed farm loans.” Available at: https://www.fsa.usda.gov/Internet/FSA_File/guaranteed_farm_loans.pdf.

U.S. Department of Agriculture Farm Service Agency. 2021. “Farm Loans Programs.” Available at: https://www.fsa.usda.gov/programs-and-services/farm-loan-programs/index.

U.S. Department of Agriculture Natural Resources Conservation Service. 2018. “Farm Service Agency Conservation Loan Program.” https://www.fsa.usda.gov/Assets/USDA-FSA-Public/usdafiles/FactSheets/archived-fact-sheets/Conservation_Loan_Program_Fact_Sheet_November_2018.pdf.

U.S. Department of Agriculture National Agricultural Statistics Services. 2019a. “2017 Census of agriculture highlights: Asian Producers.” *ACH-17-8*. Available at: https://www.nass.usda.gov/Publications/%0AHighlights/index.php %0A.

U.S. Department of Agriculture National Agricultural Statistics Services. 2019b. “2017 Census of agriculture highlights: Black Producers.” *ACH-17-9*. Available at: https://www.nass.usda.gov/Publications/%0AHighlights/index.php%0A.

U.S. Department of Agriculture National Agricultural Statistics Services. 2019c. “2017 Census of agriculture highlights: Female Producers.” *ACH-17-11*. Available at: https://www.nass.usda.gov/Publications/%0AHighlights/index.php %0A.

U.S. Department of Agriculture National Agricultural Statistics Services. 2019d. “2017 Census of agriculture highlights: Hispanic Producers.” *ACH-17-10*. Available at: https://www.nass.usda.gov/Publications/%0AHighlights/index.php %0A.

U.S. Department of Agriculture National Agricultural Statistics Services. 2019e. “2017 Census of agriculture highlights:American Indian/Alaska native producers.” *ACH-17-7*. Available at: https://www.nass.usda.gov/Publications/%0AHighlights/index.php %0A.

U.S. Department of Labor Employment and Training, and Administration. 2021. “Findings from the National Agricultural Workers Survey (NAWS) 2017–2018: A Demographic and Employment Profile of United States Farmworkers.” Available at: https://www.dol.gov/sites/dolgov/files/ETA/naws/pdfs/NAWS Research Report 14.pdf.

U.S. Government Accountability Office. 2019. “AGRICULTURAL LENDING Information on Credit and Outreach to Socially Disadvantaged Farmers and Ranchers Is Limited.” Available at: https://www.gao.gov/assets/gao-19-539.pdf.

Wolbers, M., M.T. Koller, V.S. Stel, B. Schaer, K.J. Jager, K. Leffondré, and G. Heinze. 2014. “Competing Risks Analyses: Objectives and Approaches.” *European Heart Journal* 35(42):2936–2941.

Yinger, J. 1996. “Why Default Rates Cannot Shed Light on Mortgage Discrimination.” *Cityscape* 2(1):25–31.

Zhang, M.J., X. Zhang, and T.H. Scheike. 2008. “Modeling cumulative incidence function for competing risks data." *Expert Revue of Clinical Pharmacology* 1(3):391–400.

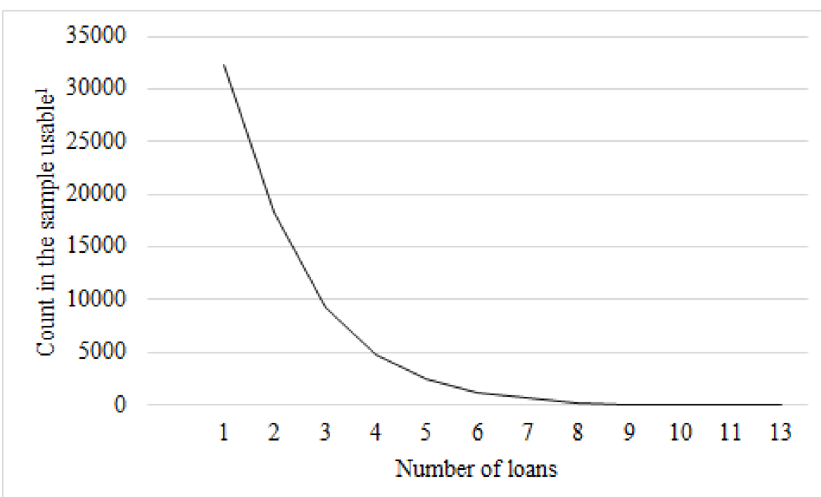
## Appendixes

Appendix 1. Loans Amount and Borrowers Amount in the Observations

Table 7. Number of Borrowers and Loans in the FSA Observations

| **Loans count** | **Loan count** | **% of usable[1]** | **Borrowers count** | **% of borrowers with usable[1] loans** | **Estimated borrower count in the sample** |
|---|---|---|---|---|---|
| 0 | 342 | | | | |
| 1 | 32,218 | 46.47 | 32,218 | 69.32 | 32,218 |
| 2 | 18,256 | 26.33 | 9,128 | 19.64 | 4,564 |
| 3 | 9,273 | 13.37 | 3,091 | 6.65 | 1,030.3 |
| 4 | 4,792 | 6.91 | 1,198 | 2.58 | 299.5 |
| 5 | 2,500 | 3.61 | 500 | 1.08 | 100 |
| 6 | 1,116 | 1.61 | 186 | 0.40 | 31 |
| 7 | 679 | 0.98 | 97 | 0.21 | 13.86 |
| 8 | 240 | 0.35 | 30 | 0.06 | 3.75 |
| 9 | 117 | 0.17 | 13 | 0.03 | 1.4 |
| 10 | 50 | 0.07 | 5 | 0.01 | 2 |
| 11 | 77 | 0.11 | 7 | 0.02 | 0.63 |
| 13 | 13 | 0.02 | 1 | 0.00 | 0.08 |
| Total | 69,673 | | | | |
| Total usable[1] | 69,331 | 100 | 46,474 | | |
| Total sample | 46,161 | | | | 38,263 |

[1]Usable refers to observations with complete data (without the 342 observations with incomplete data




[1]Usable refers to observations with complete data (without the 342 observations with incomplete data
n = 69,331; Loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
Source: Farm Service Agency Farm Loan Program and calculation

Figure 30. Distribution of Multiple Usable Loans in the Complete Data

Appendix 2. Other Information used to Code the Program
Table 8. Code for Identification of Outcomes

| Outcome | Debt Settlement Code | Count |
|---|---|---|
| Censored calculated | | 19632 |
| Delq calculated | | 4703 |
| Delq | D00 | 1 |
| Delq | G00 | 380 |
| Delq | Q00 | 4 |
| Delq | R00 | 2284 |
| Delq | R10 | 18 |
| Delq | S00 | 38 |
| Delq | T05 | 4025 |
| Delq | Y01 | 464 |
| Delq | Z97 | 64 |
| Paid | E00 | 4 |
| Paid | G00 | 2583 |
| Paid | G07 | 1 |
| Paid | Q00 | 3 |
| Paid | R00 | 14956 |
| Paid | R07 | 2 |
| Paid | R10 | 421 |
| Paid | S00 | 33 |
| Paid | T05 | 6996 |
| Paid | Y01 | 4156 |
| Paid | Z90 | 3 |
| Paid | Z97 | 528 |
| LongTermDelq calculated | | 3626 |
| LongTermDelq | A00 | 39 |
| LongTermDelq | C00 | 2 |
| LongTermDelq | G00 | 200 |
| LongTermDelq | Q00 | 15 |
| LongTermDelq | R00 | 1055 |
| LongTermDelq | R10 | 2 |
| LongTermDelq | S00 | 493 |
| LongTermDelq | T05 | 2785 |
| LongTermDelq | Y01 | 133 |
| LongTermDelq | Z97 | 24 |

n = 69,331; Loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
Source: Farm Service Agency Farm Loan Program and calculation

Table 9. Functions and Packages Necessary to Run the Program

| Specific functions used | Description | Packages necessary |
|---|---|---|
| crr | Competing Risks Regression<br>Regression modeling of subdistribution functions in competing risks | cmprsk |
| cuminc | Cumulative Incidence Analysis<br>Estimates cumulative incidence functions from competing risks data and tests equality across groups | cmprsk |
| UPpoisson | Draws a Poisson sample using a prescribed vector of first-order inclusion probabilities (unequal probabilities, without replacement, random sample size). | sampling |
| ggcompetingrisk | Cumulatives Incidence Curves for Competing Risks<br>Plots Cumulative Incidence Curves | ggplot2<br>survminer<br>survival |
| plot_usmap | Plot the map of the United States | usmap<br>Ggplot2 |

Appendix 3. T-Tests for the Difference in Probability of Loan Outcome by SDFR Status Pair

Table 10: Results of Test of Difference in Probability of Loan Outcome by SDFR Status Pair, by Outcome

| **SDFR status 1** | **SDFR status 2** | ***Difference in probability Paid*** | ***Difference in probability Delq*** | ***Difference in probability LongTermDelq*** |
|---|---|---|---|---|
| American Indian | Asian | -0.076 | 0.032 | 0.026 |
| American Indian | Black | 0.075**** | -0.022 | -0.143**** |
| American Indian | Hispanic | 0.052*** | 0.012 | -0.100**** |
| American Indian | Pacific Islander | -0.066 | 0.038 | 0.011 |
| American Indian | Non Hispanic White men | -0.115**** | 0.041**** | 0.024*** |
| American Indian | Women | -0.076**** | 0.031*** | 0.005 |
| Asian | Black | 0.151**** | -0.054 | -0.168**** |
| Asian | Hispanic | 0.128*** | -0.020 | -0.126**** |
| Asian | Pacific Islander | 0.010 | 0.006 | -0.015 |
| Asian | Non Hispanic White men | -0.039 | 0.009 | -0.002 |
| Asian | Women | 0.000 | -0.001 | -0.021 |
| Black | Hispanic | -0.024 | 0.034 | 0.042 |
| Black | Pacific Islander | -0.141* | 0.060 | 0.154*** |
| Black | Non Hispanic White men | -0.190**** | 0.062**** | 0.167**** |
| Black | Women | -0.151**** | 0.053**** | 0.148**** |
| Hispanic | Pacific Islander | -0.117* | 0.026 | 0.111* |
| Hispanic | Non Hispanic White men | -0.166**** | 0.028 | 0.124**** |
| Hispanic | Women | -0.127**** | 0.018 | 0.105**** |
| Pacific Islander | Non Hispanic White men | -0.049 | 0.003 | 0.013 |
| Pacific Islander | Women | -0.010 | -0.007 | -0.006 |
| Non Hispanic White men | Women | 0.039**** | -0.010 | -0.019**** |

[a] Paid: Paid In Full, Delq: Delinquent, LongTermDelq: Long Term Delinquent;
n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
* *p*-value<0.05; ** *p*-value<0.01; *** *p*-value<0.001; **** *p*-value<0.0001
Source: Farm Service Agency Farm Loan Program and calculation

Appendix 4. Comparison Censored and All data to verify the non-Informative censoring requirement

Table 11. Comparison All sample loans and censored loans in the sample

| DEPENDANT | | |
|---|---|---|
| | **Overall Sample** | **Censored** |
| Count Loans | 46,161 | 15,710 |
| **Variable Description** | Means | |
| Non-Hispanic White men | 0.688 | 0.680 |
| Women | 0.138 | 0.139 |
| Hispanic | 0.036 | 0.031 |
| Black | 0.039 | 0.030 |
| American Indian | 0.128 | 0.117 |
| Asian | 0.008 | 0.006 |
| Pacific Islander | 0.003 | 0.002 |
| Beginning or young farmer | 0.773 | 0.807 |
| Marital status | 0.575 | 0.568 |
| Low debt coverage | 0.287 | 0.288 |
| Low solvency | 0.407 | 0.400 |
| Medium solvency | 0.302 | 0.301 |
| High solvency | 0.292 | 0.299 |
| Illiquidity | 0.609 | 0.610 |
| Total discretionary income | 3.383 | 3.300 |
| *Gross Revenue* | | |
| Small farm | 0.621 | 0.667 |
| Mid-size farm | 0.256 | 0.217 |
| Large farm | 0.123 | 0.112 |
| *Farm Type* | | |
| Beef cattle farm | 0.564 | 0.613 |
| Row crop farm | 0.226 | 0.200 |
| Dairy farm | 0.076 | 0.557 |
| Specialty crop | 0.048 | 0.419 |
| Other livestock | 0.084 | 0.091 |
| Binary for current term point-of-sale loans | 0.053 | 0.050 |
| *Categorical indicator for intermediate point-of-sale balance* | | |
| POS_Balances $0 | 0.789 | 0.794 |
| POS_Balances $1-10K | 0.051 | 0.050 |
| POS_Balances $10-50K | 0.102 | 0.100 |
| POS_Balances $50K+ | 0.058 | 0.056 |

n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
Source: Farm Service Agency Farm Loan Program and calculation

Appendix 5. Descriptive statistics of the variables implemented for the subdistributional hazard competing risks model by SDFR status

Table 12. Descriptive statistics of the variables implemented for the subdistributional hazard competing risks model by SDFR status

| | **All** | **Non-Hispanic White Men** | **Women** | **Hispanic** | **Black** | **American Indian** | **Asian** | **Pacific Islander** |
|---|---|---|---|---|---|---|---|---|
| | | | | **VARIABLES STUDIED** | | | | |
| Duration | 1,205.2 | 1,584.6 | 1,187.0 | 1,157.0 | 1,143.8 | 1,154.0 | 1,165.0 | 1,045.0 |
| *Loan Outcome* | | | | | | | | |
| Censored | 0.340 | 0.335 | 0.345 | 0.348 | 0.296 | 0.385 | 0.366 | 0.368 |
| Paid in Full | 0.422 | 0.449 | 0.410 | 0.283 | 0.260 | 0.334 | 0.410 | 0.400 |
| Delinquent + LongTermDelinquent | 0.238 | 0.217 | 0.245 | 0.370 | 0.445 | 0.281 | 0.223 | 0.232 |
| | | | | **EXPLANATORY VARIABLES** | | | | |
| Beginning or young farmer | 0.773 | 0.766 | 0.834 | 0.745 | 0.702 | 0.796 | 0.816 | 0.781 |
| Marital status | 0.575 | 0.572 | 0.571 | 0.569 | 0.538 | 0.606 | 0.548 | 0.555 |
| Low debt coverage | 0.287 | 0.305 | 0.258 | 0.164 | 0.205 | 0.265 | 0.299 | 0.194 |
| Low solvency | 0.407 | 0.402 | 0.416 | 0.352 | 0.374 | 0.461 | 0.387 | 0.458 |
| Medium solvency | 0.302 | 0.319 | 0.255 | 0.236 | 0.226 | 0.268 | 0.348 | 0.213 |
| High solvency | 0.292 | 0.278 | 0.329 | 0.412 | 0.400 | 0.271 | 0.265 | 0.329 |
| Illiquidity | 0.609 | 0.589 | 0.650 | 0.620 | 0.720 | 0.666 | 0.514 | 0.523 |
| Total discretionary income | 3.383 | 3.6236 | 2.434 | 3.199 | 2.210 | 3.269 | 3.712 | 1.967 |
| *Gross Revenue* | | | | | | | | |
| Small farm | 0.621 | 0.567 | 0.774 | 0.740 | 0.845 | 0.696 | 0.561 | 0.819 |
| Mid-size farm | 0.256 | 0.285 | 0.175 | 0.184 | 0.120 | 0.222 | 0.294 | 0.129 |
| Large farm | 0.123 | 0.148 | 0.051 | 0.077 | 0.035 | 0.082 | 0.145 | 0.052 |
| *Farm Type* | | | | | | | | |
| Beef cattle farm | 0.564 | 0.526 | 0.609 | 0.458 | 0.662 | 0.785 | 0.190 | 0.303 |
| Row crop farm | 0.226 | 0.267 | 0.108 | 0.243 | 0.179 | 0.118 | 0.106 | 0.330 |
| Dairy farm | 0.076 | 0.094 | 0.059 | 0.028 | 0.113 | 0.020 | 0.003 | 0.006 |
| Specialty crop | 0.048 | 0.018 | 0.088 | 0.130 | 0.086 | 0.017 | 0.543 | 0.240 |
| Other livestock | 0.084 | 0.027 | 0.134 | 0.140 | 0.062 | 0.059 | 0.156 | 0.123 |
| Current term point-of-sale loans | 0.053 | 0.064 | 0.024 | 0.030 | 0.038 | 0.032 | 0.013 | 0.013 |
| POS_Balances $0 | 0.789 | 0.767 | 0.863 | 0.864 | 0.869 | 0.805 | 0.826 | 0.897 |
| POS_Balances $1-10K | 0.051 | 0.054 | 0.047 | 0.039 | 0.035 | 0.043 | 0.052 | 0.013 |
| POS_Balances $10-50K | 0.102 | 0.109 | 0.068 | 0.072 | 0.067 | 0.095 | 0.096 | 0.058 |
| POS_Balances $50K+ | 0.058 | 0.067 | 0.022 | 0.026 | 0.029 | 0.057 | 0.026 | 0.032 |

n = 46,161; Sample of loans originated 2011-2020; Loan outcomes occurred by April 30, 2021.
Source: Farm Service Agency Farm Loan Program and calculation

Appendix 6. CIF results for the robustness analysis

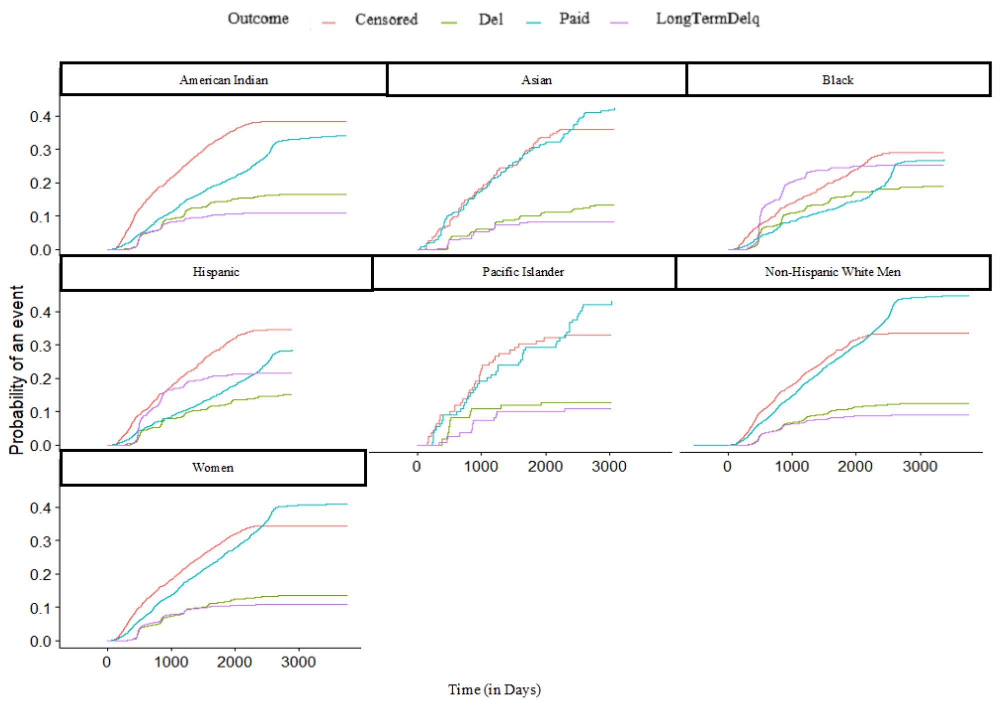



Figure 31. CIF results for the robustness analysis for the sample 2

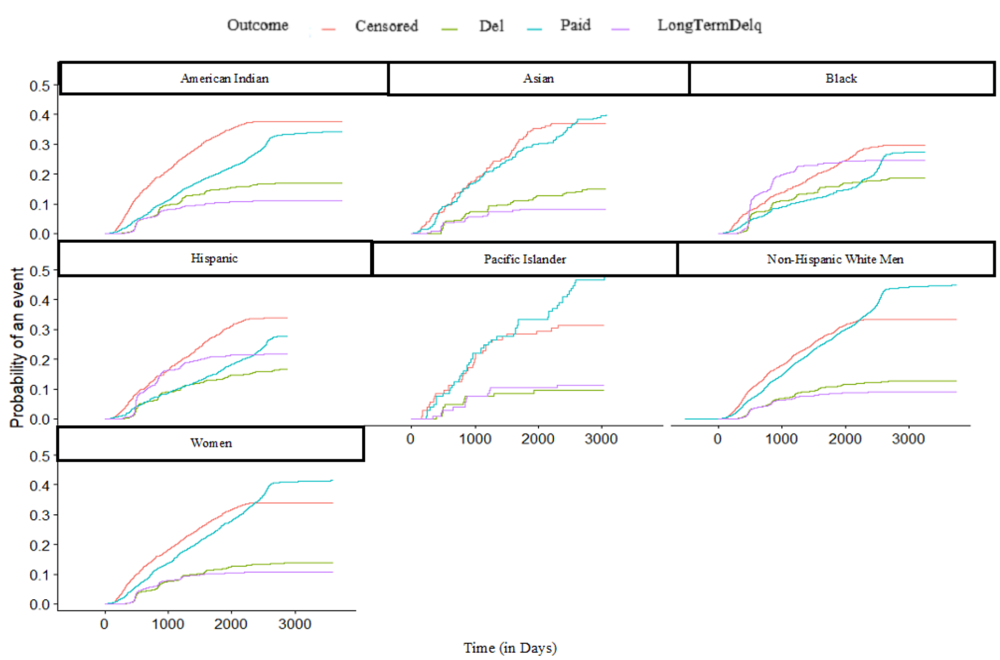



Figure 32. CIF results for the robustness analysis for the sample 3

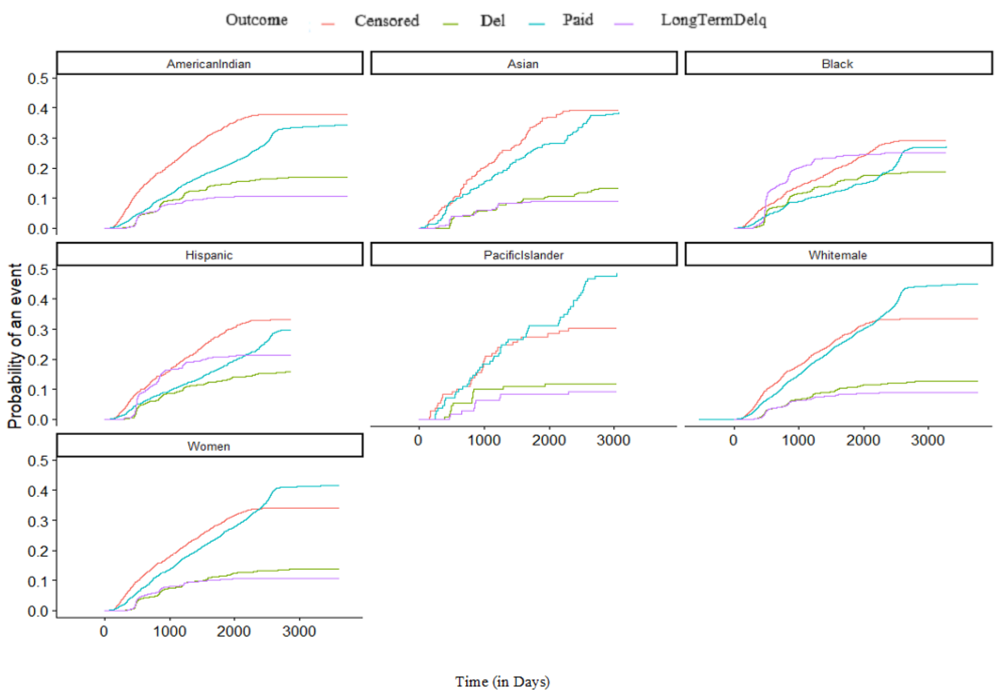



Figure 33. CIF results for the robustness analysis for the sample 4

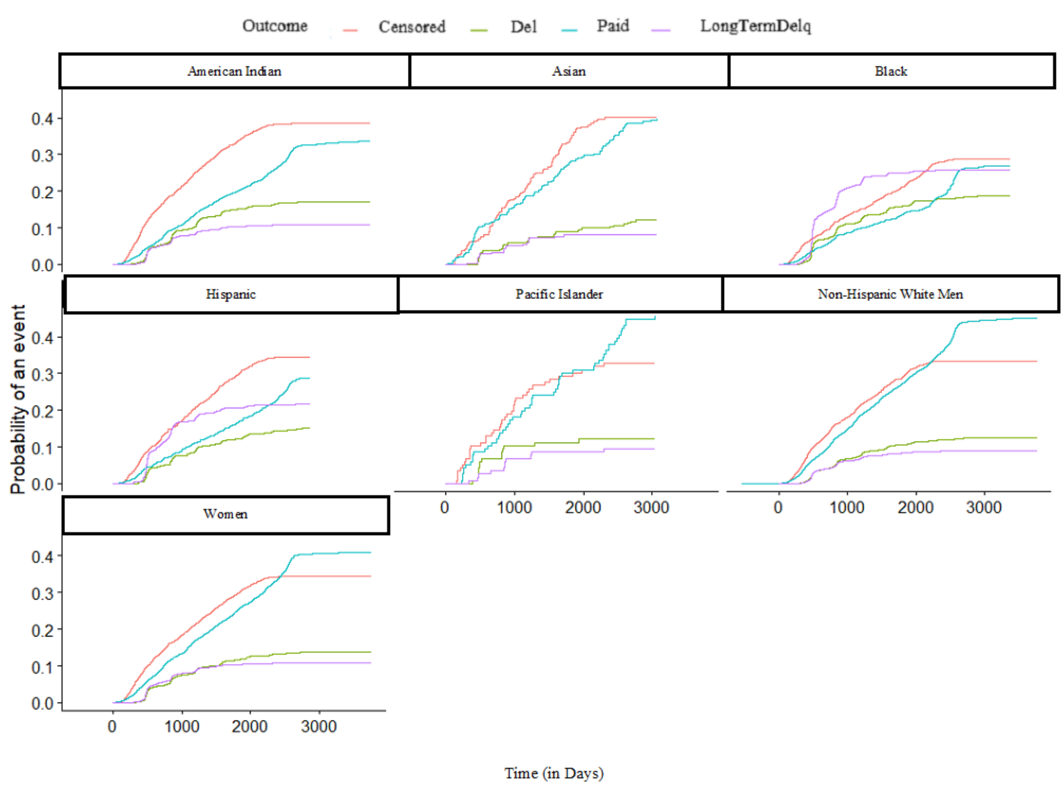



Figure 34. CIF results for the robustness analysis for the sample 5