Examining the Role of U.S. Agricultural Policy

on Chapter 12 Bankruptcy Filings and Active Cases

by

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Abstract

Farm bankruptcy enables eligible farmers the opportunity to reorganize debts while remaining operational. Providing safety nets for farmers is a long-standing U.S. agricultural policy that has recently reached historic levels because of trade disputes and market disruptions. Research has looked at the effect of government payments on farm survivability, and the impacts of payments on state level bankruptcy filings numbers (Dinterman & Katchova, 2018; Key & Roberts, 2006; Dixon et al., 2004). These studies looked at state aggregates that do not consider local geographic variation in agricultural activity. In this research, we evaluate the relationship between government payments and the number of county, district, and state bankruptcy filings and active cases. We use bankruptcy data from the Federal Judicial Center and government payment data. A fixed effect Poisson regression is used, finding that Gross Domestic Product, land values, certain government payments and net farm incomes are significant indicators of filings and active cases at different geographic levels of observation from 2008-2020.

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List of Abbreviations

COA	Census of Agriculture
BEA	Bureau of Economic Analysis
BLS	Bureau of Labor Statistics
NASS	National Agriculture Statistics Service
ERS	Economics Research Service
USDA	United States Department of Agriculture
FSA	Farm Service Agency
RMA	Risk Management Agency
FEMA	Federal Emergency Management Agency
NRCS	Natural Resource Conservation Service
IDB	Integrated Data Base
BAPCPA	Bankruptcy Abuse Prevention and Consumer Protection Act
CRP	Conservation Reserve Program
ARC	Agriculture Risk Payments
GDP	Gross Domestic Product
PPI	Producer Price Index
NFI	Net Farm Income
OLS	Ordinary Least Squares
GLM	Generalized Linear Model

Chapter 1

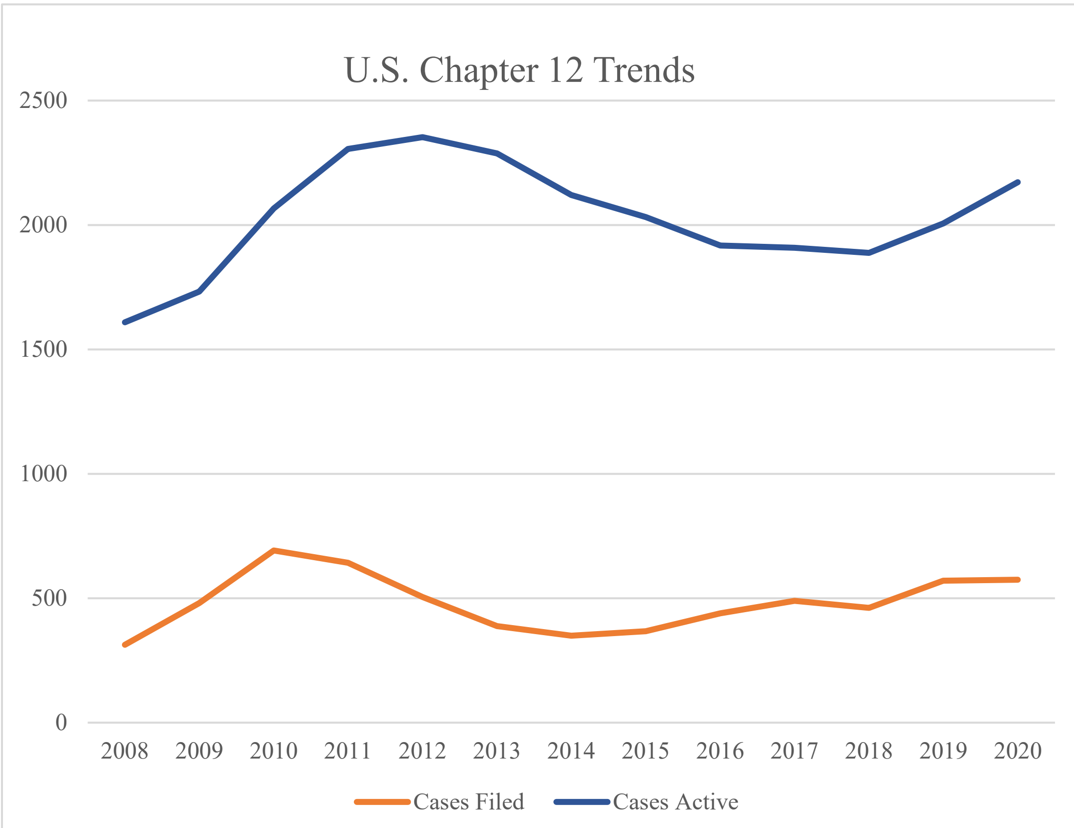
Introduction

According to the Economic Research Service (ERS) of the USDA, farms are decreasing from a national total of around 2.5 million individual farms in the early 1980s to just above 2 million in 2020 (Economic Research Service, 2021). There has also been minimal growth in the average farm size from just below 600 acres per farm in the early 1980s to roughly 444 acres in 2020 (ERS, 2021; MacDonald, Korb, & Hoppe, 2013). Citing that the current trends in farm size see an increase of very small operations and a shift from medium sized operations to larger sizes (MacDonald et al., 2013). American farms often operate on razor thin margins in an extremely volatile market. After 2014, farm income tanked to a national low of $68 billion in 2016, finally rebounding in 2020 to an estimated $123 billion, in large part because of COVID-19 emergency payments. At the same time, however, farm debt has been increasing from $276.5 billion in 2005 to $440.1 billion in 2020 (Rabinowitz & Secor, 2021). One option for farmers struggling financially is to seek filings under Chapter 12 bankruptcy to restructure and repay debts while maintaining farming operations. The number of farm bankruptcies has been steadily increasing over the years, likely associated with the tumultuous nature of the agricultural economy. Farm bankruptcy filing numbers are used as a proxy for financial health, especially over periods in which bankruptcy laws have not made substantial and significant changes (Dixon et al., 2004; Stam et al., 1991; Dinterman & Katchova, 2018). To date, agricultural economists use bankruptcy as a measure for farm financial health at the national and state-level, citing that these numbers offer a glimpse into the health of the local agricultural economy.

For our purposes, we focus on filed and active bankruptcy cases. The courts have periods of time referred to as a “snapshot” period, which acts as a temporal benchmark for what is occurring in the court system at that specified time. This snapshot period is used as our yearly level of observation to determine how many cases are filed in the court each year. Similarly, we use this measure to determine the number of active cases in the courts. We observe an increase in both cases filed and cases active until the year 2020. Figure 1 tracks the numbers of both filed and active cases from the Federal Judicial Center's Integrated Database system (IDB), which we will cover in more detail in our data chapter. As evident in Figure 1, we observe an overall increase in active cases. We can also observe a steady increase in cases filed, dipping slightly around 2020, coinciding with a spike in federal payments displayed in Figure 2. The ERS recognizes that observing the Chapter 12 phenomenon at the national level can mask geographic variation, misrepresenting the overall state of agricultural financial health (Key, Law, & Whitt, 2021).

As such the ERS researched the bankruptcy trends in 15 states, which they considered to be the top producers by cash receipts. These states are Florida, Georgia, Wisconsin, Arkansas, North Carolina, Missouri, Washington, Indiana, California, Iowa, Minnesota, Nebraska, Texas, Kansas, and Illinois. In this research, they estimated that the total bankruptcy rate for these 15 main producers was 6.7 per 10,000 eligible farms for the year 2019 (Key et al., 2021). Finding that for all but two of the states observed, bankruptcy rates surpassed 10-year highs (Key et al., 2021). The two standouts were Florida and California which seem to be less affected by microeconomic variables such as price volatility, which the authors cited as a major factor in the increased bankruptcy rates in the other states. The authors posit that because California and Florida produce a diverse mix of commodities, they are less impacted by price changes (Key et al., 2021). They argue that unemployment figures and land values are more impactful drivers of California's bankruptcy rates. This research points to the need for more disaggregate estimations on farm bankruptcies. While the national level provides a very baseline understanding of U.S. agriculture's financial health, it misses geographic variations that are important. Our research will provide the much needed disaggregate levels of observation for Chapter 12 occurrences.

Figure 1



In Figure 1, the number of active and filed cases from the Federal Judicial Court's Integrated Database (IDB) are laid out across the period we have chosen to observe. As seen above, there is a steady increase in the number of cases active from 2008 into 2020. In subsequent chapters, we will briefly cover the topic of Chapter 12 case time from filing to time of completion, which is an important aspect when seeking to understand the increase in active case numbers. Time to completion impacts the number of active cases in the court. We also observe a slight increase in filed case numbers.

Figure 2

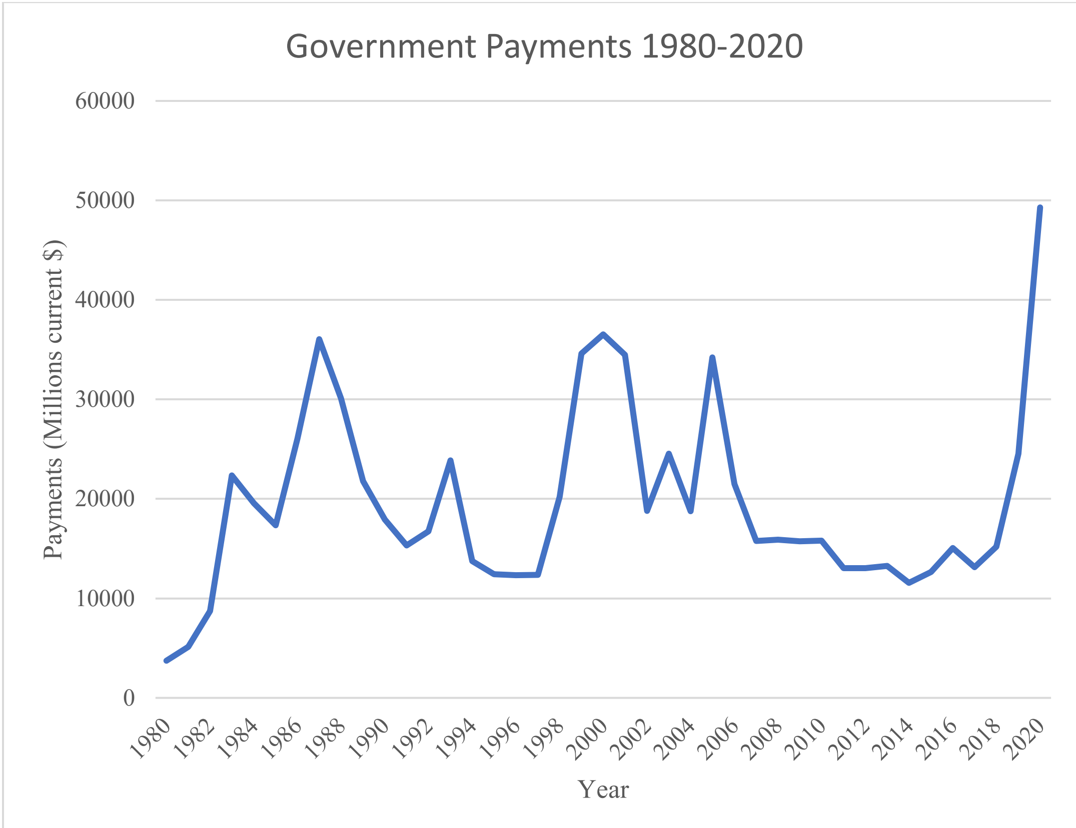


Figure 2 tracks the aggregate amount of government payments made to agricultural producers from 1980-2020, recorded by the ERS (ERS, 2021). In this figure, we observe a growing amount of government payments being distributed to farmers. 2020 saw a massive increase in federal funding as a response to trade wars and the damage caused by the COVID-19 pandemic. Periods of financial turmoil tend to see increased government payments to support farmers, which can be seen around the early 2000s coinciding with various market downturns and finally in 2020 with the coronavirus crash. As previously mentioned, our observation period ranges from 2008-2020, which is why we are focusing on this area of the graph. We can observe in Figure 2 that there was an initial decrease in payments from 2008-2014 and an increase from 2014 onward. This coincides with our previously stated decrease in net farm income around and after 2014. In these periods we observe that net farm income increases in conjunction with increased government payments. Leading us to observe that these payments are increasing their share of net farm income. Given that government payments are increasing, especially in times of financial turmoil, it is important to evaluate the impacts that government payments may have on financial health in the agricultural sector of the economy.

Figure 3

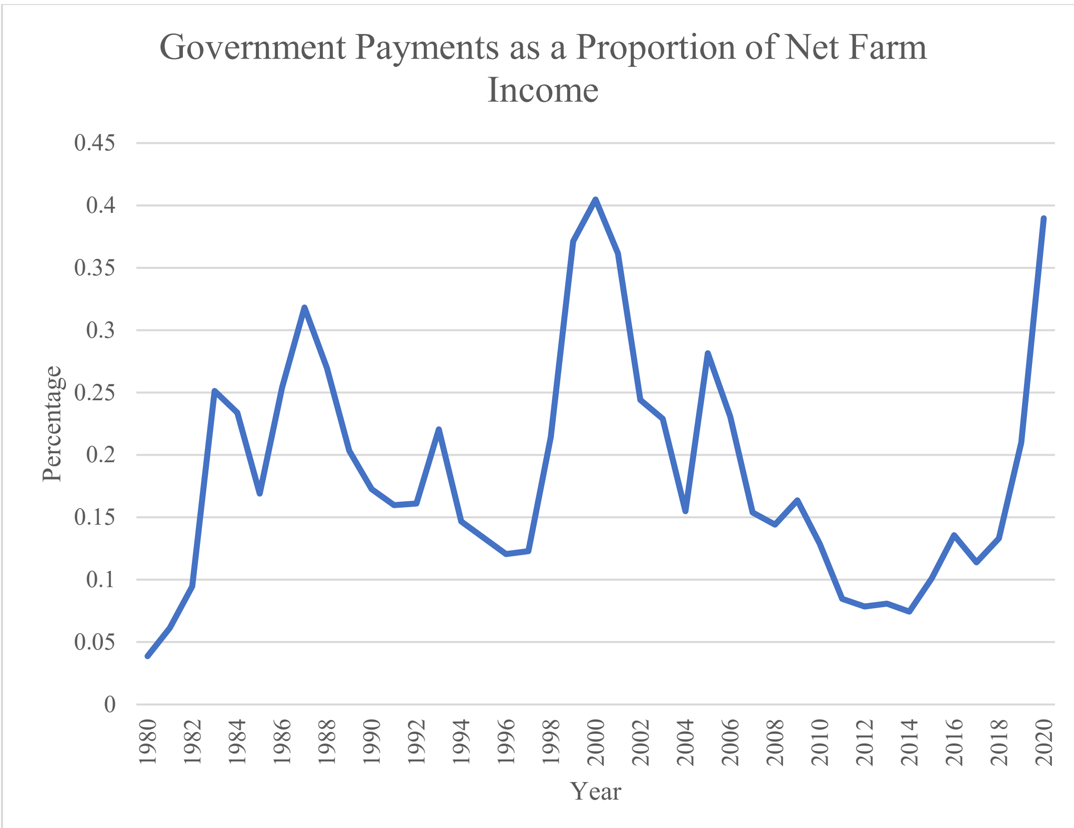


Figure 3 above tracks the changes in the percentage of government payments as a proportion of net farm income. The ERS publishes historical farm income data which includes government payments made to farmers for that year (ERS, 2021). The proportion of government payments is measured by dividing the total amount paid by the net income. As previously mentioned, we observe that in periods of higher relative government payments, the percentage of net farm income derived from government payments subsequently increases. As with Figure 2, this graph's period ranges from 1980-2020, yet we are focusing our research on only 2008-2020.

During our period of observation, we can see that government payments are a steadily increasing proportion of net farm income post 2014. As government payments' role in farm income increases alongside an increase in Chapter 12 filed and active case numbers, it is important to evaluate the impacts that payments may have on farm bankruptcy numbers.

Figure 4

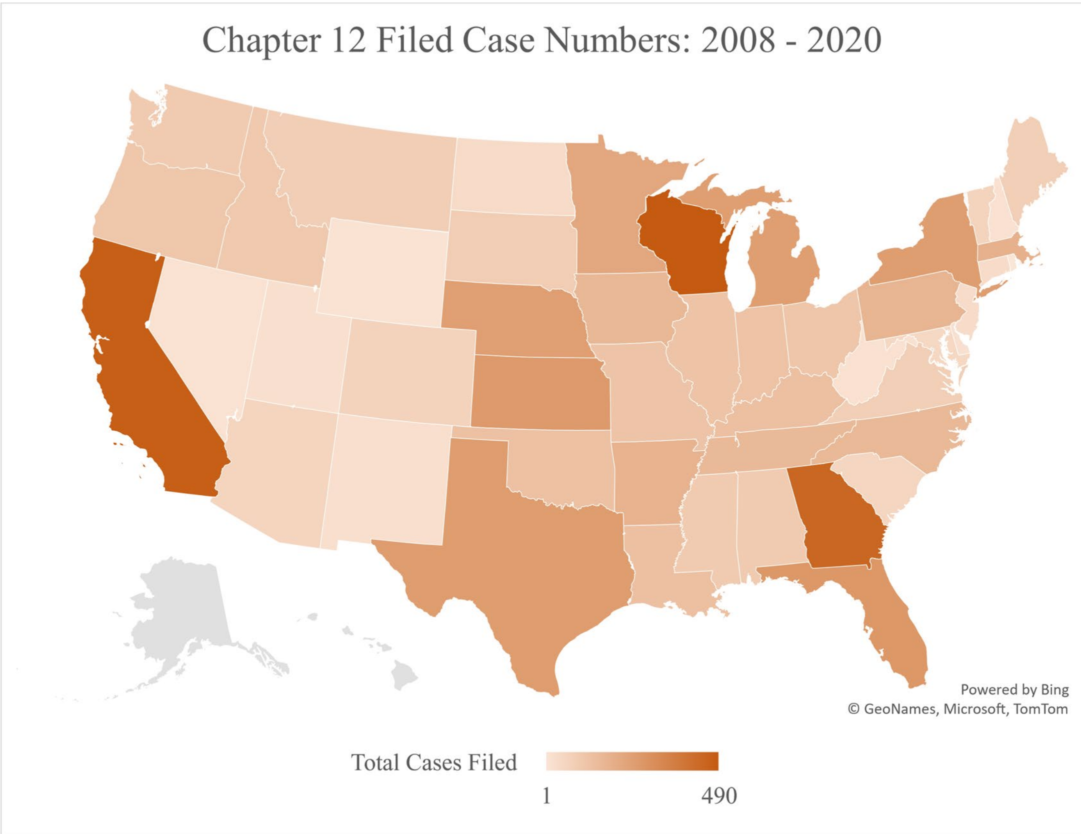


Figure 4 above captures the total number of filed cases in our IDB data from 2008-2020. As represented in the Figure, Chapter 12 is not a localized issue, affecting only a handful of states. Instead, farm bankruptcy affects farmers in every state in the contiguous United States, making it a topic of great concern to policy makers and economists alike.

There has been some research into the role of government payments in farm bankruptcy filing numbers. To date the major level of observation has been at the state level or isolated to the counties in a handful of states. The National Agricultural Statistic Service (NASS) collects county characteristics at the state level and creates districts. These districts are comprised of counties that share similar geographic and agricultural characteristics. These districts are called NASS districts and serve important statistical purposes. We introduce a relatively new level of observation to the existing body of research in that we observe farm bankruptcies at the county and NASS district level. By observing Chapter 12 filings and active cases at varying disaggregate levels of observations we seek to determine which method produces the most robust and economically significant results. It is our goal that this research will enable us to observe significant economic indicators so that we may better insulate farming operations from negative financial outcomes. We hope to accomplish this by identifying key indicators of Chapter 12 numbers, providing this information to extension agents in the hopes that they will be able to inform operators, raising financial awareness both off and on the farm. We expect to find that government payments are negatively associated with both number of cases filed and active. The measurable impacts of federal payment policy help us to determine in what ways we might better inform federal funding decisions, as government payments become an increasing proportion of net farm income.

Chapter 2

Background of the Farm Bankruptcy Process

The bankruptcy procedure in the United States is broken into different chapters. Debtors can choose from are Chapters 7, 11, 12, and 13. Chapter 7 focuses on the liquidation of assets to satisfy the debt, while 11 requires a restructuring of the business but does not require the total liquidation of assets. Debtors pursuing Chapter 13 are subject to lower relative debt limits and face more restrictions on debt types as opposed to other chapters. Chapter 13 also requires the debtor to provide evidence of a regular disposable income stream to meet repayment obligations (US Courts, 2021).

Chapter 12 was modeled after Chapter 13 and was initially meant to be a temporary solution in response to the 1980s farm financial crisis. Initially set to end in 1993, Chapter 12 became a useful tool for farmers and was extended until 2005. It then became a permanent fixture to bankruptcy law with the Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA) of 2005 (Dinterman & Katchova, 2018). Chapter 12 is better described as a debt adjustment process, as it seeks to restructure debts, and establish a repayment plan while maintaining property needed for operations to continue (Walker, Suri, & Goeringer, 2020). Farming operations largely receive payment after a successful selling of that season's yields, so a measure of regular income is not applicable to farming operations. Chapter 12 was designed without as many financial barriers as other chapters to serve farmers and fishermen more effectively. A unique aspect of Chapter 12 is its debt cap and debt structure. Specifically, 50% of the reported debt must come from the operation in question, meaning that the remainder of debt can come from other areas, often personal debt. The Family Farmer Relief Act of 2019 increased the total debt limit for Chapter 12 to not exceed $10 million in the fourth quarter of 2019 (Public

Law No: 116-51). The debt limit is periodically adjusted for inflation; however, this change represents a dramatic increase in the debt limit from earlier limits of $1,500,000 and $4,031,575 in 2003 and 2013, respectively (Wyche, 2021; Dinterman, 2020; U.S. Courts). In addition to the debt limit, at least 50% of the income must come from farming (Walker, Suri, & Goeringer, 2020).

Another difference between chapters is that Chapter 13 can only be filed by a sole proprietorship, while Chapter 12 allows for various forms of business structures. When an operation filing for Chapter 12 is a corporation or a partnership, 80% of the assets must be related to farming operations (Dinterman & Katchova, 2018). The previously mentioned 50% farming related debt and income requirement along with the 80% asset requirement for corporations/partnerships are referred to as the "income test". Once the debtor passes the income test, they file a voluntary petition to the court indicating that they wish to file for Chapter 12. The debtor must meet with the creditors within the first 60 days where they prioritize claims, based on secured and unsecured debts. Within 90 days of the creditor meeting with the debtor, they must provide a proposed repayment plan with a schedule of repayments and/or any business restructuring plans (Wyche, 2021). This repayment plan typically spans from a 3 to 5-year repayment period. In special circumstances, the repayment can continue past the 5-year mark. These payments are given to a court-appointed trustee who provides the funds to the creditors in order of priority (Kunkel & Peterson, 2015).

There is a clear distinction made in the categorization of debt into three different categories. The debt types are secured, priority unsecured, and nonpriority unsecured (Walker et al., 2020). The type of debt is an important piece of the repayment schedule as it helps in determining which creditors receive priority in repayment schedules. Secured debt is a form of debt which is backed by some form of collateral, meaning that there is a secured asset to support the claim, often a property mortgage or machinery loan. In the case of Chapter 12, the secured assets are often loans on farming machinery or mortgages on land and farm buildings. Unsecured debt is broken down by priority and non-priority, where priority unsecured denotes that the debt in question is a result of some governmental or legal action, often unpaid taxes. Finally, unsecured nonpriority refers to any debt that does not have a form of collateral backing, this is often credit card charges (Rabinowitz & Secor, 2022). Unsecured nonpriority debt is the least likely to be repaid within the period. With a lack of liquidation requirement and a goal of Chapter 12 to maintain farm operations, any unsecured debt not repaid is discharged by the court.

Chapter 12 can end in discharge or dismissal, with discharged cases being the preferred of the two, as it often indicates a successful reorganization of operational debt. Dismissal may occur due to a farmer not completing the initial administrative requirements or from being unable to fulfill their payments as laid out in the agreed upon repayment plan. When this situation occurs, the farmer no longer has the court's protection from collection activities (Rabinowitz & Secor, 2022). Due to the structure of Chapter 12, the debtors and creditors may negotiate optimal settlements outside of court. As such, dismissals do not always indicate a negative outcome for the filer (Wyche, 2021). These instances are considered "voluntary dismissals", indicating that filers and creditors were able to successfully reach an agreement apart from the court, and does not necessarily reflect a failure of the creditors and debtors to reach a repayment agreement (Faiferlick & Harl, 1988; Harl, 1992). This voluntary dismissal outcome can expedite the speed at which the case exits the court.

Another important part of Chapter 12 bankruptcy is the process of "cramming down". Cramming down is the process in which the debtor repays the secured claims at the market value of secured collateral, this is further supported by the court's evaluation of assets (Walker et al., 2020; Wyche, 2021). The process of cramming down is an important fixture of Chapter 12 and has a profound effect on how repayments are scheduled. For example, a farmer filing for bankruptcy can request that their secured debt be reduced below the amount currently owed, due to a lower current value for that asset, further strengthening the ability to reconcile debts. When observing what micro- and macroeconomic variables impact filing rates, it is important that we maintain a clear understanding of the cram down process, as it portrays the larger farm financial picture. As well as playing an integral role in debt repayment strategies. Chapter 12's goal is not to necessarily increase an operations' financial health to a high level, instead its purpose is to restructure business and debts while maintaining operations to repay creditors to a satisfactory and minimum level (Wyche, 2021).

Chapter 3

Literature Review

Previous research into Chapter 12 focuses on the effectiveness of Chapter 12 bankruptcy, at the state-level, as well as identifying key variables that impact Chapter 12 numbers. Stam, Dixon, and Rule (2003) observe Chapter 12's effectiveness and find that from 1986 – 2002, the first 16 years of Chapter 12's existence, Chapter 12 increased the farmers' bargaining power significantly. This is largely in part to the newfound ability to consolidate debts and offer a fair value of collateral, referred to as cramming down, as previously mentioned. Stam et al. (2003) found that land values, interest rates, and farm income are significant factors that affect filing rates.

As previously discussed, most of the Chapter 12 research observed the filing rates and numbers at a national and state level of aggregation. Of particular interest to some economists is the time to completion for Chapter 12 cases. As cases remain in the court, the number of overall active cases increases (refer to Figure 1), both filing numbers, rates and active cases provide a picture of agricultural financial health. When observing time to completion, the type of outcome is considered, again ending in dismissal or discharge. Researchers have focused on what micro and macroeconomic factors affect the time to completion for these cases, and why case completion times are increasing within the courts (Wyche, 2021; Dinterman & Katchova, 2021).

Using a survival analysis of Chapter 12 filings, Dinterman and Katchova (2021) found that the time to case completion is increasing at a rate not observed in other forms of bankruptcy proceedings (Dinterman & Katchova, 2021). Because Chapter 12 has a higher debt cap relative to other forms of bankruptcy, this longer completion process was initially hypothesized to be due to increasing amount of debt filed, but no clear connection could be made. Dinterman and

Katchova (2021) also found that land values specifically are connected to Chapter 12 filing rates (Dinterman & Katchova, 2021). It is postulated that the process of cramming down likely has some confounding effects on the time to case completion, due to the change in land valuation over time (Wyche, 2021, Dinterman & Katchova, 2021). Wyche (2021) finds that property value is a statistically significant variable associated with a decrease in discharged cases because land values increased the likelihood of trustee dismissal (Wyche, 2021). The importance of land value as a statistically significant variable has been largely supported by the growing body of literature.

In seeking to observe which economic variables influence filing rates, a study by Dinterman and Katchova (2018) used a fixed effect model to determine that land values, interest rates and unemployment rates are major indicator variables of Chapter 12 filing rates at a state level (Dinterman & Katchova, 2018; Rabinowitz & Secor, 2022). In this model, they lag agricultural variables by a year, due to "lumpiness" in financial variables. They include a dummy variable for the previously mentioned BAPCPA as an indicator of Chapter 12's permanent installation in bankruptcy law. They find that the only negatively associated variable is that of lagged land values. They hypothesize that this is due to differing managerial reactions as land values fluctuate given certain levels of financial status (Dinterman & Katchova, 2018; Davies, 1996). This further supports the growing body of literature that points to agricultural land values as a reliable predictor of filing rates (Dinterman, Katchova & Harris, 2018). Similar research done by Dinterman and Katchova (2017) supports the theory that there is a link between farm financial stress, land values and farm bankruptcies (Dinterman & Katchova, 2017). The authors indicate that agricultural land values are a worthwhile bankruptcy indicator variable in Chapter 12 regression outcomes (Dinterman & Katchova, 2017). Wyche (2021) further supported the use of land values as a significant indicator variable (Wyche, 2021). This was accomplished by using a NASS district level of observation for the state of Georgia, finding that land values remain significant at a more disaggregate level of observation (Wyche, 2021). In their regressions, Dinterman and Katchova (2018) found that unemployment rates and interest rates were positively and significantly associated with bankruptcy filing rates, which is explained through the assumption that higher unemployment rates often indicate less off-farm income, further straining a farmer's financial health (Dinterman & Katchova, 2018). The significance of unemployment figures is observed in initial research into Chapter 12 filings in which Key and Roberts (2006) found that an increase in state level unemployment rates significantly increased the rate of filings (Key & Roberts, 2006). Similarly, the significance of interest rates indicates that as rates increase, it becomes more difficult for a farmer to repay loans in the short term. Dinterman and Katchova (2018) found that government payments were significant when observing filing rates (Dinterman & Katchova, 2018). They determined that improvements need to be made to agricultural indicators so that supplemental income solutions, like increased government payments, could be used in the attempt to mitigate financial stress on farmers.

To our knowledge, there is sparse research into the role of government payments at the county or district level. Wu and Turvey (2020) recognized that government payments made directly to farmers are a stabilizing force in farm financials as they are becoming an increasing amount of total net farm income (ERS, 2021). Dixon, Ahrendsen, Settlage and Stam's (2004) panel fixed effect model observed the role that government payments, as well as unemployment figures, financial ratios and farm incomes had on Chapter 12 filing rates at a state level of observation (Dixon, Ahrendsen, Settlage & Stam, 2004). The purpose of their research was to determine what, if any, economic variables impact Chapter 12 filing rates. They determined that government payments did indeed aide in decreasing Chapter 12 filing rates. Their findings are similar in nature to previously mentioned studies, in that they also found that unemployment rates and debt-to-asset ratios, as well as other financial ratios, and farm structure types were positively associated with bankruptcy filings.

Of specific interest to this research is that Dixon et al. (2004) found that government payments lessened the Chapter 12 filing rates and were significant indicators of rates over time. (Dixon et al., 2004). Government payments, as recognized by Dixon et al. (2004), are often vital to an agricultural operation's financial success, especially in times of natural disasters. They went on to add that animal producers receive downstream benefits from government payments to crop producers, in the form of cheaper feed prices (Dixon et al., 2004). Supporting literature is accomplished by Key and Roberts (2006), in which a probit regression model was used. They observed the impact of government payments on operation survivability and farm size. Finding that "(government) payments are negatively associated with farm exit rates" (Key & Roberts, 2006). Specifically, an increase in government payments at the acre level was positively associated with farm survivability in the following five years (Key & Roberts, 2006). This is statistically significant with small to medium size farms, citing also that lagged government payments were positively associated with farm size over time. This might indicate that not only do government payments increase farm survivability but that these payments may also increase operation size over time. Interestingly, Key and Roberts (2006) found that government payments were important for farm survival both for farmers who have off-farm income streams as well as those who do not (Key & Roberts, 2006).

Wu and Turvey (2020) observed the impacts of the US-China trade war on Chapter 12 filings aggregating at the state level. They employed both an ordinary least squares (OLS) regression as well as a panel fixed effect model, as utilized in previous research. Wu and Turvey included previously proven variables in their models, such as loan interest rate data, GDP amount and a government payment variable. This research compiled annual government payment data and divided by 12 to establish a monthly payment subsidy which was then lagged by one year (Wu & Turvey, 2020). It is important to note that they were interested in trade war related government payments, specifically the Market Facilitation Program (MFP), and used a dummy variable to indicate when those payments would have occurred. They found that the government payments had varying impacts, concluding that this was due to the delayed nature of payments which can arrive in the farmer’s account too late to make up for operational losses. With soybeans being the major agricultural export affected by the U.S-China trade war, they also controlled for variables that affected soybean production. U.S. wet areas were used as a proxy for flooding which can negatively affect soybean production and in turn drive farms closer to filing for bankruptcy. As modeled initially by Dinterman and Katchova (2018), Wu and Turvey (2020) applied their reasoning to bankruptcy rates per 10,000 farms, for ease of interpretation. The GDP variable was at the national level, which differed from previous research done at the state level, yet they found that GDP was negatively associated with filing rates. This is supported by the idea that an increase in an economy’s health generally translates to stabilized incomes and reduced financial risks (Wu & Turvey, 2020). Following results from prior research, they found that nonreal estate farm loans, were a significant indicator. Interestingly, they found that the effective interest rates were negatively associated with filings rates. Citing that these higher rates likely decrease credit demand, which can in turn reduces solvency risk while increasing credit supply (Wu & Turvey, 2020).

Dinterman and Katchova (2018 & 2021) used farm debt to asset ratios in their models to act as a financial measurement for farming operations. We have chosen not to include such financial ratios in our models. The primary reason being that it is difficult to ascertain such ratios accurately at an aggregate level beyond the specific operation.

Chapter 4

Data

This research documents the role that governmental, agricultural, and financial factors play on the number of Chapter 12 bankruptcy filings and active cases at a county, district and state level. This chapter introduces the various data points, the source of collection, the level of observation and our logic behind their inclusion. The next chapter covers the econometric methods used for this analysis. Our most disaggregate level of observation is at the county level which includes 3,073 counties over the years 2008-2020. This provides us with 39,949 observations over the 13-year period. We limit our scope to only the contiguous United States, dropping Hawaii, Alaska, and all territories. To establish a complete and up to date county list requires the merging of numerous federal county datasets. This is due to state level changes made to county designations. We compile county lists with their accompanying Federal Information Processing System codes (FIPS) from the Natural Resource Conservation Service (NRCS), the United States Census, the Farm Service Agency (FSA), the U.S. Census of Agriculture (COA), National Agricultural Statistics Service (NASS), the Bureau of Labor Statistics (BLS) and the Bureau of Economic Analysis (BEA), along with various state governments used to verify FIPS categorizations. We encounter special instances in which independent cities are considered as county level entities. This is not generally supported by the FIPS codes. In these special circumstances, we find the county body which these independent cities are attributable to and treat them as a proxy of that county. In doing so we ensure that there are no unbalanced aspects in our data set. This is important in maintaining that each variable has an accurate measurement associated with the correct geographic and yearly observation. By being thorough in our county list, we ensure that all counties or recognized bodies in the contiguous U.S. are accounted for.

The Federal Judicial Center's Integrated Data Base (IDB) acts as the main source of Chapter 12 filing reports, offering a comprehensive and thorough bankruptcy data set. As we mentioned previously, the courts have a unique time measurement called a snapshot period which captures the bankruptcy activity occurring in the courts at that specific time. We collect the year from this snapshot period and use that as our yearly indicator for both filed and active cases.

Sources

This research uses bankruptcy data gathered from the IDB. The federal government uses this system to document court cases across the country, regardless of the chapter. For the sake of this research Chapter 12 filings are parceled out to create a unique data set of strictly Chapter 12 case observations. The IDB data does not capture every county instead it captures only those counties that have bankruptcies filed or active cases at a given time. Within this set of specific cases exist cases that are either filed as another chapter and transferred to Chapter 12 or those that were originally filed as Chapter 12 and were subsequently transferred to another chapter. In this research, we assume that filings, while not an overall indicator of the financial health of an operation, are a strong indicator of financial stress in a particular geographic area. Thus, we capture all Chapter 12 filings whether they were initially filed as 12 or transferred to 12. The IDB data records various time periods for the case, including initial filing date as well as closing date. Each case has a unique case key identifier, ensuring that we are capturing unique observations in our data. We capture county and state values for the IDB using the FIPS codes.

The IDB data contains the Federal Information Processing System (FIPS) code for each case. FIPS codes are a set of federally used and recognized codes that are unique identifiers for a county and state. These codes consist of five digits with the first two digits indicating the associated state and the latter three indicating the associated county. In adhering with our desired level of observation, observations with a FIPS code for states and territories that fall outside the contiguous U.S. requirement are dropped. These FIPS codes allow us to merge observations across data sets, as they are generally identical across agencies, though there are some exceptions, which we correct. The use of FIPS codes allows us to connect our independent variable observations to our dependent (filed and active numbers), allowing us to observe the impacts at each level of observation. The FIPS codes provide us with state level indicators, given the first two numbers of their code. However, to create a list of NASS districts, we gather data sets from both NASS and the COA to link NASS districts to their respective counties. By approaching this research at varying levels, we aim to determine the most effective and robust level of observation while capturing the most significant independent variables.

Certain independent variables are adjusted for inflation. These variables include GDP, net farm income (NFI), land values, and all government payments. We adjust the current dollar values of these variables into real 2020 values. This is accomplished by collecting consumer price indexes (CPI) from the BLS for each year from 2008 to 2020. We then transform our chosen variables into real values by the following formula:

$$Real\ value\ in\ X = current\ Value\ Y * \left(\frac{CPIx}{CPIy}\right)$$

We also scale several of our variables for ease of interpretation. Our government payment and land values categories are scaled down by one million and one thousand dollars, respectively.

Governmental Factors

We collect agricultural-specific government payment information using the FSA historical payment database. These payment files detail the amount of payment made and breaks it down by FSA office location and program payment type. Based on the FSA office location, we assign payments to their respective counties using FIPS codes. Payment information is collected from 2008 through 2020. These programs can change after each new Farm Bill, or introduction of additional appropriations that are administered by FSA. As a result, we create government payment categories for ease of use and interpretation. We create the following categories for our government payments; Ad Hoc, Conservation, Safety Nets Crops, Safety Nets Dairy, Marketing, and Other. To create accurate categories, we group payments together by their similarities in purpose. The Ad Hoc category measures payments made for various forms of disaster, this can include natural disasters or trade related disasters. These forms of payment generally fall outside the realm of safety net payments. Wu & Turvey (2020) included a dummy variable for the Market Facilitation Program (MFP) payments which were made to support farmers throughout the China-US trade war (Wu & Turvey, 2020). Conservation payments are an aggregation of payments made for environmental efforts, like the Conservation Reserve Program (CRP), and grassland/grazing programs. Our Safety Net category is a grouping of various programs aimed at providing financial stability in the agricultural market, such as Agriculture Risk Coverage (ARC) and Price Loss Coverage (PLC) payments. Our Other category is comprised of programs that could not easily fit into the previously mentioned categories, these include things like organics payments. Research like that seen in Key and Roberts (2006) and Dixon et al. (2004) supports the use of government payments in our regressions as a possible indicator variable in Chapter 12 numbers.

The breakout of government payments into separate categories is an integral part of understanding the impact these programs have on financial health of farmers. Ad hoc payments and Safety Nets are based on programs that a farmer cannot always calculate into managerial decisions as they are not steady income streams. Thus payments that do not provide expected income can be indicators of previous financial troubles that are being mitigated in the current period. However, programs in the Conservation category and some programs in Other can be treated by a farmer as a steady income flow. Due to this, these payments act as a form of regular income and may influence an operators' managerial reactions to financial troubles. The presence of regularly scheduled government payments may be reflected in the increase of active cases within the court system, which we will discuss in further detail in our results.

The FSA records the government payments made to the respective county FSA office. Due to this we use the county FSA office as the proxy for farmers that are receiving payments in that county. We are not attempting to capture the location of the individual receiving payments but instead we assume that the payments distributed to a county FSA office are impacting that local economy.

Agricultural Factors

The purpose of the agricultural factor is to determine whether there could have been any adverse events that impacted either the yields of the farm or damaged the financial standing of the farm. Financially strenuous events could push a farmer closer to filing for some form of bankruptcy. In this case the USDA Secretary of Agriculture disaster declarations were compiled, and cross referenced with FEMA's disaster declarations. USDA's declarations were from 2012 onward, as such, were not suitable to use, given our period of observation. The FEMA declarations were then used to determine a binary variable for natural events that could impact an operation's bottom line. Each state has different geographical conditions which do not change overtime and as such could impact our dependent variable. Following a method employed by Wu and Turvey (2020), we control for the geographic fixed effects by introducing a dummy variable into our regression models.

Previous literature has included a form of price variable, such as historical soybean prices (Wu & Turvey 2020). However, we do not apply specific commodity prices as they cannot be linked to the operations present in our data set. As a result, we have opted to forego the use of commodity prices in our regressions. This variable may be explored in subsequent research, however, we believe this is not a limiting factor as we capture farm income that is a function of price levels for the geographic areas agricultural activities.

We collect farm financial records as a proxy for financial health of a geographic areas' agricultural activities. These records are collected from the BEA's Historical Farm Income and Expense reports. Upon collecting these reports, we subtract the government payments from the NFI at the county and yearly levels to avoid collinearity in our model. We record negative NFI measurements in our data set, it is known that operations can and will lose money from year to year, especially net of government payments.

The number of farm operations has previously been an important variable for consideration, as such we include this in our regressions (Key & Roberts, 2006). These are provided by the USDA's COA which is run in 5-year cycles. We import the COA for the years 2007, 2012, and 2017, which are the most current measurements of farm numbers. Since this provides us with only three total years of data, we interpolate between years and extrapolate beyond 2017 to estimate values for farm number in years where there are no observations. This interpolation assumes a linear relationship between known points and makes estimations based on those points. The extrapolation follows this linear assumption beyond 2017, and is restricted to only positive values.

Financial Factors

The historical land values for the contiguous United States were collected from NASS for the years 2008 to 2020. The purpose of this information is to control for the value of land over time on the likelihood of a case being filed or remaining active in the court. While land values are at a state level, we use them at the county and district level as they act as a proxy for overall land prices. The values are listed as a yearly unit. Land values may fluctuate across irrigation types and county characteristics; however, we assume that at an aggregated level these differences normalize.

County level GDP is collected from the U.S. BEA. We use total level GDP amount; it is important to note that these county level data do not include government payments.

Below is the BEA's derivation for total county level GDP:

$$GDP_{cnty,\,i} = Compensation_{cnty,\,i} + Proprietors'\ income_{cnty,\,i} + (Gross\ Operating\ Surplus\ less\ Proprietors'\ income + Taxes\ on\ Production\ and\ Import\ less\ Subsidies)_{cnty,\,i}$$

The derivation for the county level GDP is important as it does not include government payments to farmers, which removes any concern of collinearity between our government payment variable(s) and our GDP amount. While GDP data is available by industry, we use an overall GDP because not every county has agricultural activity. Furthermore, a county level GDP offers us a glimpse into the financial health of the community and the agricultural supporting sectors within.

Following the example set in Wyche (2021) we use yearly interest rates. These interest rates are collected from the Federal Reserve Bank of Kansas City. We opt to follow previous examples and use yearly effective interest rates for non-real estate agricultural loans. These rates are recorded quarterly, to create a yearly value we add the quarterly values together and divide by four to establish a yearly average effective interest rate. We introduce unlagged and lagged interest rates; our lagged interest rates are lagged by one year.

As we discuss in previous chapters, unemployment figures have proven to be a valuable indicator variable in the study of Chapter 12 outcomes. As a result, we include unemployment figures in our regressions. Our unemployment figures are created by taking the civilian labor force data from the BLS and using their method to create an accurate rate across the different geographic levels of observation. This is accomplished by taking the proportion of unemployed individuals in the labor market and dividing that by the number of overall individuals in the labor force. The number of the unemployed and total number of labor force participants are aggregated as we move up in our geographic observations to provide an accurate unemployment measure.

Data Restrictions

Initially, we sought to use the USDA Secretary of Agriculture disaster declarations as our disaster indicator variable. However, these declarations began being recorded in 2012, instead of dropping 4 years' worth of bankruptcy observations, we decide to find another form of documentation that would accomplish the same goal. Therefore, we chose to use the FEMA historical disaster data set to indicate a disaster presence. FEMA and the USDA record disasters differently, the USDA focuses on agricultural related disasters, whereas FEMA records all disasters. They are both similar in that they have overlapping types of disasters tied to date and FIPS location of the disaster in question. We collect disasters from the FEMA declarations that include, hurricanes, tornadoes, severe storms, flooding, fire, freezing, and severe ice storms. While this is not necessarily a one-to-one match of the USDA declarations, we recognize that both entities cover similar disaster types. Collecting FEMA declarations that are similar to the agricultural disasters recognized in the USDA secretary allows us to create a proxy for agricultural disasters which covers our years of observation. In subsequent research we may consider using the USDA Risk Management Agency's (RMA) insurance payments as a proxy for the extent of the agricultural disaster.

Due to the nature of government payments, we assume that though a government payment might be filed in a specific year, the actual payment may not be realized for another year, if not longer. As a result, we consider introducing a lag variable for government payments. On that note, payments like Ad Hoc, which are disaster payments, are likely to get to a farmer long after the disaster in question has caused serious financial damages. Thus payments reflected in the Ad Hoc category are effectively lags of the occurrence of the disaster that is triggering the payment. Alternatively, the current period represents the current cash inflow within the geographic area that are reflected by these payments. Since we are currently unsure as to whether it is the occurrence of the event or the cash flow that is most important, we decide not to introduce a lag variable. We can also not reasonably assume that all payments within a category take extended time to be realized by an individual. Another confounding variable is that some payments, like Conservation payments, are annual and do not require a lag. While other payments like Ad Hoc and Safety Nets cannot be equated for as they are reactionary payments that may have varying levels of lagged distribution. Furthermore, there are structural changes in some of the farm bill programs that changes the way government payments are distributed. One such example is the 2014 farm bill that eliminated direct payments in favor for payments tied to price and/or yield variation. In further research we will consider the use of varying lag amounts and these structural changes.

Operation sizes must be interpolated and extrapolated to fill in the missing years. A possible limitation of this is that a linear relationship in farm numbers between years might not actually exist. We are operating on the assumption that farm numbers at the county level move on a linear scale, which results in farm number decimals which is not possible. This assumption of linear growth or loss could limit the interpretation of farm numbers, however, without more complete data this is our best possible option.

While we include the total number of farm operations, we recognize that it may be an imprecise indicator since only a portion of those farms will meet the requirements of Chapter 12, and as such will be eligible to file. That said, the existence of other farms in these areas provides a proxy for agricultural infrastructure that can be more supportive of financial challenges.

Chapter 5

Methods

Previous research on Chapter 12 has employed the use of panel fixed effects models (Wu & Turvey, 2020; Dinterman & Katchova, 2018). At the state and national level this model is effective because of nonzero dependent variable outcomes. Since we are pursuing such disaggregate levels of observations at county and district level, we have an abundance of zero dependent variable outcomes, as such, we need a model that manage these zeroes. We use a Poisson regression with fixed effects in this research, as it is better suited to deal with the zero issue. Like in the panel fixed effect model, we include a fixed effect in our Poisson regression to account for unobserved geographic variation. Our basic empirical model is:

$$(1)\quad Y_{ijt} = \alpha + \beta\ G_{ijt} + \gamma\ F_{ijt} + \delta\ A_{ijt} + \varepsilon\ X_{ijt} + \zeta\ T_{it} + e_i$$

where Y_i denotes our dependent variable; number of active and filed bankruptcy cases at the county, district, and state levels of observation. α acts as our constant term, *i, j* and *t* represent our unit of observation, geographic variable, and time, respectively. G is our government payments, which is either an aggregate single variable or is broken down into payment type categories, depending on the model estimated. These categories are Ad Hoc, Conservation, Safety Nets Crops, Safety Nets Dairy, Marketing and Other payments. F is our financial factor term which includes the NASS state-level land values, county level GDP, effective interest rates on non-real estate agricultural loans, and finally county level unemployment rates. We then have our agricultural variable group, represented by A, which includes farm numbers. Rounding out the variables in our model is X, which is a binary variable representing the FEMA declarations, indicating the presence of a disaster in each county. T acts as our time trend, including both t and t^2, to capture trends in bankruptcy cases over time. We then have α acting as our geographic fixed effect and e_i the error term.

Poisson Regression

The Poisson regression is an example of a generalized linear model (GLM), which is known for its generalization of typical ordinary least squares regressions (OLS) as it allows for numerous error type structures for independent variables (Coxe, Aiken, & West, 2009). This tolerance in error structure enables us to effectively apply this regression to our panel set, properly equating for the zero issue. Another important aspect of the Poisson regression is that the reported scores are nonnegative counts, which matches well with our bankruptcy numbers, as we cannot have negative cases active or filed. Poisson regression, in its specifications, excels at capturing discrete nonnegative values, inferring probability outcome events, and treating zero in a straightforward manner in a multiplicative model (Winkelmann & Zimmermann, 1995). Further supporting its use as our model of choice, in a Poisson regression there is a linear relationship between predicted scores and predictors, however the predicted scores are a natural logarithmic count[1]. We must assume that there is a conditionally Poisson error distribution, as opposed to normal distribution. As laid out in Winkelmann and Zimmermann (1995), the model for counts is the traditional Poisson model's distribution displayed as a probability function below.

$$(2) \quad P(Y_i = y_i) = \frac{exp(-\lambda_i){\lambda_i}^{y_i}}{y_i!}, \lambda \epsilon_{\mathbb{R}}^{+}, \; y_i = 0,1,2 \ldots$$

Where,

[1] In this Poisson Model, which is nonlinear in nature, the fixed effects are removed by conditioning on the sum over time of the dependent variable. In instances where the dependent is constant over time, 0 in the case of bankruptcy numbers. it is normal that these observations are dropped, as they are noninformative in the model and have no effect on parameter estimates.

$$(3)\ \ E(Y_i) = Var(Y_i) = \lambda_i\ (equidispersion)$$

To accommodate a vector of x_i of independent variables and model heterogeneity, the expected distribution of Y_i given x_i is determined:

$$(4)\ \ \lambda_i = E(y_i \mid x_i) = exp(x_i\beta) \quad i = 1, \ldots., N,$$

where x_i is a (1 x k) vector of covariates, and β is a vector of coefficients. The model assumes that the number of occurrences of an event Y_i, has a Poisson distribution for the i_{th} of N observations. y_i is the actual value of the random variable and λ_i is the parameter distribution equal to mean and variance of the event Y_i. The estimated model is a Poisson regression with fixed effect for panel data (Hausman et al., 1984), which assumes that:

$$(5)\quad E(y_{it} \mid x_{i1}, \ldots, x_{iT,} c_i) = c_i m(x_{it,} \beta), \qquad t = 1,2, \ldots, T$$

$$(6)\quad m\left(x_{it,} \beta\right) = \exp(x_{it}\beta)$$

Where y_{it} is Poisson distributed with the conditional mean expressed in Eq. 4, y_{it} and y_{is} ($t \neq s$) are independent conditional on x_{it} and c_i. c_i is an unobserved effect constant in time. This model allows for arbitrary dependence between c_i and x_{it}. The parameters β are estimated using the conditional maximum likelihood method (Hausman et al., 1984):

$$(7)\quad L(\beta) = \sum_{i=1}^{N} \sum_{t=1}^{T} y_{it} \log\left[p_t(x_i, \beta)\right]$$

The probability term assumes the following form:

$$(8)\ \ p_t(x_i, \beta) = \frac{m(x_{it,} \beta)}{\sum_{s=1}^{T} m(x_{is,} \beta)}$$

The fixed-effect Poisson estimator, which maximizes the loglikelihood function, exhibits very strong robustness properties, and is consistent under the assumption of conditional mean only (Wooldridge, 2002). The first way to interpret regression results is a straightforward way shared by typical OLS models. A one unit increase in the predictor variable will increase the dependent variable by one unit as well. However, this method can be limiting when observing unit changes in the transformation of predicted count data (Coxe et al., 2009). This brings us to the second interpretation of Poisson regression, being that we can observe results not as a one-to-one unit change, but as a probability measure. Negative and positive coefficients denote changes in outcome probability. This method of interpretation is accomplished by basic algebraic manipulation of the model.

Chapter 6

Summary Statistics

Table 1 provides summary statistics for our county level panel data. The number of observations comes from a United States total county number of 3,073 unique counties over 13 years. Due to the complicated nature of county classifications, some independent cities, which are treated as counties in some states, are grouped together with their associated county, as mentioned previously. Where necessary, variables for independent cities were aggregated into the county they were assigned. This includes variables such as GDP. In creating a universal county list using the FIPS codes, some counties were renamed and/or changed their FIPS designation. To correct for this, counties that were renamed or redesignated have been identified and corrected using state government resources to determine and create the most up to date county list. This data set is balanced, indicating that each geographic entity is represented in the data during all included time periods.

Table 1

County Summary Statistics

Variable	Observation	Mean	Std. Dev.	Min	Max
Cases Filed	39,949	0.16	0.58	0.00	29.00
Cases Active	39,949	0.66	1.52	0.00	59.00
GDP Amount	39,949	6.17	26.56	0.01	799.20
Net Farm Income	39,949	0.02	0.08	-0.19	2.54
Land Value[1]	39,949	3.91	2.31	0.54	20.19
FEMA Declarations	39,949	0.27	0.45	0.00	1.00
Yearly Effective Interest Rate	39,949	4.45	0.55	3.71	5.58
Unemployment Rates	39,949	0.06	0.03	0.01	0.29
Total Government Payments[2]	39,949	4.E+06	7.E+06	0.00	3.E+08
Ad Hoc[2]	39,949	1.69	5.26	0.00	269.48

Conservation[2]	39,949	0.58	1.19	0.00	17.92
Safety Nets Crops[2]	39,949	1.67	3.22	0.00	44.47
Safety Nets Dairy[2]	39,949	0.08	0.48	0.00	31.31
Marketing[2]	39,949	0.02	0.26	0.00	23.45
Other[2]	39,949	0.08	0.33	0.00	18.32
Total Number of Farms	39,949	676.47	546.03	0.00	6496.00
Time	39,949	7.00	3.74	1.00	13.00
Time Squared	39,949	63.00	53.83	1.00	169.00

1 - Variable Scaled by 1 thousand 2020 $
2 - Variable Scaled by 1 million 2020 $

Because we are observing all counties in the U.S., and not just those where agricultural production exists, we observe that many of our minimum values are zero. This holds with our expectations and explains why we pursued a model that is better suited for numerous zeros in the dependent variable. It is important to note that the maximum for cases active is considerably higher than the maximum for cases filed. This holds true with the previous literature stating that cases tend to remain in the courts for increasing amounts of time to fulfill repayment plans (Dinterman & Katchova, 2018). Net farm income has negative minimum values, which is expected as there can be a loss of agricultural income at a given time. As with GDP, income is measured in millions of current 2020 dollars. Land values are recorded in our data as state level values, as such, they do not change across observation levels, we maintain that state level land values remain a valuable financial indicator even at the county level. The unemployment rates are interpreted as percentages. The government payment categories are scaled by one million, again for ease of interpretation. Our minimums and maximums capture the fact that not every county will receive a certain category of payment. Total farm numbers also have a minimum of zero, holding to the assumption that not every county has agricultural activity. Finally, our variables *t* and *t2* are our introduced time trend. This will remain the same across Tables 1, 2, and 3

Table 2

District Summary Statistics

Variable	Observation	Mean	Std. Dev.	Min	Max
Cases Filed	3,952	1.59	2.56	0.00	38.00
Cases Active	3,952	6.68	7.86	0.00	79.00
GDP Amount	3,952	62.33	141.16	0.73	1601.17
Net Farm Income	3,952	0.22	0.57	-0.54	11.98
Land Value[1]	3,952	3.97	2.58	0.54	20.19
FEMA Declarations	3,952	0.50	0.50	0.00	1.00
Yearly Effective Interest Rate	3,952	4.45	0.55	3.71	5.58
Unemployment Rates	3,952	0.06	0.02	0.02	0.17
Total Government Payments[2]	3,952	3.87E+07	6.07E+07	0.00	1.36E+09
Ad Hoc[2]	3,952	17.13	46.08	0.00	1303.55
Conservation[2]	3,952	5.85	9.74	0.00	66.67
Safety Nets Crops[2]	3,952	16.92	27.43	0.00	271.94
Safety Nets Dairy[2]	3,952	0.76	3.47	0.00	120.60
Marketing[2]	3,952	0.16	1.71	0.00	65.79
Other[2]	3,952	0.77	2.46	0.00	35.36
Total Number of Farms	3,952	6838.14	5617.55	15.80	52785.40
Time	3,952	7.00	3.74	1.00	13.00
Time Squared	3,952	63.00	53.84	1.00	169.00

1 - Variable Scaled by 1 thousand 2020 $
2 - Variable Scaled by 1 million 2020 $

As mentioned previously, the district level is an aggregation of counties that share agricultural and geographical similarities. These districts have been created by the USDA NASS.

Each county was linked using the FIPS codes with its respective NASS district to create this level of observation. As expected, our minimum for cases filed and active did not change, while our maximums did change. As with the county level, our GDP and NFI are both divided by millions of dollars and adjusted for inflation to current 2020 dollars. We do not observe variation in yearly effective interest rates on non-real estate agricultural loans because their values only vary by year and not geographic area.

Again, we observe that our government payments are not always distributed to every district. This could be a result of disaster presence, eligibility to receive payments, or agricultural activity in each district. Regardless of the explanation, the minimum value for government payments at the district level meets our expectations. A change occurs for farm numbers as we move from county level to district level. We observe decimals in the farm size categories resulting from the interpolation and extrapolation used to gather farm numbers in missing years.

Table 3

State Summary Statistics

Variable	Observation	Mean	Std. Dev.	Min	Max
Cases Filed	624	10.05	10.79	0.00	78.00
Cases Active	624	42.31	38.16	0.00	216.00
GDP Amount	624	394.73	478.73	31.25	3090.31
Net Farm Income	624	1.39	2.44	-0.96	21.55
Land Value[1]	624	4.62	3.59	0.54	20.19
FEMA Declarations	624	0.72	0.45	0.00	1.00
Yearly Effective Interest Rate	624	4.45	0.55	3.71	5.58
Unemployment Rates	624	0.06	0.02	0.02	0.14
Total Government Payments[2]	624	2.45E+08	3.74E+08	0.00	3.29E+09
Ad Hoc[2]	624	108.51	279.56	0.00	2605.58
Conservation[2]	624	37.04	55.61	0.00	400.15

Safety Nets Crops[2]	624	107.18	156.69	0.00	1003.52
Safety Nets Dairy[2]	624	4.82	17.80	0.00	289.88
Marketing[2]	624	0.99	6.88	0.00	101.24
Other[2]	624	4.87	12.48	0.00	117.24
Total Number of Farms	624	43308.22	39445.16	923.00	248809.00
Time	624	7.00	3.74	1.00	13.00
Time Squared	624	63.00	53.88	1.00	169.00

1 - Variable Scaled by 1 thousand 2020 $
2 - Variable Scaled by 1 million 2020 $

Table 3 represents the summary statistics for our state level of observation. As with county and district levels, we observe normal and expected minimums and maximums. Our number of observations, 624, is a product of 48 states over 13 years. As previously mentioned, Hawaii and Alaska were dropped from our data sets. It could be initially expected that all government payment categories would be represented at the state level, however, we assume that not all states will receive agricultural payments. This could be a result of agricultural activity, specific payment needs in a state, or a lack of qualification of farms in a specific state. Adhering with our expectations the total number of farms increases significantly as we move from the county to state level of observation. We observe a shift in the magnitudes for the means of both filed and active cases as we move from county to state levels. This indicates that our county level is capturing greater agricultural variation occurring within the state, as opposed to simply capturing variations on a state-to-state basis.

Unlike the regressions for the county and district level of observation, our state level regression uses all observations.

Chapter 7

Results

We estimate the poison fixed effects model, first considering that government payments are a single variable, denoted as Model 0. We can observe that government payments are significant, but the coefficients are difficult to interpret since they are so small, it is also possible that the specific nature of payments influence our regressions, but we cannot observe them at this level of aggregation in payment. The significance of payments warrants the payment breakouts we use to determine what payment types are drawing significance in the model. As previously mentioned, we add a time trend to control for the nature of Chapter 12 cases over time, although there is no relationship with filed cases.

Table 4

Model 0 - Aggregate Government Payments

Cases Filed	*County*		*District*		*State*	
GDP Amount	-0.02364	***	-0.00486	***	-0.00164	***
	(0.00715)		(0.00111)		(0.00035)	
Net Farm Income	-0.66147	***	-0.08023	**	-0.00264	
	(0.19339)		(0.03341)		(0.02475)	
Unlagged Land Value	-0.26519	***	-0.31002	***	-0.21388	***
	(0.07401)		(0.09422)		(0.08323)	
Lagged Land Value	0.00023	***	0.00028	***	0.00022	***
	(0.00007)		(0.00009)		(0.00008)	
FEMA Declarations	0.00802		-0.00627		0.05404	
	(0.04073)		(0.04003)		(0.06102)	
Lagged FEMA Declarations	0.00662		-0.01356		0.10642	
	(0.04400)		(0.06304)		(0.07647)	
Unlagged *Yearly Effective Interest Rate*	0.34324	***	0.35408	***	0.43459	***
	(0.04214)		(0.04666)		(0.05482)	
Lagged *Yearly Effective Interest Rate*	-0.16194	***	-0.16601	***	-0.17819	***
	(0.04462)		(0.05239)		(0.06139)	
Unemployment Rates	9.48011	***	8.98151	***	8.01120	***

	(1.24931)		(1.75950)		(2.07873)		
Total Government Payments	4.60E-09	***	5.47E-10		3.27E-10	***
	(1.48E-09)		(4.82E-10)		(1.14E-10)	
Total Number of Farms	-0.00013		-0.00005		-0.00003	*
	(0.00020)		(0.00005)		(0.00002)	
Time	-0.03510		-0.03937		0.01374	
	(0.06406)		(0.07923)		(0.08923)	
Time Squared	0.00404		0.00405		-0.00025	
	(0.00403)		(0.00500)		(0.00570)	
N used	22932		3809		624	

***, **, * denotes significance levels of 0.01, 0.05 ,0.1 respectively

Standard Error in parenthesis

As we discussed in Chapter 5, the Poisson regression drops several observations, to reflect this we have included in our regression tables an *N Used* variable. This represents the total number of observations used in the regression after the observation drop.

Table 5

Model 0 - Aggregate Government Payments

Cases Active	*County*		*District*		*State*	
GDP Amount	-0.01625	***	-0.00273	**	-0.00089	***
	(0.00405)		(0.00107)		(0.00023)	
Net Farm Income	0.35239	***	0.09125	**	0.04268	***
	(0.12845)		(0.04404)		(0.00950)	
Unlagged Land Value	-0.23507	***	-0.22281	***	-0.15964	***
	(0.05106)		(0.05479)		(0.06807)	
Lagged Land Value	0.00004		0.00003		-0.00001	
	(0.00005)		(0.00006)		(0.00010)	
FEMA Declarations	0.02566		-0.01725		0.03048	
	(0.01895)		(0.02134)		(0.02842)	
Lagged FEMA Declarations	0.05842	***	0.06822	*	0.09333	**
	(0.02265)		(0.03553)		(0.04626)	
Unlagged *Yearly Effective Interest Rate*	0.03997	**	0.07686	***	0.17028	***
	(0.02005)		(0.02556)		(0.03084)	
Lagged *Yearly Effective Interest Rate*	-0.08944	***	-0.09054	***	-0.10246	**

	(0.02589)		(0.02920)		(0.05096)	
Unemployment Rates	8.02569	***	8.39263	***	8.19573	***
	(0.93585)		(1.31392)		(1.43246)	
Total Government Payments	2.17E-09	*	3.59E-10		2.87E-10	**
	(1.27E-09)		(5.21E-10)		(1.13E-10)	
Total Number of Farms	-0.00015		-0.00007	*	-0.00003	***
	(0.00020)		(0.00004)		(0.00001)	
Time	0.34859	***	0.35894	***	0.40922	***
	(0.03990)		(0.05010)		(0.07706)	
Time Squared	-0.01685	***	-0.01765	***	-0.02171	***
	(0.00242)		(0.00308)		(0.00503)	
N used	22984		3822		624	

***, **, * denotes significance levels of 0.01, 0.05 ,0.1 respectively
Standard Error in parenthesis

Table 5 shows the results of our Model 0 active case regression, again we observe government payments as a significant variable. It is interesting to note that in these regressions our time fixed effects are not significant when looking at cases filed but highly significant for cases active. This will be explained in more detail in our active case regression analysis.

Filed Cases

Table 6 displays our regression results for our filed case numbers with disaggregate government payment categories. As expected, we observe that GDP and NFI are significant and negatively correlated with filings rates at the county and district levels. GDP is very significant at the 0.01 level across all observations, while NFI loses significance at the state level. It is surprising that net farm income is not significant at the state level, however, the coefficient remains negative. The negative coefficients for both GDP and NFI are explained through the assumption that increased GDP and NFI represent an increase in overall financial health of an area. GDP has been used in previous research and has been found to be a worthwhile indicator variable, this is likely in part because GDP acts as a metric for county, district, and state financial health. The lack of NFI's significance at the state level may be indicating that the state level aggregation is unable to adequately capture the relationship of NFI with Chapter 12 filings, as opposed to county and district levels which are able to observe the relationship due to their more specific relationship between agricultural activities and bankruptcy cases at the local geographic level.

Table 6

Model 1 - Government Payments Categories

Cases Filed	*County*		*District*		*State*	
GDP Amount	-0.02353	***	-0.00480	***	-0.00172	***
	(0.00711)		(0.00110)		(0.00032)	
Net Farm Income	-0.67232	***	-0.09017	*	-0.01725	
	(0.24327)		(0.05451)		(0.03007)	
Unlagged Land Value	-0.24619	***	-0.28341	***	-0.20773	**
	(0.07511)		(0.09483)		(0.08859)	
Lagged Land Value	0.00021	***	0.00025	***	0.00022	**
	(0.00008)		(0.00009)		(0.00009)	
FEMA Declarations	0.00871		-0.00493		0.05288	
	(0.04074)		(0.04045)		(0.05844)	
Lagged FEMA Declarations	0.00770		-0.01181		0.12261	
	(0.04417)		(0.06321)		(0.07739)	
Unlagged Yearly Effective Interest Rate	0.34359	***	0.35244	***	0.40176	***
	(0.04260)		(0.04730)		(0.05374)	
Lagged Yearly Effective Interest Rate	-0.15968	***	-0.16313	***	-0.22766	***
	(0.04538)		(0.05116)		(0.06027)	
Unemployment Rates	9.79304	***	9.40869	***	7.05750	***
	(1.25918)		(1.76350)		(1.91830)	
Ad Hoc	0.00426	***	0.00048		0.00035	***
	(0.00157)		(0.00049)		(0.00012)	
Conservation	0.05281		0.00785	*	0.00009	
	(0.032830)		(0.00459)		(0.00102)	
Safety Nets Crops	0.00715		0.00084		-0.00004	
	(0.00542)		(0.00095)		(0.00021)	
Safety Nets Dairy	-0.01030		-0.00234		-0.00169	***
	(0.01358)		(0.00301)		(0.00051)	
Marketing	0.04777		0.00002		-0.00027	

	(0.07918)	(0.01114)	(0.00269)
Other Government Payments	-0.02595	-0.00098	-0.00064
	(0.04529)	(0.00963)	(0.00104)
Total Number of Farms	-0.00016	-0.00006	-0.00002
	(0.00020)	(0.00005)	(0.00001)
Time	-0.02907	-0.03411	-0.05928
	(0.06569)	(0.07806)	(0.08795)
Time Squared	0.00385	0.00394	0.00414
	(0.00411)	(0.00486)	(0.00572)
N Used	22932	3809	624

***, **, * denotes significance levels of 0.01, 0.05 ,0.1 respectively
Standard Error in parenthesis

Supporting previous literature, we find that land values are very significant across all levels of observation, never dropping below the 0.05 significance level for both un- and lagged values. There is an interesting coefficient change between unlagged and lagged values, switching from negative in the unlagged version and positive in the lagged version. We consider several possible explanations for this change in signage. The first explanation is that at higher land values, a would-be filer can sell their land to gather more disposable income possibly staving off the need to file. The second, and more robust explanation is that when land values are higher, individuals can borrow more using their land as collateral. Given the higher property valuations, the individual in question could borrow more against their asset. This would stave off the need for bankruptcy filing in the short term, providing momentary financial assistance. However, this would only delay a filing event, as the debts would need to be paid back in time, which could explain the positive lagged land value coefficient. These coefficients indicate a decreased probability of filing and an increased probability of filing for higher unlagged and lagged land values, respectively.

We expect that yearly effective interest rates would have significant effects on filing numbers. This expectation is supported in our regression outputs where we find that increased interest rates are correlated to a higher probability of Chapter 12 filings in the present term. This positive relationship is likely a result of the higher cost of borrowing. Filers can no longer borrow to repay current liabilities and as such must now file. This would indicate an increased probability of lower filed numbers when interest rates are higher in the present. Lagged interest rates could be a result of an increased credit supply, as discussed by Wu and Turvey (2020), due to the higher cost of borrowing. When rates are higher borrowing activity decreases, this decreased activity can negatively affect creditors. This may make creditors more willing to provide would be filers with increased lines of credit to repay current liabilities if prior periods saw decreases in new borrowers. Or it could incentivize the creditor to meet with the creditor outside of court and restructure debts in a way that immediately benefits the creditor.

As with previous research we observe that unemployment rates are very significant across all levels of observation. The regression results indicate that higher unemployment rates will result in the increased likelihood that a Chapter 12 case will be filed. This supports previous literature which stated that unemployment rates were significant indicators of filing numbers (Dixon et al., 2004).

Our government payment categories yield the most surprising results, we expect that government payments are negatively associated with filing numbers, since we assume that payments made to producers may alleviate financial stress. However, our output shows positive and significant coefficients for Ad Hoc payments at the county and state levels. This could be capturing the impacts that a financially stressful events like trade wars or disaster events may have on operations. Like the use of the MFP payments used in the case of Wu and Turvey (2020), where they sought to observe the impact that the MFP payments, a form of Ad Hoc payment, had on Chapter 12 numbers. It is possible that the Ad Hoc payments are not received in time to make an affected operations in an area financial whole and avoid having to file for bankruptcy. The opposite could be true of the Safety Net Dairy Category, where we observe the negative and significant coefficient, although only at the state level of aggregation. This could be a result of Safety Net payment's ability to recoup producer losses more effectively, however, it is not a robust finding across geographic areas.

It is important to note that a positive relationship between government payments and filings does not indicate that increased government payments increase bankruptcy numbers. It could mean that there is a form of correlation between those receiving government payments and increased financial downturns. It is possible that what we are capturing is operations struggling financially are pursuing government payments to help stabilize their income, especially in the presence of disastrous events. This may be a result of the inability of Ad Hoc payments to make an operation financially stable in time to avoid filing for bankruptcy. This could be a situation where increased lag periods may help us observe the role of delayed nature of disaster related payments more accurately. However, because we are only observing aggregate geographic data and not farm specific data, it is also possible that we are capturing the effect of government payments going to larger more financially stable operations and it is not being directed to relatively smaller operations that are still needing the bankruptcy court protection. To parse out this issue we would need to expand our dataset to include farm level data.

Active Cases

Table 7 displays the regression outputs for active cases. Our active case regression yields interesting results. For the most part, our indicator variables represent what we were expecting to see, however, we observe changes in significance for NFI, Conservation payments, and total number of farms. Active cases are an especially difficult metric, as they can be closed out of court for reasons, we do not observe that are dependent upon the trustee or filer discretion.

Table 7

Model 1 - Government Payments Categories

Cases Active	*County*		*District*		*State*	
GDP Amount	-0.01639	***	-0.00274	**	-0.00094	***
	(0.00411)		(0.00111)		(0.00022)	
Net Farm Income	0.20930		0.07301	*	0.03073	***
	(0.13464)		(0.04302)		(0.00827)	
Unlagged Land Value	-0.23117	***	-0.21479	***	-0.15343	**
	(0.05122)		(0.05452)		(0.06704)	
Lagged Land Value	0.00003		0.00001		-0.00002	
	(0.00005)		(0.00006)		(0.00010)	
FEMA Declarations	0.02345		-0.01852		0.02549	
	(0.01899)		(0.02135)		(0.02747)	
Lagged FEMA Declarations	0.05876	***	0.06917	*	0.10258	**
	(0.02275)		(0.03539)		(0.04680)	
Unlagged Yearly Effective Interest Rate	0.03436	*	0.06500	***	0.14691	***
	(0.02002)		(0.02494)		(0.03082)	
Lagged Yearly Effective Interest Rate	-0.10368	***	-0.10572	***	-0.14880	***
	(0.02648)		(0.03109)		(0.05125)	
Unemployment Rates	7.83369	***	8.00773	***	7.33559	***
	(0.94998)		(1.42307)		(1.46645)	
Ad Hoc	0.00274	**	0.00043		0.00032	***
	(0.00132)		(0.00053)		(0.00012)	
Conservation	0.02571		0.00535		0.00041	
	(0.02066)		(0.00363)		(0.00090)	
Safety Nets Crops	-0.00963	***	-0.00136	**	-0.00029	**
	(0.00350)		(0.00058)		(0.00013)	
Safety Nets Dairy	-0.01563	*	-0.00072		-0.00073	
	(0.00835)		(0.00107)		(0.00050)	
Marketing	0.01354		-0.00003		0.00184	
	(0.07674)		(0.00853)		(0.00238)	
Other Government Payments	0.03420	**	0.00849	**	0.00125	
	(0.01347)		(0.00414)		(0.00128)	
Total Number of Farms	-0.00010		-0.00006		-0.00002	**
	(0.00022)		(0.00004)		(0.00001)	

Time	0.33090	***	0.33995	***	0.35512	***
	(0.04081)		(0.05305)		(0.07868)	
Time Squared	-0.01575	***	-0.01642	***	-0.01833	***
	(0.00246)		(0.00317)		(0.00507)	
N Used	22984		3822		624	

***, **, * denotes significance levels of 0.01, 0.05 ,0.1 respectively
Standard Error in parenthesis

GDP, as with filed cases, is significant and negatively associated with active cases, this follows our expectations. Consistent with previous literature, GDP acts as a financial health indicator variable and as it increases, the probability of financial hardship decrease as well. We expect that NFI would be significant across all levels and negatively correlated with active case numbers. However, according to our results, NFI is only significant at the district and state level, with a positive coefficient. Repayment under Chapter 12 is dependent upon revenue streams; thus, the positive sign could be an indicator of a preference for creditors to remain in the court to capture more available funds from higher incomes. It also makes it less likely that cases are dismissed for lack of payment, resulting in a higher level of active cases. This explains why we are observing a positive association between higher NFI amounts and increased likelihood of active cases.

We expect that land values would be significant for both unlagged and lagged values, as it was for the filed case regression. This expectation is partially supported by our regression results for active cases. We observe unlagged land values maintaining significance while lagged land values are no longer significant. Our unlagged land values are significant at all levels of observation. We see that unlagged higher land values have a probability of decreasing active cases. This may be capturing the use of land as a method to repay debts. When land values are higher filers may sell land to repay debts and exit the court. As discussed in the filing regression this could also be capturing the use of increased land value as collateral for new loans to repay debts. However, unlike in filed cases, the lagged land value is not significant, which may indicate that the previous assumption is more likely.

Both unlagged and lagged interest rates on non-agricultural loans are significant across geographic levels. Again, we observe a sign change as we move from unlagged and lagged, which is surprising and complicates interpretation. We postulate that in the present, during periods of high-interest rates, there is likely to be fewer new borrowers. High rates indicate that borrowing money is more costly and would likely deter individuals from borrowing. This is cited by Wu and Turvey (2020), in which they posited that higher rates likely decrease credit demand and increasing credit supply. This decrease in new borrowers will likely negatively affect the creditor, as such they will likely want to recoup more debt from the filer. This would increase the time to completion for cases, increasing the number of active cases.

We assume that the opposite effect would be observed in the case of lagged higher interest rates. If rates are higher in the year prior that would mean the creditors are receiving higher interest payments in the present. This increased revenue stream could incentivize creditors from negotiating with filers since they would be under less financial pressure. When interest payments are higher the creditor will likely be under less financial pressure and would likely be more willing to negotiate, moving cases out of the court. Decreasing the number of active cases in the court.

The government payment categories are somewhat surprising, like in the filed cases. We assumed that the coefficients would reflect a decreasing probability of active and filed cases as government payments increase. However, Ad Hoc, Conservation, Safety Nets and Other payments are significant with different signs and at times at different geographic levels of observation. Ad Hoc payments are only significant at the district and state level with a positive coefficient. Safety Net payments for both crops and dairy have a negative coefficient, as we observed in the filed cases, although for dairy it is only significant at the county level. This would indicate that when payments occur it is related to lower levels of active cases, thus helping farms exit bankruptcy. We may also be observing the ability of filers to repay debts that they defaulted on due to lost income given severe price fluctuations. These safety net payments may be proportional to the amount lost and as such operators can repay their debts more effectively, this could also be reflecting the effectiveness of safety net payments to reach an operation in time to offset financial losses. While Conservation payments were positive and significant in the filer model, it is not significant for active cases. Finally, we have a positive and significant coefficient in the Other payments category indicating an increased probability of active cases at higher payment values. This is an instance where further breakout of government payments is warranted to determine which payments within this category are the driving factors.

It is interesting to observe that the total number of farms is negative and significant for active cases only at the state level. This can be explained through support networks amongst producers. In areas with higher numbers of farms there may be greater availability for financial support from not only other farmers but possibly from the local economy as well, however, this is not robust across our different geographic areas.

As expected, our time fixed effects are significant for active cases. Active cases, more so than filed cases, are reliant on time. Active cases are largely determined on the time it takes the cases to reach completion, which is why time variables are such significant indicators. Given our regression results for our time effects, we observe that active cases are increasing at a decreasing rate. This is consistent with results documented in Dinterman and Katchova's (2021) survival analysis where they found that Chapter 12 case times are increasing at a rate unseen relative to other forms of bankruptcy.

Chapter 8

Conclusions

This research observes the impacts that economic variables, and in particular payments related to government programs has on Chapter 12 bankruptcy filings and active cases. We include variables that have been used in previous research on Chapter 12 to varying levels of success. Indicator variables like GDP, NFI and land values are significant indictors for probability of bankruptcy filings and active cases. Consistent with previous research, we find that unemployment rates and interest rates remain significant indicator variables when considering Chapter 12 filing and active case numbers (Wu & Turvey, 2020; Wyche, 2021). As research into Chapter 12 continues, these variables will likely become increasingly relevant. Other variables like the number of farms and government payment categories had varying roles in our model estimations. We are slightly surprised to observe some of the signs of our government payments coefficients and the varying significances, although the results can be reasonably explained.

This research set out to observe the specific impacts that government payments had on Chapter 12 cases, and the results were mildly unexpected. We expected to observe negative coefficients with high levels of significance, surprisingly we observe only a handful of significant government payments and positive correlations. The role of government payments, while not what we initially expected, does not mean that federal payments are increasing the probability of filed or active bankruptcy case numbers. Instead, this research points to a correlation between government payments and the need for financial relief in the agricultural sector.

It is important to recognize that Chapter 12 occurrences are sparse, and as such building robust modeling can be a challenge. For our purposes, the Poisson regression is the model of choice. This allows us to effectively capture and observe relationships between our dependent and independent variables while methodically equating for numerous zeros in the dependent variable. However, moving forward, we seek to apply the economic reasoning and indicator variables used in this research to new models. We hope that in exploring other models we may be able to test the robustness between dependent and independent variables. One model under consideration is the Hurdle model, which would require that government payments be the first hurdle and a case filed or active would be the second hurdle. We are also considering introducing various lags to government payment categories as well as land values. further breaking out these categories while exploring longer term and potentially compounding effects.   We also consider further breaking out government payments to isolate what payments are significant indicators of active and filed cases, including controlling for some of the structural changes that have occurred in agricultural policy during our study period. These adjustments would be done in hopes of decreasing unnecessary noise in the model and building a more robust result output in further research.

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