THREE ESSAYS ON HOUSEHOLD FINANCE AND BANKING

BY

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DISSERTATION

Submitted in partial fulfillment of the requirements
for the degree of Doctor of Philosophy in Finance
in the Graduate College of the
University of Illinois Urbana-Champaign, 2023

Urbana, Illinois

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Abstract

My dissertation focuses on the relationship between the financial status of consumers and small businesses and their economic outcomes. The first two chapters examine bankruptcy behavior, and the third chapter investigates the impact of bank consolidations on small businesses.

The first chapter explores the effects of information technologies on the bankruptcy decision. The waves of digitization in recent decades have reached the U.S. bankruptcy system since the early 2000s, transforming it from a paper-based process into an electronic filing system. Exploiting the staggered adoption of the electronic filing system across 66 bankruptcy courts in the U.S., we investigate the impacts of information technology on bankruptcy behavior. The electronic filing system brought about two major changes to the bankruptcy process. First, debtors and lawyers gained the ability to file for bankruptcy online, reducing the time and travel costs associated with filing for bankruptcy. Secondly, they could also more easily access information about a broad range of bankruptcy documents, including past bankruptcy cases using the online database. By reducing costs, as most financial technologies do, the adoption of the electronic filing system may be expected to promote bankruptcy filings. However, we find the opposite effect and show that weekly bankruptcy filings significantly decreased after the digital transformation. Heterogeneity analyses are consistent with the hypothesis that the information channel plays a key role in changing bankruptcy behavior.

The second chapter examines the impact of the COVID-19 economic crisis on the universe of business and consumer bankruptcies in the United States. Historically, bankruptcies have closely tracked the business cycle and contemporaneous unemployment rates. However, this relationship reversed during the COVID-19 crisis. While aggregate filing rates were very similar to 2019 levels prior to the onset of the pandemic, filings by consumers and small businesses dropped dramatically starting in mid-March of 2020. Total bankruptcy filings declined by 31 percent between 2019 and 2020. Consumer and business Chapter 7 filings rebounded moderately starting in mid-April and stabilized around 25 percent below 2019 levels, while Chapter 13 filings stabilized around 55 percent below 2019 levels. These trends continued through 2021. We find evidence that expanded unemployment insurance and policies aimed at homeowners such as mortgage forbearance and foreclosure moratoria were significant drivers of the decline in bankruptcies, while the staggered timing of court shutdowns, state shutdowns, and eviction moratoria had no impact. We also find evidence consistent with short-run liquidity constraints preventing some debtors from filing during the initial phase of the pandemic, but these constraints were likely mitigated in the longer run by the Economic Impact Payments and other stimulus payments. Our results shed light on how the combination of economic shocks and relief measures implemented in 2020 led to heterogeneous effects on different sectors of the U.S. economy.

The focus of the third chapter is to investigate the role of banks in the transformation of regional industry structure. It is well established that bank financing is critical for the growth of small businesses, which have limited access to the bond or equity markets. However, we have little understanding about the heterogeneity effects of bank lending on small businesses although small businesses represent a diverse group of firms. This paper investigates how banks shape regional industry structure in the U.S. by selectively promoting the start and growth of small businesses. I show that when a bank expands their branch network by merger, the industry structure of the affected counties becomes similar to that of the regions where the acquiring bank already operated before the merger. This transformation brings three important policy implications: first, the convergence of local economic characteristics has made the U.S. regional economy more homogeneous, which could weaken absorption capacities of the economy to unfavorable economic shocks. Secondly, the growth of the affected industries doesn't entail the comparable growth of employment. Lastly, the industrial transformation changes the local labor market in favor of skilled workers.

Acknowledgments

I am deeply grateful to my advisor, Jialan Wang and comittee members, Heitor Almeida, Rustom Irani, and Julia Fonseca. I would also like to extend my appreciation to my fellow Ph.D. colleagues and friends whom I have met during my doctoral program for their invaluable encouragement, camaraderie, and intellectual discussions. I owe a debt of gratitude to my wife, Seojeong Oh, whose unwavering support has been crucial to my completion of the dissertation.

Table of contents

Chapter 1

The Effects of Information Technologies on the Bankruptcy Decision

1.1 Introduction

Bankruptcy protection allows businesses or households under severe financial distress to discharge or reorganize their unmanageable debts. It is one of the largest social insurance programs that the U.S. bankruptcy courts received more than 770,000 filings in 2019. Filing for bankruptcy is often complex, time-consuming and costly, with burdensome paperwork requirements that are often believed to deter businesses and households from needed relief. In 1996, the U.S. federal courts began developing an electronic filing system to replace the existing paper-based filing process. This paper examines whether the adoption of new information technology alleviated barriers to bankruptcy and reduced the costs of filing for businesses and households in financial hardships or changed the bankruptcy decision along other dimensions.

Administrative Office of the U.S. Courts (AOUSC) developed an early prototype of the electronic filing system in 1995 and encouraged district bankruptcy courts to adopt the new system. All bankruptcy courts in the 94 judicial districts launched the electronic filing system on a rolling basis between 1996-2006. The transformation brought about two major changes to the bankruptcy process. First, filers and lawyers gained the ability to submit necessary documents online without traveling several times to a court office during the bankruptcy process. Second, the electronic database enabled would-be filers to more easily access information about a broad range of bankruptcy documents, including past bankruptcy cases, and learn about the likely outcomes.

These changes might be expected to have several different effects on bankruptcy decisions. First, electronic filing system may be expected to reduce filing costs, leading to an increase in filings, especially for Chapter 7 cases where filers have lower income. Second, debtors could have improved accessibility to past bankruptcy documents and their outcome as the online database replaced paper-based archives. This would allow debtors to adjust their assessment of the costs and benefits of bankruptcy, and either increase or decrease the number of bankruptcies. The effect of this information channel could be stronger if we consider interactions among debtors as [1] find that information gained from peers significantly affects bankruptcy filing rates using

2008-2014 data. Finally, the increased accessibility of bankruptcy filers' information to the public could discourage bankruptcy filings due to concerns about social stigma. Although filers' personal information was already open to the public in the paper-based era, the online platform technically facilitated collecting the identities of bankruptcy filers in bulk with lower costs. The number of bankruptcy filings would decrease if this stigma channel were at play. Given these potential channels drive the number of bankruptcy filings in different directions, the overall effects of electronic filing are an empirical question.

Exploiting the staggered adoption of the electronic filing system with the generalized difference-in-differences framework, we find that the digital transformation significantly decreases the number of bankruptcy filings. In our sample from October 1999 to August 2005, weekly bankruptcy cases decrease by 17.13 per court district on average after the adoption of the electronic filing system, compared with the average bankruptcy filing rates prior to the transition. Thus, reducing the costs of filing unexpectedly led to a decrease in filing rates, indicating other factors play a larger role. The result is also not consistent with the social stigma channel's prediction.

We conduct a set of heterogeneity analyses to further investigate mechanism underlying the decrease in bankruptcy filing rates. First, we compare the results among the three major types of bankruptcy process: Chapter 7, Chapter 11, and Chapter 13. Each chapter has distinct schemes for assets liquidation and debt discharge, and a would-be filer can choose a chapter based on their preference and financial situations. In sub-sample analyses, we find that the number of Chapter 7 filings significantly drops after the digital transformation, while Chapter 11 and Chapter 13 filings don't show significant changes around the adoption dates. These results don't support the cost reduction and social stigma channels as these channels are not tightly correlated with bankruptcy chapters.

Among all the potential channels, the information channel is better explain the decrease in bankruptcy filings if would-be filers adjust their assessments on net benefits of bankruptcy after gaining more information through the electronic database. To more validate this channel, we examine the physical distance between filers and court offices. If the results come from learning and information acquisition, regions further away from court offices should see a larger decrease in filings relative to regions near court offices. If the electronic filing system reduces costs associated with bankruptcy, geographically distant regions should experience a relative increase in filings. If the electronic filing system promotes social stigma, all regions could experience similar levels of decline in filings. Our estimates show that filing rates in distant areas decrease more than in adjacent regions, confirming the validity of the information channel hypothesis.

As an additional test for the information channel, we look into changes in computer ownership among filers around the adoption date. Given that computer ownership is highly correlated with digital literacy and accessibility to the bankruptcy database, we consider it as a good proxy for improvement in information gains. We find that the share of computer owners in the Idaho bankruptcy court decreases after the adoption of the electronic filing system. This result confirms that the decrease in the number of filings after the adoption is closely related to accessibility to bankruptcy information in electronic format. Moreover, filing rates among computer owners decrease only in distant regions, further supporting the information channel hypothesis.

This paper contributes to the literature investigating drivers of bankruptcy decisions. [2] summarize suggested explanations by the literature focused on explaining the decades-long increase in bankruptcy filings since the early 1980s: an increase in household income risk, the role of greater idiosyncratic expense uncertainty, composition changes in the population, the cost of filing for bankruptcy, credit market innovations, the removal of credit ceilings. [3] find the close relationship between credit supply and personal bankruptcy rates using banking deregulation in the 1980s and 1990s. [4] find that liquidity constraints prevent some households from filing for bankruptcy. [5] find relative income differences among peers can stimulate excessive debt burden and increase bankruptcy risks. To the best of our knowledge, this is the first paper to investigate the effects of digital transformation on bankruptcy filing decisions.

Our paper is also related to a growing literature examining the impacts of digital transformation on financial decisions. [6] and [7] focus on the effects of decreasing costs driven by advances in financial technologies on the mortgage market. [8] find that financial market prices have become more informative since 1960 as the finance industry has grown and information technologies have revolutionized. [9] exploit the adoption of the EDGAR system and find that internet dissemination of corporate disclosures increases information production by corporate outsiders.

1.2 The Adoption of the Electronic Filing System

An early prototype of the electronic filing system was developed in 1995 by a small working group at the Administrative Office of the U.S. Courts (AOUSC). The AOUSC established a basic model for the electronic filing system, CM/ECF, including system software, model local rules of court, and materials to educate users. The U.S. District Court for the Northern District of Ohio first adopted an early version of the system in January 1996, and the electronic filing system was revised and implemented in the U.S. Bankruptcy Court for the Southern District of New York in the fall of 1996. The electronic filing system has been introduced throughout the federal courts on a rolling basis, and each judicial district was given some flexibility in how and when to implement the new system. Pilot programs were established in bankruptcy courts in five states by 1998, and the electronic filing system was integrated on a national level in early 2001. By the end of 2006, all bankruptcy courts in 94 judicial districts completed incorporating the electronic filing system into their court operations. Table 3.1 shows the adoption dates of the electronic filing system for 94 bankruptcy courts. Figure 3.1 visualizes the adoption dates, brighter colors denoting early adopted bankruptcy courts and darker ones for late adopted bankruptcy courts. As can be seen in the map, the adoption dates do not appear to follow any discernible geographic pattern, which is one of necessary identifying assumptions for our research design. Indeed, the adoption of the electronic filing system was the independent administrative decision of each bankruptcy court, so even adjacent districts in the same state had different adoption timings.

The electronic filing system's paradigmatic features are that: (1) filing and service of case documents is done electronically, (2) the court's case files are maintained in electronic format, and (3) the court's case files are accessible by the internet. Filing a document is accomplished by accessing the internet, logging on to the court's website with a court-issued password, entering basic information relating to the case and the document to be filed, and then transmitting to the court an electronic version of the document in a portable document format (.pdf). Once the document is filed, the court immediately serves the document on all parties by transmitting a Notice of Electronic Filing e-mail to registered counsel of record, which gives notice of the court filing and provides a hyperlink to the filed document and the docket sheet.

The electronic filing system has many advantages over the former paper-based filing and case records system[1]: documents can be filed with the court 24 hours a day, seven days a week, from any location with internet service; documents in the court's case file are accessible 24 hours a day, seven days a week, from any location; the parties, the public and the judge have concurrent access to the court's case files; the cost of filing and serving documents is reduced by the elimination of most paper, postage, photocopying and courier expenses; and the time necessary to file, serve or retrieve documents is reduced.

[1] A Recommendation for the uniformity of some CM/ECF protocols, New York County Lawyers' Association (2006)

Anyone can access docket information and electronic forms of documents filed by filers, judges, and clerk offices through the integrated electronic platform, the PACER system (Public Access to Court Electronic Records). Before the PACER system launched, bankruptcy courts provided dial-up services with a per-minute fee. In the early 2000s, PACER charged only $0.07 per page, or free if users don't want to copy or download documents ([10]). Furthermore, the electronic system has significantly expanded the amount of information one is able to access. An interested party can access the bankruptcy clerk's files electronically instead of asking for permission to rummage through the file cabinets of the clerk's office.

1.3 Conceptual Framework and Hypotheses Development

U.S. bankruptcy codes provide multiple options to filers based on how to discharge the debts and the type of their debts, for example, consumer or business. A filer faces different cost-benefit structures depending on which bankruptcy chapter they choose. Among all bankruptcy chapters, the majority of filers opt for the bankruptcy process under Chapter 7 bankruptcy, which allows a filer to immediately discharge unsecured debts after liquidating assets above exemption levels. Considering all costs and benefits incurred by the bankruptcy process, a debtor under financial distress would decide to file for bankruptcy if the debtor expects to gain positive net benefits. The following equation formally describes the net benefits of bankruptcy:

$$NetBenefits = max[D_{it} - max[W_{it} - E_{it}, 0] - C_{it}, 0] \tag{1.1}$$

where D_{ti} is the total value of debtor i's debts eligible to be discharged, W_{it} is household i's wealth net of secured debts, and E_{it} is exempt assets from liquidation. Exemption levels vary across states as shown in Table 3.2 . C_{it} denotes costs associated with bankruptcy filings including court filing fees, lawyer fees, negative effects on credit records, and social stigma.

The costs and benefits are subject to bankruptcy laws and court practices, which are often complicated. Judge's discretion also affects bankruptcy process and discharge rates, creating uncertainty around bankruptcy outcomes. Therefore, the equation of net benefits can be rewritten considering that dischargeable debts (D_{it}), the amount of liquidation ($W_{it} - E_{it}$), and the success of bankruptcy process cannot be determined precisely ex ante and rely on available information that a potential filer can acquire:

$$NetBenefits = \tilde{p_{it}} \cdot max[E[D_{it}|\Omega_{it}] - max[E[W_{it} - E_{it}|\Omega_{it}], 0] - C_{it}, 0] \tag{1.2}$$

where Ω_{it} is all available information for debtor i at time t. $\tilde{p_{it}}$ is a probability to successfully complete the bankruptcy process with discharging unsecured debts. A debtor would file for bankruptcy if the net benefits of filing is greater than zero using all information the debtor can attain. However, the decision could be not optimal if the debtor has only insufficient or biased information.

The digital transformation could shift the bankruptcy decision-making process through three major channels. First, electronic filing enables debtors or lawyers to file for bankruptcy without physically visiting the court or using expensive courier service. As most innovations in information technologies do, the digital transformation in the bankruptcy process is expected to reduce the time and traveling costs associated with a bankruptcy filing. This effect cuts down filing costs (C_{it}) in Equation (2), increasing net benefits of bankruptcy. The change in costs induced by eliminating physical distance to the bankruptcy court motivates our first hypotheses.

Hypothesis 1. The electronic bankruptcy process increases the number of bankruptcy filings by reducing costs associated with travelling to the bankruptcy court.

The second is the information channel. More information on bankruptcy outcomes would improve filer's ability to assess dischargeable debts (D_{it}) and liquidation ($W_{it} - E_{it}$). The electronic system allows debtors to access information on the universe of past bankruptcy documents filed by other debtors. Some of them are in similar financial situations to the potential filer. Referring to comparable cases, the potential filer could more accurately estimate dischargeable debts ($E[D_{it}|\Omega_{it}]$) and the amount of liquidation ($E[W_{it} - E_{it}|\Omega_{it}]$), which are essential to make a decision on whether filing for bankruptcy. The effects of the information channel depend on the direction of bias in estimating bankruptcy outcomes before the launch of the electronic system.

Hypothesis 2.1. The electronic bankruptcy process increases the number of bankruptcy filings if filers overestimate the net benefits of bankruptcy before the adoption of the electronic filing system.
Hypothesis 2.2. The electronic bankruptcy process decreases the number of bankruptcy filings if filers underestimate the net benefits of bankruptcy before the adoption of the electronic filing system.

Lastly, the new system expands the exposure of filers' personal information to the public. In light of the social stigma toward bankrupt individuals, debtors face higher bankruptcy costs (C_{it}) after the adoption of the electronic system compared to the paper-based process.

Hypothesis 3. The electronic bankruptcy process decreases the number of bankruptcy filings by strengthening negative social stigma.

Chapter 11 and 13 bankruptcy involve a more complicated process. Chapter 11 bankruptcy reorganizes filers' debts after renegotiating with lenders. Chapter 13 bankruptcy entails a means test and requires the approval of long-term repayment plans from the court. In contrast to Chapter 7 bankruptcy, bankruptcy outcomes from Chapter 11 and 13 filings depend more on the discretion of judges and the interests of stakeholders. The non-standardized nature of Chapter 11 and 13 bankruptcy process complicates calculations in costs and benefits ex-ante as well as the prediction of $\tilde{p_{it}}$.

1.4 Data

Our main data for bankruptcy filings come from Public Access to Court Electronic Records (PACER), where individual-level data are available. The PACER system is operated by Administrative Office of the U.S. Courts, and it allows users to obtain case and docket information from the all the U.S. bankruptcy courts in 94 judicial districts. Each district court maintains its own internal electronic system to receive and record bankruptcy files. The PACER system integrates those individual electronic systems and puts all information on bankruptcy cases in one place. It provides access to original documents filed by debtors, creditors, trustees, and judges during the whole bankruptcy process as well as basic case information such as filings date, discharge date, filer's address, attorney, and bankruptcy chapter.

We gleaned individual bankruptcy filing data starting October 1999 through August 2005 from 66 bankruptcy district courts. We don't use observations before October 1999 because only five bankruptcy courts adopted prototype electronic systems as a pilot program. Another important consideration for our sample period is Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA). BAPCPA took effect in October 2005, incurring additional costs in bankruptcy filings. For strategic motivation induced by the act, the number of bankruptcy filings began to rise a few months before the enforcement date and sharply plummeted in October 2005. Therefore, we also drop observations after August 2005 to remove volatile movements driven by the act.

During our sample period, 54 bankruptcy courts switched over to the electronic-based process and other 12 courts adopted the system before or after the period. Figure 3.2 shows how the adoption dates of the 66 courts are distributed. The adoption dates are well dispersed throughout the sample period since each district court independently decided when to adopt the new system. This dispersion allows us to make reliable comparisons between treatment and control groups, which is essential to apply the generalized difference-in-differences framework.

Table 3.3 reports summary statistics using bankruptcy filings in the 66 bankruptcy courts. One bankruptcy court receives an average of 299.6 filings per week. Chapter 7 bankruptcy filings are 224.6 per district, accounting for 73.9% of total weekly bankruptcy cases. Chapter 7 and 13 bankruptcy filings make up 99% of all bankruptcy cases. More than 96% of Chapter 7 filings are successfully dismissed with discharging debts, while 60.6% of Chapter 13 cases are dismissed without discharges. Judges often close a Chapter 13 bankruptcy case without discharge if the filer's repayment plan is not feasible or the filer fails to meet the repayment schedule as planned.

To verify that the adoption of the electronic system is not closely related to regional bankruptcy frequency or population, we split the sample by the timing of adoptions and compare key variables between early- and late-adopted bankruptcy district courts. The third column shows statistics for 33 early-adopted bankruptcy courts, and the fourth column for 33 late-adopted bankruptcy courts. The late-adopted district courts show slightly larger weekly cases on average, but the difference is not statistically significant, as shown in the fifth column. Population or the number of cases per 1,000 residents also doesn't show noticeable differences between early and late adopted groups. These results support our identifying assumption that the adoption of the electronic system is a plausibly exogenous shock to each region.

1.5 Empirical Approach

Although the AOUSC developed a model electronic platform and encouraged district courts to adopt the electronic filing system, each court was responsible for a decision about when and how to launch the new system. This was an administrative choice and hardly related to drivers of bankruptcy or economic status in the region. This exogenous nature of the adoption shock allows us to design reliable quasi-natural experiments. Exploiting the staggered adoption of the electronic filing system across judicial districts, we use the generalized difference-in-differences (DID) approach to dynamically construct treatment and control groups. A court district switching over to the new system serves as a treatment group around the timing of the adoption and other districts are considered a control group. This treated-control group setting changes dynamically as individual district courts introduce the system in different dates ([11]). Since 12 bankruptcy courts completed the digital transformation before or after our sample period, they remain as control groups throughout our tests. 54 bankruptcy courts shift between the control group and the treatment group during the sample period.

We set one year as an event window. Specifically, we compare weekly bankruptcy filings during the 52 weeks following the adoption date of the electronic system with filings during 52 weeks before the adoption date. Week 0, which contains the adoption date, is not included in the tests to mitigate noise around the date. For robustness, we also show results with a shorter window, 26 weeks after the adoption, and a longer window, 104 weeks after the shock.

Our main specification is constructed as follows, for judicial district i and week t:

$$filings_{it} = \alpha + \beta \cdot 1(post\ adoption)_{it} + \gamma_i + \lambda_t + \epsilon_{it} \tag{1.3}$$

where the dependent variable is the number of weekly bankruptcy filings, the indicator variable equals one after the adoption date, γ_i is district fixed effects, and λ_t is week fixed effects. Bankruptcy filing rates seasonally fluctuate in a year and have had a secular upward trend since early 1980s until the global financial crises. The week fixed effects absorb the time components, which commonly affect all districts. We also include district fixed effects to control the difference in time-invariant level effects between treated and non-treated districts. Bankruptcy filing rates could also be affected by local economic cycles or uneven changes in unemployment rates across regions. We additionally present results controlling for both district-quarter and week fixed effects to minimize noise from the local economic fluctuations along with nationwide seasonal variations. Standard errors are clustered at the district levels.

In addition to the generalized difference-in-differences approach, which compares averages in the pre- and post-period, we further dissect the estimation and event windows to investigate dynamic treatment effects over time according to the event study framework:

$$filings_{it} = \alpha + \sum_{\tau=\text{-}52}^{52} \beta_\tau \cdot 1(t=\tau)_{it} + \gamma_i + \lambda_t + \varepsilon_t \tag{1.4}$$

Consistent with the generalized difference-in-differences specification, the estimation window is set to 52 weeks before and after the adoption. To construct a balanced panel, we do not drop observations that are beyond 52 weeks before or after the event, but rather bin these observations by setting $1(t = -53) = 1$ if $\tau < -52$ or $1(t = 53) = 1$ if $\tau > 52$. This binning provides more precise estimations of fixed effects using a balanced panel. We include district-by-quarter and week fixed effects, and standard errors are clustered at the district levels. Moreover, we combine weekly indicators into eight-week bins to minimize the noise in high-frequency data and interpret results more clearly. The combined leads are τ = 1-8, 9-16, 17-24, 25-32, 33-40, 41-48, and 49-endpoint weeks. The combined lags are the corresponding pairs of weeks before the shock. The reference period is $\tau = -1$ to -8 and omitted from the regression. Therefore, β_τ can be interpreted as an average treatment effect for eight weeks at each combined bin relative to the reference period. Week 0 is not combined with any other weeks for symmetry.

1.6 Results

1.6.1 Baseline Results

We start with running Equation (3) using the full sample to examine whether the digital transformation changes the total number of bankruptcy filings and, if so, increases or decreases filings. Table 3.4 reports the estimates of the difference-in-differences regressions with three different lengths of the event window and two different sets of fixed effects. In column (3), the coefficient suggests that the number of weekly filings per bankruptcy district drops by 16.7 cases on average during 52 weeks after the adoption date, compared with the average bankruptcy filing rates 52 weeks prior to the transition. Given an average of 299.6 cases per district, the drop corresponds to approximately 5.6% of all filings. The magnitude of the effect is larger if we filter out noises caused by disproportionate regional economic cycles. In column (4), we include district-by-quarter fixed effects instead of district fixed effects to control for time-varying regional economic situations. The number of weekly filings drops by 17.1, which is slightly larger than the coefficient in column (3), and the statistical significance is still achieved at the 95% confidence level. Column (1), (2), (5), and (6) show similar results using 6-month and 2-year event windows. The estimates in all specifications are statistically significant, implying that the effects of the electronic system are persistent in the long term and not driven by a temporary drop induced by irrelevant shocks.

It is unlikely any factors that cause bankruptcy are closely correlated with the timing of the adoption of the electronic system in the bankruptcy court. To formally test this identifying assumption, we split the estimation window using the event study framework to present the dynamic effects of the electronic filing system around the adoption date. Figure 3.3 visualizes point estimates with 95% confidence intervals, binning every 8 weeks. Throughout the periods before the adoption date, all coefficients are not statistically different from zero, and we don't find any discernible trends. In the post-treatment periods, however, the number of bankruptcy filings significantly drops for six months following the adoption date. Between 6 and 10 months after the adoption, coefficients are not significantly different from zero at the 95% confidence level but still negative and statistically significant at the 90% confidence level. After ten months, bankruptcy filing trends continue to edge downward relative to the reference period ($t = -1$), and are statistically significant at the 95% level.

The decrease in bankruptcy filing rates driven by the digital transformation contrasts with the outcomes of information technology adoptions in many retail financial services that have seen positive demand effects after digital transformations. Information technologies increase demand for those services by substantially reducing frictions and transaction costs. Our empirical results suggest that the cost reduction channel doesn't play a major role in the digital transformation of the bankruptcy process. Although the bankruptcy filing process is notoriously time-consuming and document-heavy, the results imply this one-time cost could be much smaller than the benefits of being bankrupted. Therefore, we rule out Hypothesis 1, the cost reduction channel, as a potential main mechanism of the changes in bankruptcy behavior after the adoption of electronic filing system. Hypothesis 2.1 is also at odds with the empirical results. This hypothesis predicts an increase in filing rates as debtors attain more information from the electronic database provided that filers underestimated the net benefits of bankruptcy before the adoption of the electronic system. In the subsequent sections, we look into heterogeneity among different groups to more examine possible channels of the downward trends in bankruptcy filings.

1.6.2 Sub-Sample Analyses by Bankruptcy Chapter

Bankruptcy codes allow filers to choose a bankruptcy chapter based on their economic situation and preference. Each bankruptcy chapter differs in how to liquidate assets and discharge debts, inducing different types of filers. For example, Chapter 7 filers tend to be more liquidity constrained than Chapter 13 filers. Homeowners are more likely to opt for Chapter 13 to keep their house from liquidation. Large corporations typically file for Chapter 11 bankruptcy to continue to operate after the bankruptcy process, reorganizing debts instead of liquidating assets. Therefore, heterogeneous effects in results by bankruptcy chapter could shed light on which type of filers is more sensitive to the digital transformation. This analysis would also add insights into the possible mechanism of the drops in bankruptcy filings.

Table 3.6 reports difference-in-differences estimates by bankruptcy chapter using Equation (3). The event window is the 52-week before and after the adoption. Column (1), (3), and (5) include district and week fixed effects, and column (2), (4) and (6) include district-by-quarter and week fixed effects. We find that the coefficients in column (1) and (2) are close to those in column (3) and (4) of Table 3.4. However, as shown in column (5) and (6) in Table 3.6, the changes in Chapter 13 filing are close to zero and statistically insignificant. Chapter 11 filing shows a marginal increase in filings in column (4), but magnitude and statistical significance are not strong relative to the estimates for Chapter 7 filing. These results suggest that the decrease in bankruptcy filing after the digital transformation mostly comes from changes in Chapter 7 bankruptcy filing.

Figure 3.4 shows the dynamic effects of the digital transformation on Chapter 7 bankruptcy filing. Looking into the pre-period, we don't find any discernible trends before the adoption, confirming the exogenous nature of the event. Over the post-treatment periods, we clearly see downward trends in the number of Chapter 7 filings. Moreover, the magnitude of coefficients tends to become larger over time. The results are similar to the full-sample event study plot but statistically stronger. All seven sub-periods following the adoption have negative coefficients and are statistically significant at the 95% confidence level, while two sub-periods in the full-sample plot show statistically weak results. In all post-periods in Figure 3.4, standard errors are smaller relative to the full-sample results since we take away Chapter 11 and 13 filings that possibly generate noise. Consistent with the difference-in-differences estimates, Figure 3.5 suggests that changes in the number of Chapter 13 filings after the adoption are close to zero in all sub-periods.

Back to the hypotheses in Section 3, the cost reduction channel, Hypothesis 1, doesn't seem to play a primary role in this sub-sample analysis. As the baseline results, we don't see a noticeable increase in bankruptcy filings in any chapter. Chapter 7 filings significantly decrease while Chapter 13 filings are stable. Although Chapter 11 filings edge up, the difference between Chapter 11 and other chapters would hardly come from the cost reduction channel. Since most Chapter 11 filers are corporations or large businesses with better workforces, they likely face fewer frictions and costs associated with filing for bankruptcy in the paper-based process, compared with small businesses and households who mostly file for Chapter 7 or 13 bankruptcy.

Moreover, the difference in treatment effects among bankruptcy chapters casts doubt on the social stigma channel, Hypothesis 3. It is unlikely that the general public strictly distinguishes one bankruptcy chapter from another and attaches social stigma only to Chapter 7 bankruptcy. Furthermore, Chapter 13 bankruptcy requires a filer to repay part of debts for three to five years. Considering this requirement, Chapter 13 bankruptcy filers should be more sensitive to social stigma given that they are more willing to continue economic activities for repayment.

The information channel, Hypothesis 2, allows treatment effects between bankruptcy chapters to diverge. Each bankruptcy chapter has a distinct liquidation and discharge scheme, and the value of information attained from the electronic database could be different between those chapters. For example, hard information about the amounts of liquidation and dischargeable debts from the database could be useful for Chapter 7 bankruptcy. However, uncertainty around Chapter 11 and Chapter 13 bankruptcy filing cannot be easily cleared by adding hard information gained from the past cases because Chapter 11 bankruptcy process entails negotiation with stakeholders and Chapter 13 filers should have a debt repayment plan approved by the court. In the following sections, we conduct a set of tests to find additional evidence on the information channel.

1.6.3 Physical Distance and Treatment Effects

The primary effect of digital transformation in the bankruptcy filing process is the removal of physical barriers. Therefore, looking into the relationship between physical distance and treatment effects could provide more direct evidence on the mechanism of changes in bankruptcy behavior. For example, if the information channel is the dominant mechanism as suggested in the previous section, treatment effects should be larger as a filer's resident location is further from the court.

The U.S. bankruptcy court system has 94 judicial districts, and many districts have more than one court office in their jurisdiction. To initiate bankruptcy process, a filer needs to complete a bankruptcy petition, often with a lawyer, and submit it to the court office which is in charge of the filer's address. The court office files all bankruptcy documents, and anyone can look up past bankruptcy cases filed by others. In the paper-based bankruptcy era, a filer had to travel to the court office to submit documents or look up stored files. After the adoption of the electronic system, they can use the online platform from any location without visiting the court office. Our data include zip codes of court offices as well as bankruptcy filers, enabling us to separate treatment effects by the distance between a filer residence and the court office.

Table 3.5 shows difference-in-differences estimates for four different groups in geographical distance. We first measured distances for all filer-court pairs using the centroids of their zip codes. Then, we computed the share of distant filings, which mean filings from residents living far from the court office. The share is used as a dependent variable in Equation (3). Column (1) defines distant filings as filings from residents living further than 5 miles from the court office. Columns (2) to (4) defines with different distance thresholds, 10, 15, and 20 miles, respectively. In Panel A, we find that Chapter 7 filings in distant regions decrease more than adjacent regions in all four distance categories, indicating that digital transformation disproportionately affects regions. Reading from columns (1) through (4), around 10 miles are critical points where the removal of physical barriers become effective. In other words, residents living further than 10 miles from the court office tend to more change their bankruptcy behavior after the adoption of electronic system, compared with those within 10 miles[2].

These results strongly support the information channel hypothesis in that residents in the distant region could benefit more from the digital transformation than those in the adjacent region in terms of information gathering. In contrast, residents within 5 miles from the court office don't substantially change bankruptcy behavior because they would be less affected by physical barriers even in the paper-based era. However, the costs reduction channel is at odds with the results. If the electronic system changes bankruptcy behavior through the costs reduction channel, bankruptcy filings should increase after the adoption of the electronic system as the distance becomes further. But the results show the opposite direction[3]. The social stigma channel also cannot explain the divergence between adjacent and distant regions. It is hardly true that societal pressure is stronger in regions further from the bankruptcy court office.

1.6.4 Heterogeneity in Computer Ownership

Investigating changes in computer ownership among filers around the adoption dates would provide more direct evidence on the mechanism. Today, almost all U.S. households (92%, 2018 Census) have at least one computer, but in the early 2000s around 40% of people in the U.S. didn't have a computer. The share of

[2] Note that column (3) and (4) are statistically weaker because those columns more broadly define adjacent regions that include many residents who change bankruptcy behavior.

[3] Although Chapter 11 bankruptcy has a positive coefficient in the previous section, the results by distance in this section don't further support the costs reduction channel for Chapter 11 bankruptcy.

computer ownership among bankruptcy filers is less than the national average because they typically come from low or lower-middle-income class. This enables us to separate computer owners with non-owners among filers and compare the bankruptcy behavior between those two groups before and after the adoption of the electronic system.

However, there are several limitations on collecting individual-level computer ownership data from the court database. First, not all district courts collect computer ownership data. Bankruptcy petition forms are similar across all district courts, but details mostly depend on the policy and practice of each court. The standard bankruptcy petition requires the list of household goods and dollar amount of them. Only a few bankruptcy courts further split the household goods into computer, refrigerator, bed, etc. Another limitation is a technical flaw of the bankruptcy database in some district courts. They have broken links to the bankruptcy documents filed more than 10-15 years ago. Lastly, old bankruptcy documents are not machine readable. Documents in the paper-based era were written by hand[4]. And some old electronic documents were recorded in poor resolution.

We find the Idaho court database has working links and contains information about computer ownership. As shown in Figure 3.6, bankruptcy petitions in the Idaho court database include a detailed list of personal properties, while many other courts have only aggregate information. We randomly sampled 2,000 of Chapter 7 bankruptcy petitions from the Idaho database, 1,000 petitions for the six months before the adoption of the electronic filing system and 1,000 for the six months after that. This sample accounts for 23.2% of total Chapter 7 filings in Idaho during the sample period[5]. Then, we hand-collected computer ownership information from the documents.

Table 3.7 presents computer ownership statistics. Column (3) in each panel compares the share of computer owners before and after the adoption date. Column (3) in Panel A shows the share of computer owners decreases in the post-adoption period relative to the pre-period. This change implies that debtors with possibly easier access to the electronic filing system are less likely to file for bankruptcy after the adoption, compared with debtors without a computer. Panel B and Panel C dropped filers in distant regions to see the effect of distance on changes in computer ownership among filers. Although sample sizes are much smaller in these panels, it is clear that filers in the adjacent region don't show a negative relationship between computer ownership and bankruptcy filing rates. All these statistics are consistent with the results in the previous sections. Considering the tight relationship between computer ownership and accessibility to the court database, the results strongly reinforce the validity of the information channel.

1.7 Conclusion

This paper examines the impact of the digital transformation in U.S. bankruptcy courts on bankruptcy behavior. Exploiting individual-level data on bankruptcy cases recorded in the court database, we find that the number of bankruptcy filings decreases after the adoption of the electronic filing system. This contrasts to digital transformations in other areas, which usually bring about an increase in demand. In our sub-sample analyses, the changes in bankruptcy filings are mainly driven by a reduction in Chapter 7 bankruptcy filings. We don't find evidence that Chapter 11 or Chapter 13 bankruptcy filings significantly change after the digital

[4]Bankruptcy staff scanned the paper-based documents and uploaded them to the electronic system before introducing the electronic filing system.

[5]The pre-period is from June 2004 to December 2004, and the post period is from February 2005 to July 2005. The sample period is restricted to 6 months to remove the significant effects of BAPCPA in October 2005 on bankruptcy filings and to minimize upward trends in computer ownership at the time.

transformation. In addition, we find that residents living in distant regions from the court office show stronger results than those living near the court office.

Our evidence is most consistent with a hypothesis that additional information from the electronic database changes the bankruptcy decision of debtors who are considering bankruptcy. Alternative explanations are not consistent with our results. Remote filing by using the electronic system could reduce frictions and travel costs associate with filing for bankruptcy. But the cost reduction hypothesis is inconsistent with the results that the digital transformation only affects Chapter 7 bankruptcy filings. Moreover, stronger results from distant regions support the information channel hypothesis and reject the cost reduction channel.

Our findings contribute to understanding about drivers of bankruptcy filings. The information channel implies that a lack of information led to sub-optimal bankruptcy decisions, and information provision about bankruptcy outcomes could improve the welfare of debtors under financial distress. Also, our results expand understanding about the role of information technology in financial areas. Our results suggest that information technology does not always stimulate an influx of users.

Chapter 2

Bankruptcy and the COVID-19 Crisis

2.1 Introduction

In 2020, the COVID-19 pandemic disrupted normal life and triggered a sudden economic slowdown in the United States, inducing significant drops in consumer spending and the highest levels of unemployment since the Great Depression. The crisis prompted rapid action from Congress and the Federal Reserve, including a $600 weekly increase in unemployment benefits through the Federal Pandemic Unemployment Compensation (FPUC) program, $1,200 Economic Impact Payments (EIP), and over $1 trillion in lending and grants allocated to support businesses through the Paycheck Protection Program (PPP), Economic Injury Disaster Lending program, and Main Street Lending program. Meanwhile, numerous state and local governments, federal agencies, and industry participants instituted moratoria on evictions and foreclosures and other measures aimed at forestalling acute financial strain for households and businesses. This paper examines and disentangles the effects of the economic crisis and major mitigation measures on bankruptcies in the U.S.

Historically, bankruptcy filings have closely tracked economic conditions as businesses and households sought relief from macro-economic shocks. Figure 3.7 plots the time-series of nationwide unemployment rates and bankruptcy filings. While other factors besides the business cycle affect bankruptcy filing rates, Figure 3.7 shows that bankruptcy filings rise alongside unemployment rates during NBER recessions. This relationship is more pronounced after the 2005 Bankruptcy Abuse Prevention and Consumer Protection Act (BAPCPA), with the two time series showing a strong correlation of 0.94.

In this paper, we use detailed microdata on the universe of bankruptcy filings in the United States to examine how the pandemic and subsequent policy interventions affected bankruptcy rates. Our goals are twofold. First, our paper sheds light on how financial distress evolved during the COVID-19 pandemic across the consumer, small business, and corporate sectors as well as across geographic regions and different subgroups within these sectors. Due to the frequent nature of bankruptcy in the United States and its long historical time series compared with some other pandemic-era indicators, bankruptcy provides a useful lens for understanding the economy during the pandemic relative to previous recessions. Second, we leverage the evolution of bankruptcies during the pandemic to better understand the more general drivers of consumer and firm distress both in normal times and during crisis periods. In particular, empirical research on small business bankruptcy has been relatively sparse relative to that on consumer and corporate bankruptcy, and our paper contributes several new stylized facts about small business financial distress.

Overall, we find that total bankruptcy filings fell by 31 percent year-over-year in 2020 relative to 2019.

Both consumer Chapter 7 and 13 filings dropped dramatically starting in mid-March, but their trends subsequently diverged. While consumer Chapter 7 filings initially declined by 34 percent year-over-year from March 15th to April 30th, they began rebounding in mid-April and stabilized at around a 20 to 30 percent year-over-year decline from May through December 2020. Consumer Chapter 13 filings did not rebound in April and remained at around 50 to 60 percent below 2019 levels through the end of 2020.

Business bankruptcy filings also fell during the pandemic. Similar to consumer Chapter 7's, business Chapter 7's (which are dominated by small and medium-sized enterprises) declined by 20 to 30 percent year-over-year during most of the period from mid-March to the end of December 2020, and were down by 18 percent year-over-year. Business Chapter 11 filings declined slightly in 2020, ending the year down 9 percentage points relative to 2019. While many media reports described increases in corporate bankruptcy filings in 2020, this is only true for the largest firms. Filings with greater than $50 million in assets increased by 18 percent year-over-year from 2019 to 2020.[1] Consumer and business bankruptcy filings remained well below 2019 levels through the end of 2021, and the general patterns described above remained consistent through the second year of the pandemic.

Thus, while unemployment rates skyrocketed during 2020, bankruptcy rates declined in a reversal of historical patterns.[2] The cross-sectional relationship between state unemployment and bankruptcy rates also became negative in 2020. In contrast to patterns during the global financial crisis between 2007-10, states that had the largest increases in unemployment simultaneously had the largest declines in bankruptcy filings. Why did bankruptcy filings behave so differently during the COVID-19 crisis? And what can these trends tell us about pandemic-era policies and consumer and business bankruptcy more broadly?

We shed some light on these issues by focusing on four possible mechanisms that could be causing the disconnect between macroeconomic conditions and bankruptcy filings. The first of these is a category of policies that involve creditor leniency. These types of policies were instituted by both the public and private sectors and at the federal, state, and local levels. At the national level, the Coronavirus Aid, Relief, and Economic Security (CARES) Act suspended loan payments on the majority of student loans and provided forbearance and a foreclosure moratorium for federally-backed mortgages.[3] Focusing on the mortgage market, we show that delinquencies more than doubled during 2020 but foreclosure rates fell to historically low levels.

The decoupling of delinquency and foreclosure rates in residential mortgages suggests that lender leniency targeted at homeowners likely played a role in the decline in bankruptcy. In support of this channel, we find that bankruptcy filing rates declined considerably more for homeowners than for non-homeowners. By December 2020, the share of consumer filings that included real property fell by 4 percentage points (37% relative to the 2019's average of 41%), a decline that corresponded with the start of the CARES Act effective date. Of course, it is possible that other simultaneous events disproportionately reduced homeowner bankruptcies through other channels, but the evidence is consistent with the idea that mortgage forbearance and foreclosure moratoria depressed bankruptcy rates in 2020. By shutting down acute mortgage distress, variation in these pandemic-era policies also help quantify the share of bankruptcies that are driven by mortgage delinquency and the threat of foreclosure during normal times.

While the foreclosure moratorium on federally-backed mortgages was extended multiple times into 2021,

[1] This increase is calculated by consolidating business filings to the lead case level (Table 3.8). The increase in business Chapter 11's with greater than $50 million in assets rises to 66 percent when counting each affiliated filing separately (Table 3.12). Consumer filings are unaffected by the choice to consolidate to the lead case level.

[2] If the historical relationship between the unemployment rate and consumer bankruptcy filings had continued, we would have expected to see over 200,000 additional consumer filings in the second quarter of 2020 alone relative to the second quarter of 2019. Instead, there were about 90,000 fewer consumer filings year-over-year in the second quarter (see Table 3.8).

[3] [12] estimate that 60 million borrowers missed payments on loans in forbearance during the first year of the pandemic, including mortgages, student loans, and other forms of household debt.

and homeowners could request forbearance of up to 360 days, leniency policies aimed at renters were much less generous. The eviction moratorium originally instituted by the CARES Act on buildings backed by the GSEs ended in July, 2020, and was replaced by a patchwork of eviction policies that only covered some circumstances and some of the rental market. In stark contrast to the relationship between mortgage-related leniency policies and homeowner bankruptcies, neither the CARES Act eviction moratorium expiration nor the staggered timing of state eviction moratoria affected bankruptcy filings in 2020.

Second, we examine the role played by changes in the financial liquidity of debtors. Changes in liquidity could affect bankruptcies through two separate channels operating at different horizons. In the short run, potential filers on the brink of bankruptcy may lack cash to pay the lawyer and court fees needed to officially file. These liquidity constraints were likely to have been exacerbated by sharp job losses in March 2020 and then alleviated by the injections of liquidity starting in mid-April as stimulus payments, enhanced unemployment insurance (UI), and PPP disbursements were rolled out. Consistent with these predictions and the patterns documented by *gross2014 following the 2001 and 2008 stimulus payments, Chapter 7 bankruptcies decreased and then rebounded in March and April 2020, while Chapter 13 bankruptcies did not respond to the rollout out of liquidity in April.[4] Thus, while liquidity constraints may have contributed to the larger initial drop and then rebound in both consumer and business Chapter 7 filings, cash payments from stimulus programs were likely to have alleviated them by the spring of 2020.

In the longer run, the unprecedented scale of stimulus measures undertaken in 2020 may have increased liquid wealth enough for some potential filers to delay or avoid bankruptcy altogether. This increase in liquidity may contribute to the persistent decline in bankruptcies we document.[5] Consistent with this interpretation, we find that the generosity of unemployment benefits is strongly correlated with the decline in bankruptcies. Rationalizing the negative relationship between bankruptcy and unemployment described above, multivariate regressions show that the normally positive relationship between unemployment rates and bankruptcy filings is restored once we control for UI generosity.

A third possible reason for the decline in bankruptcy is increased uncertainty. While we lack good cross-sectional proxies for variation in economic uncertainty, we note that it is likely that many debtors delayed bankruptcy in the early stages of the pandemic when it was unclear how long it would last and what the long-term effects would be. Consumer Chapter 13 and business Chapter 11 filings require debtors to create long-term plans of repayment which may have been difficult to create during the initial period of economic volatility. Furthermore, Chapter 7 filers cannot re-file in the subsequent 8 years, increasing the incentive to delay during times of high uncertainty. Nonetheless, the timing of the bankruptcy trends don't seem to line up perfectly with established measures of economic uncertainty. Given the substantial resolution of policy and pandemic-related uncertainty over the course of 2020 and 2021, it seems unlikely that uncertainty is the main driver for the persistent decline in bankruptcies that we document [14].[6]

Finally, we examine the role played by physical distancing in possibly slowing the bankruptcy filing rate or reducing access to the courts. For example, as courts physically shut down and some required electronic documents to be filed by lawyers, filers who would have filed pro se may have been unable to navigate the

[4]Chapter 13 filings have historically been associated with housing distress and are less affected by liquidity constraints because filers tend to have higher wealth and income than Chapter 7 filers, and Chapter 13 costs are more likely to be amortized through a 3 – 5 year repayment plan instead of being required up front in the majority of Chapter 7 cases. Consistent with these distinctions, *gross2014 show that consumer Chapter 7 but not Chapter 13 filings increased after the 2001 and 2008 tax rebates, the same pattern we find in 2020.

[5]Taking into account the $600 increase in weekly unemployment benefits implemented by the CARES Act, potential replacement rates for lost income were above 100 percent for the median qualifying unemployed worker [13].

[6]Despite the massive stimulus measures included in the CARES Act, its enactment on March 27 did not noticeably alter or reverse the downward trend in filing rates already underway at that time.

electronic and telephonic systems. However, we do not find any difference in filing rates or pro se rates between the 51 bankruptcy courts that physically shut down during 2020 and the 39 courts that did not, or any effect of the staggered timing of court shutdowns in an event study framework. Furthermore, discussions with judges and court practitioners yielded no anecdotal evidence of potential filers losing access due to physical or procedural constraints. Thus, we conclude that it is unlikely the decline in bankruptcy filings was due in large part to physical barriers to filing.

Our paper contributes to a large literature that examines the drivers and performance of the economy during the COVID-19 pandemic. [15] examine bankruptcy dynamics in the third Federal Reserve district (Delaware, New Jersey, and Pennsylvania) during the early pandemic. Outside of bankruptcy, [12] document widespread loan forbearance during the pandemic, and [13] show that unemployment insurance provided broad replacement of income for unemployed workers. Also closely related are *crane2022business and *decker2022business, who measure the rate of business exit during the pandemic. The most recent update by *decker2022business using the Bureau of Labor Statistics (BLS) Business Employment Dynamics (BED) data indicates that nearly 1.1 million establishments closed permanently in 2020, exceeding pre-pandemic rates by about 181,000. While the BED's measure of establishments does not map precisely onto the business units that would potentially file for bankruptcy, the disparity between business exit and bankruptcy in 2020 is an important area for future research. Finally, *chetty2020did document the performance of the overall economy during the pandemic and evaluate the impacts of government stabilization policies.

Our paper is also related to work documenting the determinants of bankruptcy for consumers and small businesses. Earlier work, such as [16] and [17], examines the strategic decisions of individuals relative to the generosity of current bankruptcy law. More recent work has shown how liquidity shocks and debt relief play a fundamental role in determining whether individuals enter bankruptcy [18], [19]. Taken together, our evidence is consistent with the idea that debt forbearance and general liquidity needs are principal drivers of bankruptcy for many consumers and small businesses. Meanwhile, the lack of a decline in filing rates for the largest businesses suggests that they may view bankruptcy more as a strategic option, to be used when it is economically optimal, regardless of temporary liquidity needs.

This paper proceeds as follows. Section 2.2 covers reasons for filing for bankruptcy and COVID-19's impact on bankruptcy filings. Section 2.3 describes the data and analyzes common chapters of bankruptcy filings. Section 2.4 presents our methods and results. Section 2.5 presents likely explanations for the decrease in filings during the COVID pandemic, and Section 2.6 concludes.

2.2 Background

In this section we briefly outline the main motivations that lead to individuals and businesses choosing to file for bankruptcy. This discussion will help to frame our results and the mechanisms that have caused a sharp decline in bankruptcies in the COVID pandemic.

Why would an individual or business file for bankruptcy? The most ready answer is to obtain relief from debt that the debtor cannot repay. For consumers, bankruptcy provides a fresh start that frees up cash flows and potentially protects key assets such a house or a vehicle from repossession. Businesses can use bankruptcy for various purposes depending on the viability of the business. For a business that is no longer viable, bankruptcy is one option for liquidating the firm. Meanwhile, bankruptcy can provide a fresh start to businesses that are still viable but need a new capital structure to maintain financial health. Similar to individuals, firms can also use bankruptcy to protect assets from seizure by secured creditors.

While bankruptcy clearly has benefits, there are also costs to filing. Direct costs of bankruptcy include administrative and attorney fees. Individuals who file for bankruptcy will see their credit scores decline, which could limit credit access in the future. Also, an individual who has filed for bankruptcy loses the option to file again for a certain period of time depending on the chapter of bankruptcy. Businesses that enter bankruptcy cede some control of the firm to a trustee and judge, which can at times lead to the liquidation of the firm. These risks are extra costs that businesses must weigh before filing.

With these costs and benefits in mind, it is unsurprising that bankruptcies typically rise during economic downturns, as shown in 3.7. Job loss can make it impossible for individuals to service their debt without forgoing other necessary consumption, thereby increasing the benefits of debt discharge while keeping the costs relative fixed. Meanwhile, recessions can make some firms non-viable, forcing them into liquidation. Other firms may still be viable but need to restructure their assets or liabilities after falling behind on payments.

Listing the costs and benefits of bankruptcy can help to provide a framework to think about channels which will affect bankruptcies in the aftermath of COVID-19. In particular, we will focus on four main mechanisms that could explain the decline in bankruptcies seen in the pandemic.

First, the principal reason that most individuals and firms file for bankruptcy is to get protection from creditors. If creditors do not pressure debtors, it is natural to expect a decline in bankruptcies rather than an increase. Thus, leniency of creditors – either of their own accord or through government mandates – is a key mechanism that can affect bankruptcy trends.

Second, liquidity plays a fundamental role in the bankruptcy decision. Additional liquidity stemming from government stimulus could prevent bankruptcies by giving debtors enough cash to pay creditors until their normal cash flows resume. On the other hand, debtors need liquidity to pay the fees associated with bankruptcy in the first place [18], and so a sudden drop in liquidity could actually lead to a decline in bankruptcy filings as debtors who would like to use bankruptcy cannot afford to.

Third, increases in uncertainty could cause declines in bankruptcy. Increases in uncertainty can make it hard to determine if a debtor even needs bankruptcy at all, or which type of bankruptcy would be the most beneficial. This increases the option value of waiting to file, thereby depressing bankruptcies initially after an uncertainty shock. Uncertainty can also make it harder for business Chapter 11 and individual Chapter 13 cases to be successful, as they need to create detailed reorganization or repayment plans. Due to the difficulties of measuring uncertainty empirically, this paper does not contain tests of its role in affecting bankruptcies in the COVID-19 recession. But we note that it could have played a significant role, particularly at the beginning of the pandemic.

Finally, COVID-19 created unique physical barriers that could have preventing some bankruptcy filings. Physical distancing and moving to online or telephonic meetings with lawyers and judges could have been particularly difficult for potential filers who lack good Internet access or technological savvy.

We will organize our evidence around these four possible mechanisms to better understand the principal drivers of bankruptcy during COVID-19.

2.3 Data

We collect data on the universe of bankruptcy filings in the United States from the Federal Judicial Center (FJC) databases. The FJC database provides information on all petitions filed under the Bankruptcy Code beginning in October 2007 and is updated quarterly under a working arrangement with the Administrative

Office of the U.S. Courts.[7] The most recent update included data through the third quarter of 2021, and we use FJC data for January 2019 through December 2020 to provide benchmarks for year-over-year comparisons. We also use the FJC data to analyze the detailed characteristics of filers and compositional changes during the COVID period. In addition, the FJC data allows us to identify business bankruptcies that have separate filings for each subsidiary or branch of the business that entered bankruptcy. In these cases, we consolidate all associated cases so that we report only one bankruptcy filing per business and accurately measure the assets and liabilities of the full business entity.

Our analysis focuses on the three most common chapters of bankruptcy filing. Consumer Chapter 7 ("fresh start") bankruptcy allows an individual to discharge eligible debts and keep exempt assets without requiring additional repayment out of future income. Chapter 13 ("repayment plan") bankruptcy, in contrast, allows a debtor to keep all of their assets, discharge debts above what they can afford to repay, and repay the remaining debts out of their income over the next five years according to a plan approved by a bankruptcy judge. Businesses mostly file under Chapter 7 or Chapter 11. Business Chapter 7 ("liquidation") bankruptcy requires the sale of all assets of a business with proceeds used to pay creditors. Chapter 11 ("reorganization") bankruptcy allows the debtor to negotiate with lenders to create a reorganization plan so that the distressed business can continue to operate; nearly all reorganization plans involve a restructuring of the liabilities and equity of the firm, often including asset sales as part of the bankruptcy terms. While Chapter 11 is designed to allow for reorganization, historically about two-thirds of business Chapter 11 cases are either converted to Chapter 7 or dismissed from court entirely [20].

2.4 Methods and Results

Our main empirical objective is to document the effect of the COVID-19 pandemic and economic crisis on bankruptcy filings. In our main analysis, we use 2019 filing rates as the counterfactual, and also compare these results to historical benchmarks below.

Table 3.8 computes simple year-over-year changes in nationwide bankruptcy filings by the type and chapter of filing for six time periods and the year to date using filings from FJC. Business filings are reported after consolidating all subsidiary filings to a single filing per business (Table 3.12 reports the unconsolidated results for comparison). While media reports have focused on the record number of filings among corporations with more than $1 billion in assets and spikes in filings among retail and dining firms [e.g., 21], overall bankruptcy filings are down by 31 percent (230,820 filings) relative to 2019.[8] This decline is driven by a 31 percent year-over-year decline in consumer filings, but overall business filings are also down 17 percent year-over-year. Across all filings types, Consumer Chapter 13's are down the most, falling 45 percent relative to 2019. On the opposite extreme, business Chapter 11's are only down 5 percent year-over-year, and are up by 40 percent on an unconsolidated basis. As shown in the last three rows of the table, small business filings, defined as businesses with less than $10 million in assets, have consistently been down about 18 percent year-over-year since the pandemic began. Meanwhile, large business filings, businesses with greater than $10 million in assets, have not varied dramatically from 2019.[9] Overall, the media narrative describing a "tidal wave" of bankruptcies has not materialized to this point in the pandemic.

[7] The database is publicly available at https://www.fjc.gov/research/idb/bankruptcy-cases-filed-terminated-and-pending-fy-2008-present

[8] See Figure 3.22 for year-over-year changes in Chapter 11 filings by industry, which are consistent with media reports.

[9] Consistent with media reports, filings with greater than $50 million in assets have increased by 18% percent year over year. However, these large businesses make up a very small portion of total filings.

Business filings similarly diverge from a forecast based on unemployment. Given unemployment numbers in the second quarter, we would have expected approximately 5,500 additional business filings in this time period relative to 2019. Instead, Table 3.8 shows there were around 720 fewer business filings in the second quarter of 2020. The drop in business bankruptcies is particularly striking given reports of widespread permanent business closure. [22] estimate that roughly 98,000 businesses on Yelp have permanently closed during the pandemic through September 2020. Even through March 2021, data from [23] show that 32 percent of small businesses remain closed in the U.S. Historically, 8.4 percent of businesses that permanently close file for bankruptcy, based on business closure statistics from the Census Bureau's Business Dynamics Statistics. Based on estimated business closures in Yelp alone, we would have expected at least 300 additional business filings over and above the 5,799 in the second quarter of 2019.

We estimate weekly panel regressions to pinpoint the dynamics of these changes in bankruptcy filing rates as they relate to the evolution of the pandemic and subsequent policy responses. Specifically, we first compute the number of nationwide bankruptcy filings of each type on each week of our sample period from January 1, 2019 to December 31, 2020, again consolidating business filings to remove subsidiary filings. We then partial out intra-month and seasonal variation with fixed effects for week of the month and month of the year.

Bankruptcy filings in 2019 determine the counterfactual and pin down the recurring variation in these regressions. We estimate weekly changes in bankruptcy filings in 2020 using separate week indicators for each calendar week t with the following specification:

$$y_t = \alpha + \sum_{\tau=2020\text{w}1}^{2020\text{w}52} \beta_\tau \cdot 1\{t=\tau\} + \lambda_{wom} + \gamma_{month} + \varepsilon_t, \tag{2.1}$$

where γ_{wom} and γ_{month} are week-of-the-month and month-of-the-year fixed effects, respectively. The dependent variable throughout is the log total number of bankruptcy filings per week, split by the chapter of the filing and whether the filing is a consumer or business case. We are interested in the $\hat{\beta}_\tau$ coefficients, which estimate differences in bankruptcy filings in 2020 relative to 2019 after partialing out recurring calendar variation.

We plot these results in Figure 3.8. The $\hat{\beta}_\tau$ coefficients prior to the severe onset of the pandemic in the United States allow us to assess whether 2019 is a reasonable counterfactual for the 2020 filings. For all chapters and both consumer and business filings, 2019 filing rates appear to be a reasonable counterfactual for those in 2020. As shown in the figure, there are no systematic pre-trends in either total consumer or business filings, or filings by chapter and filer type in advance of the National Emergency declared on March 13, 2020. These trends are also clearly observable in the raw data as presented in Figure 3.20, albeit with more seasonal and intramonth noise.

Business filings are rarer and noisier, but business Chapter 7 filings follow very similar trends as consumer Chapter 7 filings throughout the year. Business Chapter 11 filings are even less common, but show a clear decline between March and May before rebounding back to 2019 levels for the rest of the year. Given that we do not include a dummy variable for 2020, the point estimates near zero up to mid-March for all filing types show that both the level and trends of these bankruptcy filings remained consistent with 2019 prior to the onset of the COVID-19 crisis. Consistent with the lack of pre-trends, column (1) of Table 3.8 shows that total bankruptcies only changed by 0.1 percent (274 filings) year-over-year between January 1st and March 14th, and was 10 percent or less for all filing types except for large businesses and Chapter 11.

In contrast to the period from January to mid-March, total bankruptcies declined by 39 percent year-over-year from March 15 through April 30 following the escalation of the pandemic and economic crisis in the United States. This period included the first lockdown and social distancing measures in the U.S., with a number of bankruptcy courts either ceasing in-person hearings or substantially modifying their procedures to mitigate public health risks and comply with statewide and federal judicial orders.[10] In addition, there was presumably a sharp increase in overall uncertainty during this period that likely depressed filings. Much was unknown about the length of lockdowns, the severity of the virus, or proper protocols to mitigate its spread. The sharp decline across all bankruptcy types is likely due at least in part to increased uncertainty. However, increased uncertainty is not the whole story, as bankruptcy filings did not fully rebound, ending up down 31 percent year-over-year from January through December.

When breaking down the initial drop in filings by chapter and filer type, we find that consumer Chapters 7 and 13 and business Chapter 7 all fell by between 30 and 49 percent in the initial period between March 15th and April 30th, with consumer Chapter 13 falling the most. Both consumer and business Chapter 7 filings began rebounding in mid-April, stabilizing around 25 percent below 2019 levels by mid-May. This 25 percent decline persisted through the end of 2020 for both consumer and business Chapter 7 filings. In contrast to Chapter 7, consumer Chapter 13 filings continued to decline through late spring and stabilized between 54 and 61 percent below 2019 levels.[11] Finally, after an initial decline in the early part of the pandemic, business Chapter 11 filings returned to baseline 2019 levels for the rest of the year, ending up down 9 percent year-over-year by the end of the year.

Our focus in this paper is on the drop in bankruptcy filings at the onset of the pandemic in 2020. For completeness, in Figure 3.21 we show similar figures to Figure 3.8 with data extending through the end of 2021. In general, the level shifts in filing rates that begin with the pandemic persisted through 2021 for both consumer and business filings. For all bankruptcy types, filings in 2021 were significantly below 2019 levels, and were similar to or even slightly lower than filing rates in 2020. Thus, the drop in filings that began in March 2020 was a long-lived shift, lasting at least for the next 20 months.

In Figure 3.9 we break business bankruptcy filings by asset size instead of by chapter, where small businesses are defined as those with less than \$10 million in assets at the time of bankruptcy. The figure shows that large business filings largely stayed at 2019 levels. Meanwhile, small business filings fell dramatically in the March-April time period and never fully rebounded, much like consumer Chapter 7 filings. These differences highlight how differently the bankruptcy system functions for large and small businesses. In particular, both personal and business considerations play important roles in the bankruptcy decision for small business owners since many small business owners give personal guarantees for their business debts [24]. Meanwhile, larger firms view bankruptcy as a strategic option that can be used to restructure when necessary, rather than as a last resort.

Having established the basic trends in bankruptcy filings during the COVID-19 recession, we highlight three facts that can help explain the channels at play. We call attention to these facts because they can help point towards the mechanisms that are driving the overall trends. First, as is clear from Figure 3.8, consumer Chapter 13 bankruptcies have remained substantially more depressed than consumer Chapter 7 filings. These two filer populations differ along a variety of dimensions. Chapter 7 filers have lower income and fewer assets, and must generally pay filing fees in full at the time of filing, while Chapter 13 filers may roll their court and legal fees into their repayment plan. Chapter 13 filers are significantly more likely to have non-exempt assets (such as home equity or vehicles) that they are seeking to protect in bankruptcy. Finally, Chapter 13 filings

[10]The most common changes include the suspension of all in-court hearings, postponement of Section 341 meetings, and the waiver of wet signatures on court documents. Most courts that moved to telephonic hearings did so between March 16th and March 23rd. Court orders related to COVID-19 are available at: https://www.uscourts.gov/about-federal-courts/court-website-links/court-orders-and-updates-during-covid19-pandemic

[11]There are several key differences between Chapter 7 and 13 for consumers that could be driving their divergence during the COVID-19 economic crisis. We discuss some reasons for these differences in more depth the next section.

are more complex and require more involvement both from bankruptcy attorneys and bankruptcy judges.

Second, as noted above, business bankruptcy filings and consumer Chapter 7 bankruptcies declined dramatically in the first few weeks of the pandemic, and then rebounded to stabilize around 25 percent below 2019 levels for the remainder of the year. The third and final fact relates to the cross-sectional relationship between changes in bankruptcies and unemployment at the state level. As described above, bankruptcy rates decreased significantly as unemployment skyrocketed starting in March, counter to the historical correlation. This negative correlation doesn't have to hold in the cross section. It could still be the case that states that experienced larger unemployment shocks saw a smaller decline in filings.

We show scatter plots of the relationship between unemployment and bankruptcy rates on a state level in Figure 3.10. For these plots, we compute the average monthly unemployment rate for each quarter of 2019 and 2020, and compute the year-over-year percentage point change in these average unemployment rates for each state. We conduct the same exercise for cumulative bankruptcy filings in each state to compute the year-over-year percentage change in bankruptcy rates for each filing type. Regression lines weighted by state population are also shown in each graph. In 2020Q2, it is clear that states with larger increases in unemployment experienced larger declines in both consumer Chapter 7 and Chapter 13 bankruptcies. The reversal of the historical relationship is surprising, and suggests that special circumstances in the COVID-19 crisis initially suppressed consumer bankruptcy filings in the hardest-hit areas. Meanwhile, panels (c) and (d) show that the negative relationship also applies to business Chapter 7 and 11 filings, although the slope estimates are more noisily estimated.[12] These relationships contrast strikingly with those during 2007-9 recession, which show strong positive cross-sectional correlations between unemployment and bankruptcy filings (Figure 3.23).

In the third and fourth quarters of 2020, a positive relationship between unemployment and bankruptcy began to re-emerge for consumer Chapter 7 cases, as can be seen in the red and green lines in Panel (a) of Figure 3.10. However, consumer Chapter 13 cases continued to be depressed especially in areas that saw the largest increases in unemployment through the end of 2020. Put differently, the initial large declines in consumer bankruptcies in the second quarter of 2020 were especially pronounced in areas who economies were most affected by COVID-19, and this is true across all types of bankruptcy. As the year progressed and consumer Chapter 7 cases rebounded somewhat, this rebound occurred in areas that continued to experience the worst unemployment.

In Table 3.9, we show the results of cross-sectional regressions of the relationship between ex ante state economic characteristics and the characteristics of bankruptcy filers by district in 2019 and the year-over-year change in filings from 2019 to 2020. This multi-variate framework allows us to show that proxies for the various channels we discuss seem to affect bankruptcy filings independently, and to compare the relative magnitudes of their effects on different types of bankruptcies. We use the specification below:

$$\begin{aligned} \Delta Filings_s^i = \alpha &+ \beta_1 unemp_{s,2019} + \beta_2 forecl_{s,2019} + \beta_3 prose^i_{s,2019} \\ &+ \beta_4 prop^i_{s,2019} + \beta_5 assets^i_{s,2019} + \varepsilon_t, \end{aligned} \tag{2.2}$$

where $\Delta Filings_s^i$ is the percentage change in bankruptcies of type i in state s between 2019 and 2020 (i.e. $(Filings^i_{s,2020} - Filings^i_{s,2019})/Filings^i_{s,2019} \cdot 100$. The variables $unemp_{s,2019}$ and $forecl_{s,2019}$ are the monthly averages of the unemployment rate and foreclosure rate in each state from the BLS and Black Knight (1 = 1pp). The variables $prose^i_{s,2019}$, $prop^i_{s,2019}$ are the fraction of bankruptcies of type i in state s in 2019 that

[12] The courts with the largest increases in Chapter 11 cases are those that are known to attract the largest corporate cases, such as Delaware, New York, Houston, and, more recently, Eastern Virginia.

are pro se or have nonzero real property, and $assets^i_{s,2019}$ is the median total asset level of those bankruptcies in 2019.

The results show that all five proxies for state-level economic and filer characteristics have economically significant relationships to the change in filings between 2019 and 2020, although the low power of the cross-sectional regression generates large standard errors and low statistical significance in this specification. In column (1), the results show that a one percentage point increase in the 2019 state-level unemployment rate is associated with a 1.5% greater decrease in total bankruptcies in 2020. Similarly, a one percentage point increase in the 2019 foreclosure rate is associated with a 3.9% decrease in the bankruptcy rate.

The 2019 state-level pro se and and property owner rates are expressed as fractions, so interpreting the coefficients means that states that had a 10 percentage point higher number of pro se filers in 2019 experienced a 0.6% greater drop in bankruptcy rates in 2020. Similarly, a 10 percentage point increase in the fraction of property owners in 2019 is associated with a 2.5% greater drop in 2020 bankruptcies. Finally, the last row shows that a $10,000 increase in the median asset size of filers in 2019 is associated with a 1.3% smaller drop in bankruptcies.

Altogether, the table shows that in a multivariate setting, states that had higher ex ante unemployment rates (that also experienced greater increases in unemployment in 2020), had bigger declines in bankruptcy in 2020. States with more property owner bankruptcies, pro se bankruptcies, and foreclosures in 2019 also experienced greater declines in bankruptcies. Finally, states with relatively wealthier filers saw smaller declines in the bankruptcy rate in 2020.

This last point relates to [23], who show that the COVID-19 pandemic caused the largest economic disruptions in high-income zip codes. They find that consumption fell the most in high-income zip codes, leading to larger declines in employment in these same zip codes. Corresponding to this, we find that bankruptcies fell the most in low-income zip codes with the onset of the pandemic. This is shown in Figure 3.11, which plots the evolution of bankruptcy filings in high-income zip codes relative to low-income zip codes. To create these figures, we modify the regression expressed in Equation 2.1 to include an interaction term of a *high income* indicator with the indicators for each calendar week ($1t = \tau$). Figure 3.11 plots these coefficients along with 95% confidence intervals. A clear pattern emerges: bankruptcies fell the most in low-income zip codes with the onset of COVID-19, particularly for consumer bankruptcies. This is consistent with consumption falling the most in high-income zip codes, leading to more financial distress and, hence, a smaller decline in bankruptcy rates.

Overall, our findings can be summed up as follows. Geographically, bankruptcies fell the most in areas with the largest increases in unemployment and in low-income zip codes. This is consistent with policies that targeted the most vulnerable areas with economic relief and loan forbearance. Cross-sectionally, we find that bankruptcies fell the most among homeowners, pro se filers, and the lowest-wealth individuals. Policies that provided liquidity and forbearance to these groups likely played a role in reducing bankruptcies for these individuals. At the same time, we note that these results could also be consistent with pro se filers and low-wealth individuals losing access to bankruptcy protection during the pandemic. Thus, the results indicate that multiple channels may be acting simultaneously, instead of being driven by a single force.

2.5 Mechanisms and Discussion

The dramatic drop in bankruptcy filings is surprising given the historically positive correlations between unemployment and bankruptcy rates both in the time series and cross section. Clearly, no single explanation can account for these striking trends. However, we discuss what we believe are the most likely set of explanations below. In particular, following the discussion in Section 2.2, we focus on the role played by creditor leniency, debtor liquidity, uncertainty, and unique physical distancing constraints imposed by COVID-19.

2.5.1 Creditor Leniency

The COVID-19 pandemic has seen widespread loan forbearance policies. [12] estimate that by the end of 2021:Q1 more than 60 million borrowers will miss $70 billion on their debt payments. This leniency has come both through government mandates and private actions. The CARES Act included provisions which suspended debt payments for almost all student debt and all federally-back mortgages if the borrower has experienced financial hardship due to the pandemic. Throughout the summer of 2020, many state governors instituted eviction moratoria, and the CDC issued a nationwide eviction moratorium in September 2020 to slow the spread of COVID-19. Even when not mandated, many lenders and landlords have chosen to forbear on debt collection given the unprecedented nature of the pandemic [12].

An important aspect of these debt forbearance policies is that missed payments do not get reported as delinquencies on credit reports. For this reason, reports based on credit bureau data show that delinquency is down.[13] This, however, does not mean that there is a lack of financial distress in the economy. Financial distress has increased dramatically during the pandemic. In Figure 3.12 we display data from Black Knight/McDash Mortgage Monitor to show that mortgage delinquencies rates more than doubled immediately after the COVID-19 pandemic began, and remained at elevated levels through early 2021. Meanwhile, due to moratoria, the foreclosure rate began to decline at the same time, falling 40% by mid-2020.

Cross-sectional evidence illuminates this point further. In Panel (a) of Figure 3.13 we display the correlation between changes in unemployment rates and mortgage delinquencies across states. As one would expect, the correlation is significantly positive throughout 2020; states who were most affected by the pandemic saw both rising unemployment and increases in mortgage delinquency. However, in Panel (b) we show that the correlation between changes in unemployment and foreclosure rates was negative in the second and third quarters of 2020. States that saw the largest increases in unemployment actually saw the largest declines in foreclosure rates. Thus, counterintuitively, foreclosures actually fell the most in those states that had the largest increases in delinquency.

While our evidence focuses on mortgages, [12] show that forbearance was also widespread in auto debt, student loans, and credit cards. The unprecedented forbearance by creditors has likely played a major role in depressing bankruptcy filings during the pandemic. Simply put, if creditors are not pressuring debtors to repay delinquent loans there is little reason many debtors would file for bankruptcy. In support of this, Figure 3.14 shows that states with the largest declines in foreclosure rates also experienced the largest drops in bankruptcy filings during the COVID-19 pandemic.

While loan forbearance should decrease all bankruptcy filings, this may be especially true for Chapter 13 filings. Individuals who file for Chapter 7 must give up any non-exempt assets to repay creditors. In Chapter 13, an individual can retain their assets and instead agree to a repayment plan that reinstates secured debts. Indeed, housing-related distress is a common trigger for Chapter 13 filings [25]. For example, suppose an individual owns a home worth $500,000 with an outstanding mortgage balance of $300,000. The home equity of $200,000 owned by the individual is above the home equity exemption limit of most states, and so if the

[13] For example, the New York Federal Reserve's Quarterly Report on Household Credit and Debt shows a sharp decline in delinquency starting 2020:Q2 (https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data/pdf/hhdc_2020q4.pdf)

individual enters Chapter 7 bankruptcy they may have to sell their home and give up some of their equity to repay unsecured creditors. However, if the individual files for Chapter 13 they can keep their home by pledging to pay all of their disposable income for the next 3-5 years to unsecured creditors. Because of this, essentially all bankruptcy filers that have assets above exemption limits choose to file for Chapter 13.[14] Given this, to the extent that loan forbearance was especially strong among mortgage lenders it could help explain why Chapter 13 filings were significantly more depressed in 2020 than Chapter 7 filings.

Consistent with this idea, Figure 3.15 displays changes to the fraction of bankruptcy filings in which the debtor owns real estate such as a house or business location. These figures are estimated in regressions similar to those in Figure 3.8 except here the dependent variable is the share of bankruptcy filings of a given type in which the debtor owns real property, as reported by FJC. In Panel (a), we see that prior to about April 1st, the share of consumer filings by property owners was very similar to 2019 level. Then, the share of property owners dropped quickly and continued to decline through the end of 2020, ending the year down almost 8 percentage points. This decline corresponds almost exactly with passage of the CARES Act mortgage foreclosure moratoria on March 27th, 2020. Importantly, the share of real property owners did not decline between March 13th (when a national emergency was declared) and the end of March, when overall bankruptcy filings first declined. In fact, in the small window between the national emergency and the CARES Act, the share of filings that were by home owners increased to some extent. This can be seen more clearly when examining consumer Chapter 7 and Chapter 13 filings separately (Panels (c) and (d)). In both of these graphs, there is a temporary spike in the share of real property owners between the middle and end of March 2020, followed by a decline in the share afterwards.

The other notable finding from Panel (d) is that the share of Chapter 13 filings that are property owners was actually quite similar to 2019 for much of the year. Thus, the overall drop in the share of homeowner bankruptcies seen in Panel (a) is reflective of the large overall decline in Chapter 13 filings, rather than a decline in the share of homeowners conditional on choosing to file for Chapter 13. In addition, the share of homeowners in Chapter 7 was lower in 2020 (Panel (c)) and this also played a role in the overall decline.[15]

Panel (b) of Figure 3.15 shows the share of business bankruptcies that report owning real property. Similar to consumer filings, the share of business bankruptcies with real property appears to fall soon after the CARES Act, and remains about 5 percentage points below 2019 levels throughout 2020.

Taken together, the evidence suggests that creditor leniency – and in particular leniency from mortgage lenders – likely played an important role in reducing overall bankruptcy filings.

While mortage leniency appears to have played a role in reducing bankruptcy, eviction moratoria do not appear to affect bankruptcy rates. We examine this by testing whether bankruptcy filing trends differed after the implementation of eviction moratoria in each states[16]. We gather the dates of these eviction moratoria from Eviction Lab as well as hand-collected orders by state governors.[17] Panel (a) of Figure 3.25 shows the timing of eviction moratoria in each state. By exploiting the staggered implementation dates, we estimate the impact of eviction moratoria based on the standard event study framework as follows:

$$y_{it} = \alpha + \sum_{\tau=-30}^{60} \beta_\tau \cdot 1\{t = \tau\} + \gamma_i + \lambda_t + \varepsilon_{it}, \tag{2.3}$$

where y_{it} denotes the log number of daily filings, γ_i state fixed effects, and λ_t day fixed effects.

[14] In 2019, 99.7% of Chapter 13 filers had non-exempt assets, while only 5.6% of Chapter 7 filers did, according to FJC data.
[15] table 3.10 showed that, on average, about 30% of consumer Chapter 7 filings are by property owners
[16] During the pandemic, 43 states implemented eviction moratoria, while 7 states did not.
[17] See evictionlab.org

The results are displayed in Figure 3.18. We find little difference in the bankruptcy rates between before and after eviction moratoria, with point estimates being not significantly different from zero. Interpreting this finding is complicated by a variety of competing hypotheses. First, it is possible that eviction is not a main driver of bankruptcy filings.[18] Second, it is possible that state-level eviction moratoria had only small effects on actual evictions, as landlords may have been reluctant to evict tenants even in states that did not have moratoria in place. However, *benfer2022covid find that evictions were 50% lower in states that imposed eviction bans relative to those that did not during the pandemic. It thus appears that eviction moratoria were effective in reducing evictions. Finally, selection effects make interpretation difficult. States that imposed eviction moratoria may have also differed along other dimensions that led to the observation of little difference between moratoria and non-moratoria states. Regardless, Figure 3.18 suggests that eviction moratoria did not play a major role in reducing bankruptcy filings in 2020.

2.5.2 Liquidity

The enactment of the CARES Act on March 27 created immediate forbearance for student loans and mortgages, and it is at this point that we see the share of homeowner filings begins to decline. However, we find no noticeable change in the overall downward trend in filing rates already underway at that time (Figure 3.8). Instead, we see the rate of business and consumer Chapter 7 filings begin to rebound at the onset of stimulus payments, PPP loans, and other forms of relief mandated by the CARES Act and other policies.

Consumer Liquidity

As shown in Figure 3.8 and Table 3.12, Chapter 7 filings began rebounding within a few days of the April 15 disbursement of the $1,200 stimulus checks, a rebound that leveled off around early May at 20 percentage points lower than 2019 levels. Thus, bankruptcy rates surprisingly increased in the time series as households received more aid. This pattern is consistent with the importance of binding liquidity constraints and the use of stimulus payments to pay for court fees, which disproportionately affect Chapter 7 filings since Chapter 13 filing fees can be rolled into the repayment plan [18].

Additional evidence on the importance of liquidity constraints can be gleaned by looking at the characteristics of bankruptcy filers in the FJC data. In Figure 3.16, we plot kernel density distributions of the log of total assets across bankruptcy types. While the distributions are broadly similar across 2019 and 2020, there are a few notable differences. Examining the left tails, we can see that during the pandemic (especially in the March-April 2020 period) there were significantly fewer low-asset bankruptcy cases. This is true across all bankruptcy types for both consumers and businesses. While this is not conclusive evidence of liquidity constraints, it points toward liquidity constraints potentially preventing those with the fewest assets from being able to file for bankruptcy.[19]

Another way to potentially isolate liquidity constrained filers is to focus on "pro se" bankruptcies–when a debtor files for bankruptcy without a lawyer. This is typically done when a filer cannot afford to pay for a lawyer. In Panels (a) and (b) Figure 3.17 we show how the fraction of filings that are pro se evolved for both consumer and business filings. Concurrent with the onset of the pandemic, the fraction of filings that are pro

[18] A bankruptcy filing halts all debt collection efforts, including eviction by landlords. It is thus natural to expect that eviction attempts by landlords would lead individuals to enter bankruptcy. However, we are unaware of academic work showing a clear link between eviction and bankruptcy filings.

[19] Of course, an alternative explanation is that government support aided these debtors enough that they did not need bankruptcy. Given that stimulus payments were not targeted in this way, this seems unlikely. Similarly, increased unemployment insurance was not targeted to low-asset individuals but to those who lost their jobs, which are distinct groups.

se fell by about 5 percentage points for both consumer and business filings. On average, pro se filings only constitute 8.4% and 6.7% of total consumer business filings, respectively. Thus, pro se filings have almost disappeared entirely during the pandemic. Additionally, in Panel (c) we show that those debtors who did continue filing pro se were increasingly those with non-zero assets, while this trend does not appear in among the set of filers who file with lawyers (Panel d). This shows that many of the pro se debtors who stopped using bankruptcy during the pandemic were those with zero assets who are potentially liquidity constrained.

We note that pro se debtors potentially differ from other filers along many dimensions other than liquidity constraints. Thus, there are other possibilities that could explain these results. For example, if these debtors received the most benefit from loan forbearance or received the most government support during the pandemic the this could explain why there was a sudden drop in pro se filings. However, the decline in pro se occurred immediately when the national emergency was declared, rather than when moratoria went into effect or when stimulus checks were distributed, making it less likely that these channels explain the time series patterns. Another possibility is that physical distancing made it difficult to file pro se, a possibility we discuss below. Because of this, we urge caution in over-interpreting these trends as being due solely to liquidity constraints.

While liquidity dried up for some debtors in the COVID-19 crisis, there is also evidence of significantly *increased* liquidity for others during the pandemic, driven by massive federal aid, other types of relief efforts and reduced discretionary spending. The CARES Act included $300 billion in stimulus checks and $260 billion in increased unemployment benefits, which were associated with a median income replacement rate of 134 percent for those able to claim this benefit [13]. The personal savings rate hit a 60 year peak of 33.5 percent in April 2020 [26]. On the small business side, the Paycheck Protection Program (PPP) provided $518 billion in support to businesses early in the pandemic.[20] These and less-publicized relief measures enacted by localities and industry participants have no doubt helped reduce demand for bankruptcy among some households and small businesses.

However, it is unlikely that these relief efforts were large enough to reduce bankruptcy demand by 20 percent during the pandemic. This can be seen clearly from Figure 3.12, which shows that mortgage delinquency rose more than twofold during the pandemic. Similarly, New York Federal Reserve's Quarterly Report on Household Debt and Credit shows that credit card delinquencies rose about 25% during the pandemic.[21] If stimulus payments and declines in discretionary spending were enough to make large numbers of consumers and businesses solvent, delinquency rates would have declined during this period. The increase in delinquency rates is evidence that financial distress has increased on aggregate during the pandemic, even if some debtors have seen increased solvency during this time.

2.5.3 Uncertainty

An additional explanation for the initial decline in filings is that the COVID-19 shock caused a great deal of economic uncertainty for households and businesses, and some may delay filing until the severity and duration of the crisis become more clear. Households are only allowed to file for Chapter 7 bankruptcy once every eight years and Chapter 13 once every two years [29], so some who might benefit from bankruptcy may nonetheless delay due to the option value of filing in the future [30]. This option value may be even greater for small businesses, which are very likely to be liquidated if they file for bankruptcy [31].

[20] *autor2020evaluation estimate that the PPP increased aggregate employment by 2.3 million through mid-July. [23] find similar effects on employment. [27] present early evidence that PPP helped small businesses build up liquidity and meet obligations, though [28] finds that this benefit is limited to microbusinesses.

[21] https://www.newyorkfed.org/medialibrary/interactives/householdcredit/data/pdf/hhdc_2020q4.pdf

Unfortunately, we lack a good proxy for uncertainty that would allow us to cross-sectionally test the role it played in affecting the bankruptcy decision by individuals and businesses. While we believe that uncertainty likely explains the quick decline in filings in the initial weeks of the pandemic, it is notable that bankruptcy filings did not rise after passage of the CARES Act or around other notably events that might have resolved some of the uncertainty surrounding the length and depth of the COVID-19 recession. Instead, filings rates remained significantly depressed through the end of 2020. While uncertainty is likely a contributing factor to the decline, without lender forbearance and other government support it is unlikely that uncertainty alone would depress filings for this length of time.

2.5.4 Physical Barriers

A final possible reason for the initial decline in filings is state and local social distancing policies. Approximately 67 of 94 United States Bankruptcy Courts moved to telephonic hearings between March 13 and April 1, 2020, with 51 courts physically shutting down their offices. In addition to the court closure, state-level policies in response to the Covid-19 pandemic also discouraged mobility, with all states declaring a state of emergency in February and March 2020, and 42 states issuing stay-at-home orders.

The changes in court operations may have made it particularly difficult for vulnerable populations such as the recently-furloughed and poorer and rural filers to access the bankruptcy system, since updated filing rules often made it more difficult to file without an attorney and/or internet access, and wet signatures on printed documents were more difficult to obtain during the pandemic [32]. Foot traffic to bankruptcy attorney offices has also likely declined, and may disproportionately decrease "supply-driven" Chapter 13 filings relative to "demand-driven" Chapter 7 filings [33]. These physical distancing requirements may have played a role in the distinct drop in pro se filings shown in Figure 3.17 and described in Section 2.5.2 above.

However, other tests suggest that physical barriers were not the main driver of the decline in bankruptcy filings. We test the effects of court closure on the bankruptcy rates by exploiting staggered shutdown dates of each bankruptcy court. In Figure 3.19 we display regression coefficients using a event study design similar to Equation 2.3. In this analysis, we use district-day panel data with i denoting court district and t day. Therefore, γ_i and λ_t are district fixed effects and day fixed effects, respectively.

As can be seen in Panel (a) and (b), there is essentially no difference in filing rates following court closures. Further, in unreported results, we find no difference in the fraction of pro se filers across these two sets of courts. Moreover, the figures in Panel (c)-(f) show similar tests for mobility restrictions at the state level using varying timings of those policies. Despite the potential for stay-at-home orders and state of emergency declarations to limit mobility, there is no sufficient evidence to suggest that the state restrictions had any significant impact on bankruptcy behaviors.

While it is surely true that physical barriers played some role in reducing bankruptcy filings, results from these analyses suggest that other mechanisms were more important.

2.6 Conclusion

Our research contributes to an understanding of what causes consumer and corporations to file for bankruptcy, and also to the growing body of work studying the impacts of the COVID-19 crisis on the U.S. economy. We document large and persistent declines in bankruptcy rates for both households and small businesses after the onset of the crisis in mid-March, in a surprising reversal of the close historical relationship between bankruptcy and unemployment rates in both the time series and cross section. While some of this decline is likely to be attributable to the substantial aid offered by federal, we argue that much of the decline is due to widespread loan forbearance. This highlights that most debtors do not view bankruptcy as a strategic option (as opposed to large corporations), but rather as an option only to be used as a last resort.

We also find evidence consistent with liquidity constraints preventing some debtors from accessing the bankruptcy system. On the other hand, it does not appear to physical barriers played a large role in reducing bankruptcy rates.

A unique feature of our study in understanding not only the bankruptcy system but the economy as a whole is that we observe a consistent time series of the universe of all bankruptcy filings. Although the bankruptcy system reflects the many forces affecting the economy during the COVID-19 crisis in complex ways, our work has the advantages of granular real-time analysis while being free from the sample selection bias that is present in other studies using private-sector or other unrepresentative sources. Future versions of this paper will continue to update these results and leverage cross-sectional variation in exposure to the various forces described above to further disentangle the mechanisms behind the trends in bankruptcy filings and the implications for the overall U.S. economy.

Chapter 3

Do Banks Transform the Regional Industry Structure?

3.1 Introduction

Bank lending has long been considered a critical financing source for the growth of small businesses. While large businesses have a range of external financing options, including deep-pocketed bonds and equity markets, small businesses may find it more challenging to access these public capital markets due to the fixed costs and reporting requirements involved. small businesses often lack detailed financial information or a long credit history that public market lenders request. To overcome this limitation, banks rely on their branch network for the due diligence process, capitalizing on personal relationships and other non-financial information when deciding whether to lend to small businesses. This lending process requires the proximity between business locations and bank branches (see [34]). Consequently, bank lending has a significant impact on local businesses and the overall regional economy.

The banking sector has experienced a trend of consolidations over the past several decades. As banks and small businesses have close ties, shakeups in the banking sector can affect the availability and terms of financing for small businesses, and may have broader consequences for the region's business landscape. The literature on bank consolidations has long examined the impact of these events on the quantity of small business lending. However, the effects of bank consolidations on small business lending can vary depending on the specific circumstances of the consolidation and the local economic conditions. It is important to carefully consider the heterogeneous impacts of bank consolidations on small businesses and local industries in order to gain a deeper understanding of the role that banks play in supporting the regional economy.

This paper examines how regional industry structure changes following bank merger events. When a bank acquire existing branches in a region through a merger, the incoming bank would choose a different set of small businesses to lend to based on its own lending strategies. This is because small business lending relies on intangible factors and the personal judgment of the lender, and each bank may have its own unique standards and processes for evaluating and approving these loans. Banks would try to make the most of the limited observable data available as [35] has shown that visible factors such as race, ethnicity, and gender can impact a small business owner's chances of obtaining a bank loan. A type of business, such as industry classification, is one of the easiest information banks can look at if they don't have access to more detailed data. Through this channel, a merger can potentially have an impact on the overall industry structure of the region, and the impact of bank mergers may be more significant if the acquiring bank has different lending strategies than the bank being acquired.

To estimate changes in industry structure resulting from bank mergers, I create a measure of the acquiring banks' exposure to different industries across their branch network. For example, if a bank has branches in counties that have a total of 1,000 establishments, and 100 of them are in the retail industry, then the bank's exposure to the retail industry would be 10%. This measure can be used to assess the extent to which the acquiring bank is focusing on specific sectors and how this affects to the regions the acquiring bank enters through mergers. If a particular industry has a greater number of establishments compared to other industries in the regions where a bank has branches, it could suggest that the bank has more experience and expertise in lending to businesses in that industry. This could be because the bank has a larger number of clients in that industry and therefore has developed a deeper understanding of the risks and opportunities associated with lending to businesses in that industry. This proxy can provide insight into the types of businesses to which the bank is most interested in lending following mergers.

One benefit of using a bank's exposure to different industries is that it enable to take the intensity of merger shocks into account. Contrary to binary indicators that represent treatment shocks in the basic event study framework, the exposure measure in this paper is allowed to vary from zero to one. A value of zero indicates no exposure to the industry, while a value of one indicates complete exposure. In my research design, it is important to estimate the extent of a bank's exposure to each industry in order to accurately measure treatment effects. However, using binary indicators to measure this exposure can be subject to measurement error, which can introduce bias into the estimates.

In my research design, the unit of analysis is a county-industry pair, and some of these pairs have experienced multiple merger events during the sample period. To analyze the impact of multiple shocks, I employ the distributed-lags model. This model has similar properties to the event study framework but can estimate the impact of multiple shocks on a unit of panel data, while most event study designs are typically used to analyze the impact of a single shock on a unit of panel data. The distributed-lags model is often adopted in fields such as public finance and labor economics to estimate the effects of recurring policies or interventions, including changes in tax rates.

with these empirical approaches, I found that bank mergers have a significant impact on the structure of industries in a region. When a bank enters a regional credit market through a merger, the industry in which the acquiring bank had more exposure prior to the merger tends to experience faster growth in the newly incorporated regions, compared to other industries that had less exposure prior to the merger. The transformation of the industry induced by banks entering the market are noticeable among small businesses with less than 100 employees, however, large businesses employing 100 or more people do not exhibit the same pattern. The greater impact on small businesses aligns with the established observation that small businesses are more responsive to bank credit than larger ones.

As bank mergers become more prevalent, the resulting changes in industry structure may lead to increased homogeneity across different regions. The loss of diversity means that local business cycles are more likely to move in tandem and that a single macroeconomic shock can more easily ripple through the entire economy. This co-movement would be stronger among small businesses as [36] shows that small businesses are more sensitive to economic cycles than large firms.

In addition to examining the impact of bank mergers on the number of establishments, I also investigate how these industrial transformations affect the types of workers that firms are seeking in the local labor market. I find that the impact of the bank-led transformation on the local labor market is weak. The growth of employment is weaker compare to the strong growth of the number of establishments in the affected industries. Moreover, results show that the industrial transformation promotes industries that generally employ skilled workers, which has a significant effect on the labor market by causing an increase in the demand for skilled labor and a decrease in the demand for unskilled labor. Consequently, the shifts in the labor market brought on by bank mergers amplify the secular trend of a widening gap between skilled and unskilled workers.

The remainder of this paper is structured as follows. Section 2 describes the data used in the analysis and details empirical approaches. Section 3 reports results, evaluates their robustness, and discuss the policy implications of the results. Section 4 concludes, suggesting possible future extensions.

3.2 Data

Data on merger activities in the banking sector are from the FDIC Report of Changes. This report covers all bank merger activities since August 1999, providing information about the banks involved, both the acquirer and the acquired, and the dates of when the mergers took place. In this paper, I use bank mergers in which both acquiring banks and target banks held assets greater than $1 billion. The sample period is from 2000 through 2019. Figure 3.26 shows the number of bank merger activities during the sample period. The merger events are well dispersed throughout the sample period, allowing a quasi-natural experiment design.

To identify a bank's branch network, I use the Summary of Deposits (SOD) data from the Federal Deposit Insurance Corporation (FDIC), which includes annual information on the location of each branch office. In addition, I use the County Business Patterns (CBP) data published by the U.S. Census Bureau for key outcome variables. The CBP data provide the number of establishments and employees at the county level as well as industry codes using the North American Industry Classification System (NAICS).

Combining all the data sets, I construct a county-industry-year panel and the industry is defined using 4-digit NAICS codes. The county-industry pair is the basic unit of this panel, with annual time-series data for estimation.

3.3 Empirical Approach

I estimate the effect of bank financing on regional industry structure using time-series variation in the the number of establishments and employees at the county-industry level. To isolate causal effects, I exploit bank merger events as plausibly exogenous shocks to regional industry composition.

However, a single industry within a county could experience more than one merger event over the course of the sample period. In this case, it is not feasible to compare the pre-period and post-period using a binary indicator as in a basic event study design. To estimate average treatment effects in case where shocks repeat, recent studies apply the distributed-lags model with non-binary indicators ([37], [38], [39], [40], etc.). Another advantage of using non-binary indicators is that it allows to consider the intensity of treatments. For this reason, the distributed-lags model is often used in fields such as public finance and labor economics to evaluate the effects of repeated tax changes over time[1].

In this paper, I construct a measure to capture the degree of bank exposure to different industries. To determine this, I calculate the proportion of establishments in each industry within all counties where a bank

[1] [41] shows that the distributed-lags model is identical to the event study framework (i.e., the generalized difference-in-differences model) under certain conditions.

has a presence, and use this as a proxy for the bank's exposure to that industry. The following equation formally describes the exposure to an industry n for a bank b:

$$Exposure_{c,n,t} = \begin{cases} \frac{Est_{b,n,t}}{Est_{b,t}} & \text{if an acquisition event occurs by bank } b \\ 0 & \text{otherwise} \end{cases} \tag{3.1}$$

where $Est_{b,n,t}$ is the number of establishments classified as NAICS n for acquiring bank b at year t. $Est_{b,t}$ is the total number of establishments for bank b at year t. This measure illustrates the extent to which a bank is impacted by a specific industry in the regions where it operates. The underlying assumption is that exposure represents the likelihood of a bank to extend credit to that industry. Banks with more experience and knowledge in a particular industry are assumed to be more inclined to lend to that industry in new regions as well, as they have a greater understanding of the risks and opportunities presented by that industry. By using this measure, I run a regression model as follows:

$$y_{n,c,t} - y_{n,c,t-1} = \alpha + \sum_{\tau=\text{-}5}^{8} (Exposure_{n,c,t} - Exposure_{n,c,t-1}) + \lambda_{n,s,t} + \varepsilon_{n,c,t} \tag{3.2}$$

where the dependent variable is the first difference in the share of establishments for industry n within county c. λ denotes year $\times$ NAICS $\times$ state fixed effects. This specification eliminates the influence of the industry-level business cycle within a particular state, isolating unique variations specific to the county-industry pair. Unit fixed effects (i.e., county-NAICS pairs) are subsumed by the first differences, so time-invariant differences in the county-NAICS pairs are also removed.

3.4 Results

Figure **??** shows the dynamic treatment effects around bank merger events. Panel (a) displays estimates for each year using Equation 3.2. The objective variable is the proportion of impacted industries at the county level, relative to unaffected sectors. Impacted industries refer to industries to which acquiring banks have exposure in their present areas. Examining the figures, the coefficients obtained during the pre-merger timeframe indicate that bank mergers do not take place in regions where affected industries are experiencing substantial growth. Consequently, acquiring banks do not seem to choose regions where their preferred industries are expanding.

Looking at the post-merger period in Panel (a), we observe a significant increase in the share of affected industries 2-3 years after bank consolidations. The rise in the proportion of impacted industries suggests that banks could be selectively promoting certain industries to grow, based on their level of exposure to those industries. Banks with a high level of exposure to specific industries may actively support the growth of those industries, as they stand to benefit from their success. This selective promotion of particular industries could, in turn, influence the structure of regional industries. This finding highlights the potential role of banks in shaping regional economic development and the importance of their strategic decision-making in the growth of specific industries. It also raises questions about the potential impact of such selective promotion on the broader economy and whether it results in an uneven distribution of economic growth across different regions or sectors.

However, it appears that the impact of bank consolidation on the regional industry mix is primarily driven by small businesses. Panel (b) presents a comparable graph to Panel (a), but it focuses on large businesses with 100 or more employees. The post-merger period estimates indicate that affected industries increase their share, but the results are not statistically significant. Additionally, the coefficients' magnitude is lower than those observed for small businesses. This finding aligns with the notion that small businesses rely more heavily on bank lending than larger firms do. Small businesses have limited financing options, making them heavily reliant on bank loans. As a result, the impact of bank consolidations would have a weaker effect on large businesses compared to small businesses. To compare results between small businesses and large businesses more directly, I run a difference-in-differences specification as follows:

$$y_{it} = \alpha + \beta \cdot cum\_exposure_{it} + \gamma_i + \lambda_{st} + \epsilon_{it} \tag{3.3}$$

where cum_exposure denotes cumulative exposure in the county-NAICS pair in year t. For example, if a county-NAICS pair is affected by a merger with an exposure of 0.1 in 2003, the cumulative exposure is 0.1 from 2003. If the county-NAICS pair is affected again in 2005 with an exposure of 0.2, the cumulative exposure is 0.3 from 2005 onward. γ_i is unit fixed effects where the unit is the county-industry pair. λ_{st} is state-year fixed effects, which eliminate annual business cycles for each industry at the state level.

Table 3.14 presents estimates by the employment size of establishments using Equation 3.3. The analysis reveals that small establishments are more impacted by bank consolidations compared to large establishments, as demonstrated in columns (1) and (3) of the table. This outcome suggests that bank loans play a crucial role in the growth and development of small businesses. The increased or reduced access to bank loans for some industries due to bank consolidations may result in a disproportionate impact on small businesses, which are often more dependent on banks as a source of external financing.

Next, I delve deeper into each industry to identify the primary sectors responsible for the observed results. The variations that drive the outcomes in **??** stem from the differences in industry structures between the regions where the acquiring bank operates and the regions newly incorporated after a merger event. Figure 3.27 illustrates the gap in industry structure between these two groups, using 2-digit NAICS codes instead of the 4-digit codes employed in other analyses throughout the paper for simplicity. The industries at the top of the chart exhibit the most substantial gaps between acquiring and acquired banks, while those at the bottom display the least significant gaps. Following a merger, it is likely that the transportation and manufacturing sectors will increase their share, while the retail trade sector is expected to experience a decline. These findings shed light on the sector-specific effects of bank mergers on industry structures, highlighting the potential impacts on different industries and their respective regions.

As labor demands adjust accordingly to the growth of specific industries, the shift in industry structure resulting from bank consolidations has also significant implications for the labor market. Column (2) in Table 3.14 reveals that the number of employees in the affected county-industry pair increases in comparison to the non-affected pair following consolidation events. As the number of establishments in affected industries expands, employment in those industries also increases However, the magnitude is much smaller than establishment growth. For large establishments, employment does not increase significantly. This outcome suggests that the transition involves employment lags that persist over an extended period. The slower rate of employment growth in affected industries may be attributed to the time required for newly established businesses to ramp up their operations and for the labor market to adjust to the changing industry structure.

Each sector has its unique requirements for employees, and as the industry mix changes, the job market's demand for workers also shifts in terms of the necessary skill sets. To assess the level of job skills needed for each sector, I capitalize on the U.S. Department of Labor's ONET program classification of occupations, as outlined by various studies, including [42], [43], [44], and [45]. The ONET's Job Zone categorizes the necessary job skills in each sector into five different scales, with a rating of 5 indicating the highest level of required skills. Job Zone 1 denotes occupations with little or no preparation needed, while Job Zone 5 denotes occupations that require extensive preparation [2].

Table 3.15 presents the heterogeneity effects across job skill levels. Columns (1) and (3) indicate that the impact of bank consolidations on the number of establishments weakens as the Job Zone level increases. Columns (2) and (4) demonstrate that the negative relationship between Job Zones and the effect of bank mergers holds true for employment. These findings suggest that consolidations stimulate growth in industries previously exposed to acquiring banks, but these industries tend to employ workers with lower skill levels compared to industries not affected by consolidations.

3.5 Conclusion

In the past few decades, the banking sector has seen a wave of bank mergers, while the local industry and labor market has been under continuous transformations induced by various macroeconomic factors including globalization. The results of this paper disentangle the contributions of bank mergers to those transformations. In this section, I discuss the implications of the industrial transformations to the macro-economy and labor market.

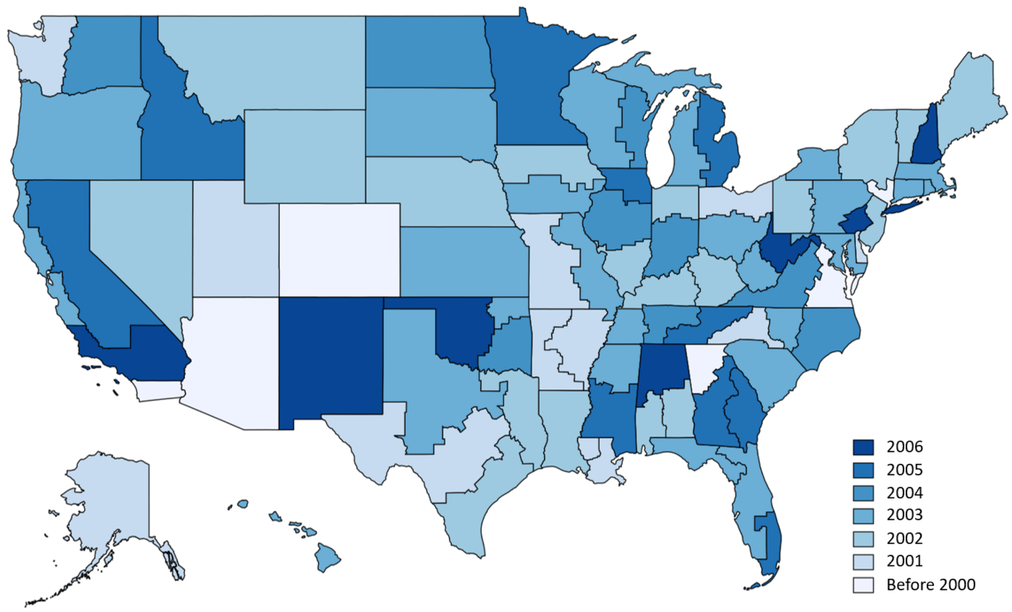
The convergence of local industry structure suggests that the regional economies have become more homogeneous. The decreasing diversity in the industry structure means the local economy would show more co-movements and has less buffers to the macroeconomic shocks. This change would lead the economy to be more sensitive to fluctuating industry-level business cycles that can ripple through the economy more quickly and widely.

In the labor market, the industrial transformations doesn't contribute to the job-creating capacity of the economy. The industries that benefit from bank mergers strongly grow without a hiring boom. The growing industries are less labor intensive and incline to skilled workers. This shift would exacerbate the gap among workers based on their skill and education levels.

[2] The definition of ONET occupation is not identical to NAICS code. Similar to [42], we adjusted Job Zone for each NAICS code by using the OES data from BLS. The adjusted Job Zone is as follows: $Adj.JobZone_i = \sum_{j=1}^{O}(\frac{E_{ji}}{E_i} * Zj)$ where E_{ji} is the number of employees in industry i, occupation j and E_i is the total number of employees in industry i. Z_j is the ONET occupation classification.

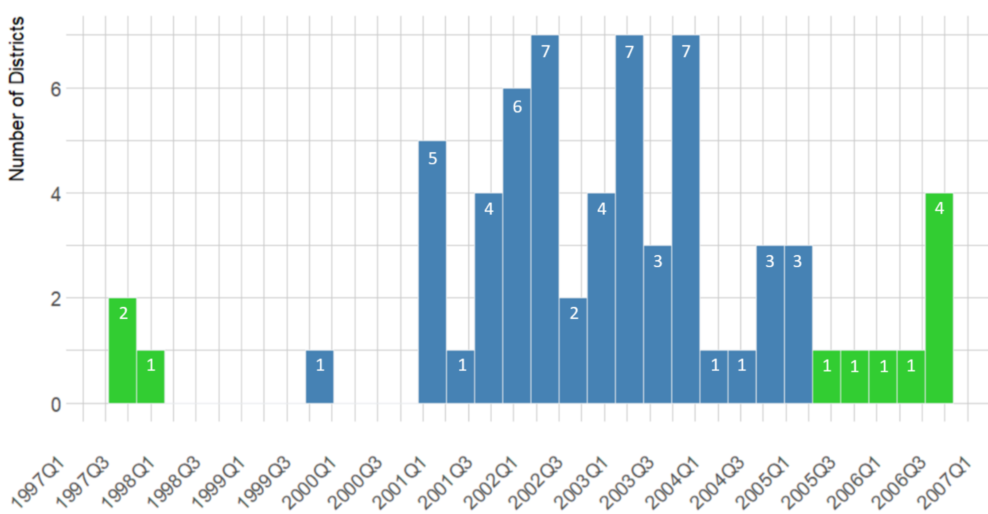
Figures and Tables

Figure 3.1: The Adoption Dates of the Electronic Filing System by District



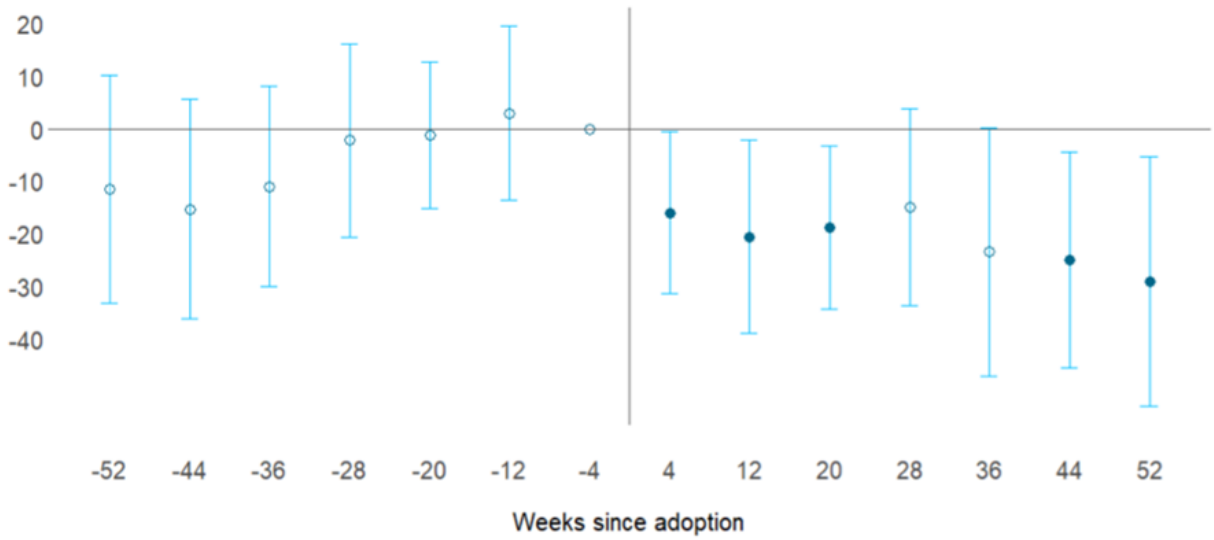
Notes: Source: PACER

Figure 3.2: The Adoption Dates of the Electronic Filing System by District



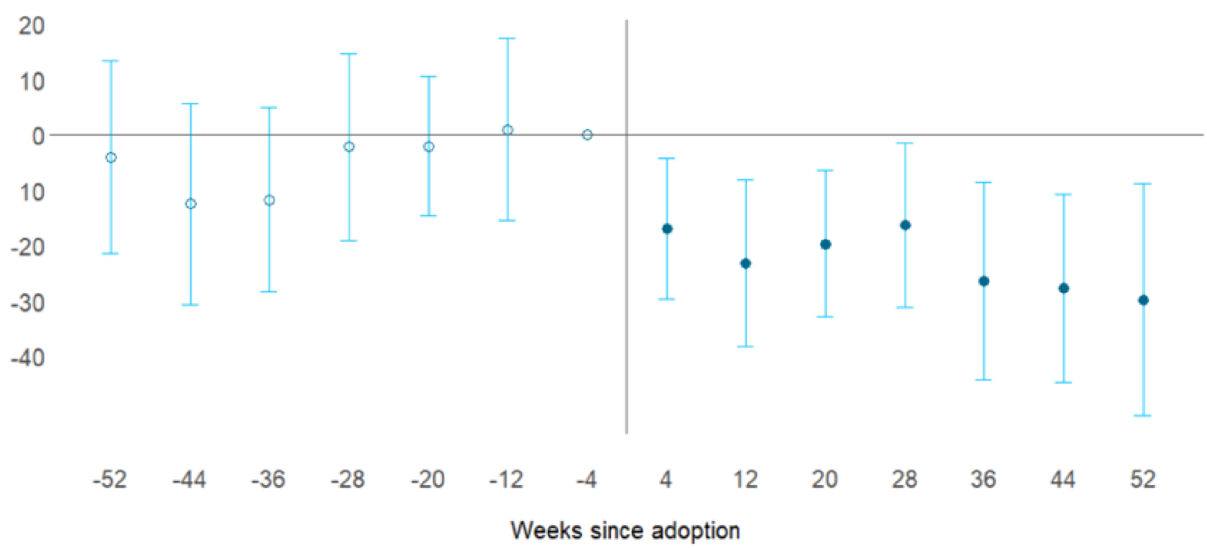
Notes: Source: PACER

Figure 3.3: Full Sample



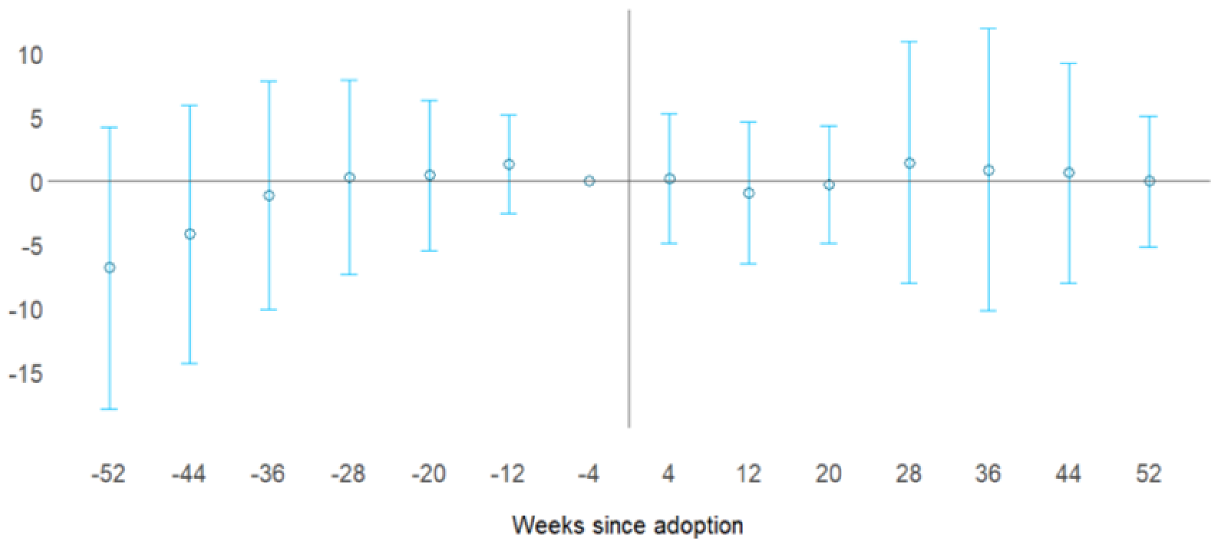
Note:This figure presents the effect of the electronic filing system adoption on the number of bankruptcy filings. Weekly data are combined into eight-week bins. The point estimates are what is left over after removing district-quarter and week fixed effects. Standard errors are clustered at the district and week levels.

Figure 3.4: Chapter 7 Bankruptcy



Note:This figure presents the effect of the electronic filing system adoption on the number of Chapter 7 bankruptcy filings. Weekly data are combined into eight-week bins. The point estimates are what is left over after removing district-quarter and week fixed effects. Standard errors are clustered at the district and week levels.

Figure 3.5: Chapter 13 Bankruptcy



Note: This figure presents the effect of the electronic filing system adoption on the number of Chapter 13 bankruptcy filings. Weekly data are combined into eight-week bins. The point estimates are what is left over after removing district-quarter and week fixed effects. Standard errors are clustered at the district and week levels.

Figure 3.6: An Example of Personal Property Items Lists

EXHIBIT "A"

(Debtor's Household Goods & Furnishings)

Kitchen Furnishings

Qty.		Value
	refrigerator	100
	stove	
	freezer	
	microwave	
	food processor	10
	bread maker	
	dishes/glassware	20
	pots & pans	20
	cooking utensils	10
	silverware	5
	toaster	2
	coffee pot	1
	crock pot	3
	blender	3
	mixer	3
	electric knife	

Dining Room Furnishings

	dining Table	75
	dining chairs	75
	hutch	
	stools	
	dishwasher	
	china	
	crystal	
	high chair	

Living & Family Room Furnishings

	couch	200
	loveseat	
	recliner	75
	coffee table	
	end tables	25
	floor lamps	
	table lamps	20
	entertnmnt cntr	
	color televisions	95
	vcr/dvd	30
	pool table	
	acquarium	
	sewing machine	
	bookcase/shelves	
	vacuum	20
	play-pen	

Master Bedroom Furnishings

Qty		Value
	bed	75
	dresser	
	chests	
	armoires	
	hope chest	
	chairs	
	lamps	2
	nightstands	
	tv	20
	vcr	

Other Bedroom Furnishings

	beds	
	dressers	
	chests	
	cribs	
	chairs	
	lamps	
	nightstands	
	desks	
	toys	
	toybox	
	tv	
	vcr	

Yard/Patio/Shop Furnishings

	lawn mower	50
	lawn/garden tools	10
	roto-tiller	
	weed-eater	
	picnic table	20
	patio/lawn chairs	
	power tools	50
	hand tools	5
	tool boxes	

Office Equipment & Furnishings

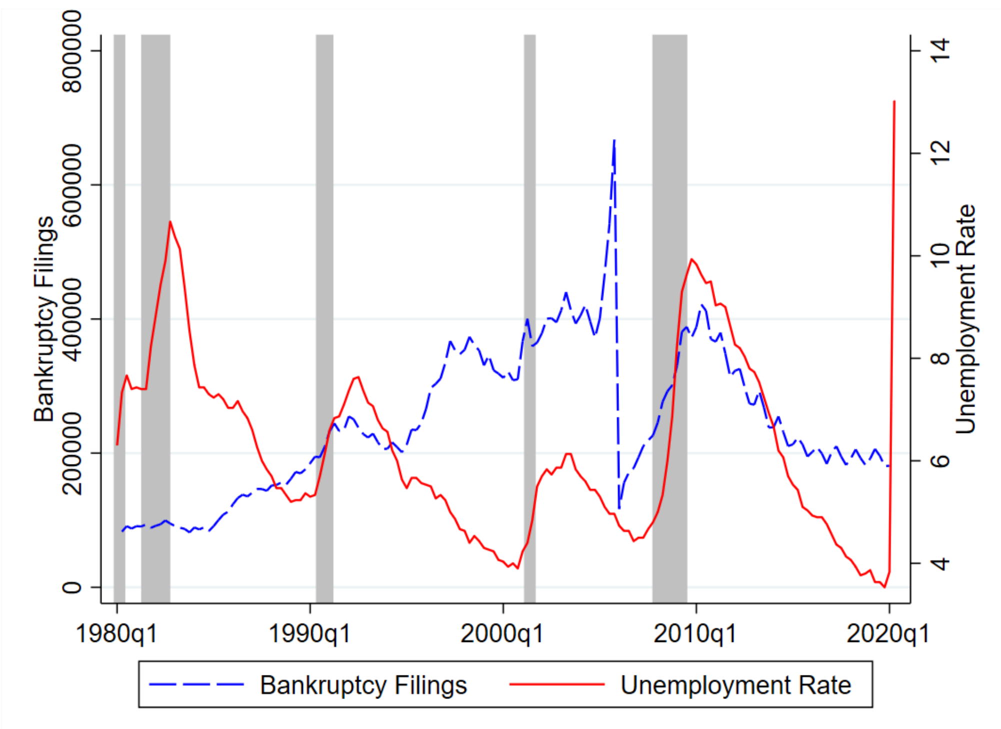
	computer	250
	printer	25
	desk	20
	chair	10
	filing cabinet	20
	copier	
	typewriter	
	fax machine	50

Other Furnishings

	washer/dryer	150
	camping equip	20
	sports equipment	
	bicycles	50

TOTAL $ . . . 1,619.00

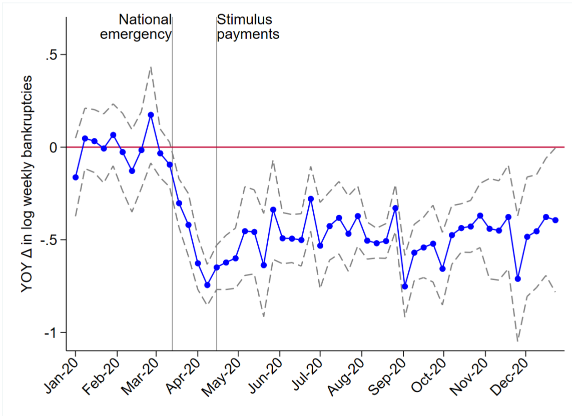
Figure 3.7: Time-Series of Bankruptcy Filings and Unemployment Rate



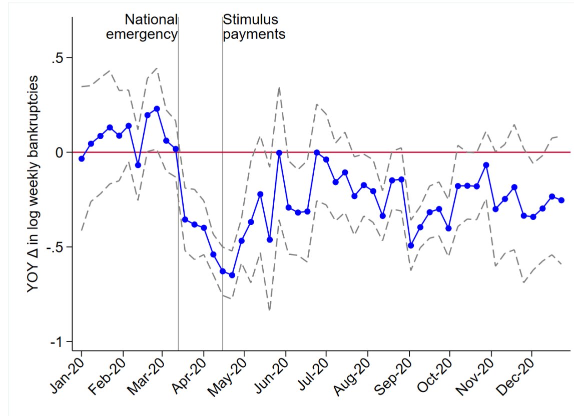
Notes: The figure presents the time-series of total quarterly U.S. bankruptcy filings and the unemployment rate. Shading reflects NBER recessions. Source: U.S. Courts Filings Statistics; BLS.

Figure 3.8: Year-over-Year Change in Weekly Bankruptcy Filings (2019-2020)

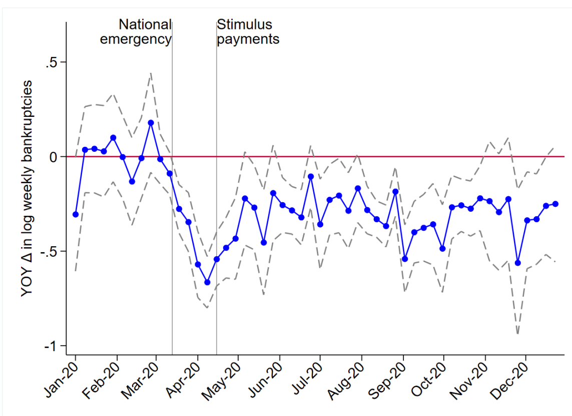
(a) Consumer



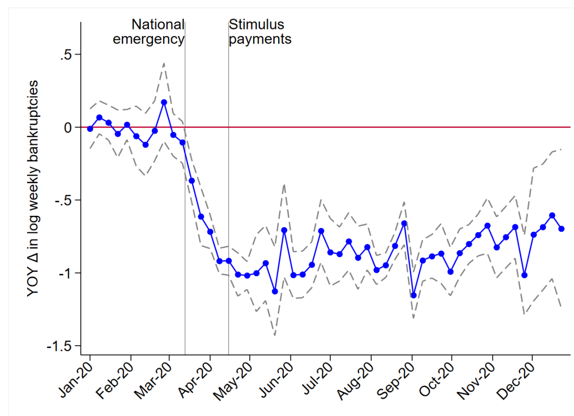
(b) Business



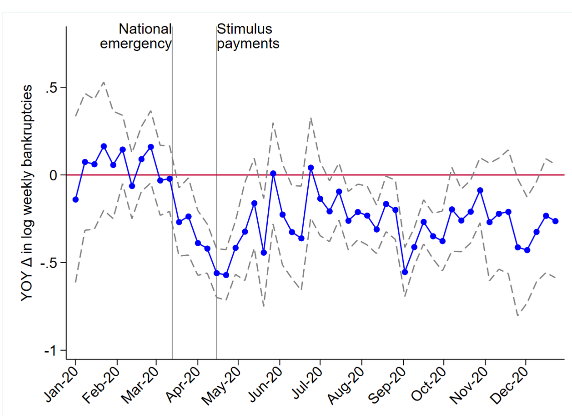
(c) Consumer Chapter 7



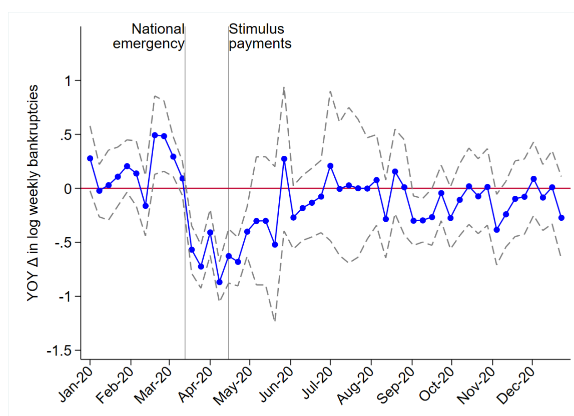
(d) Consumer Chapter 13



(e) Business Chapter 7



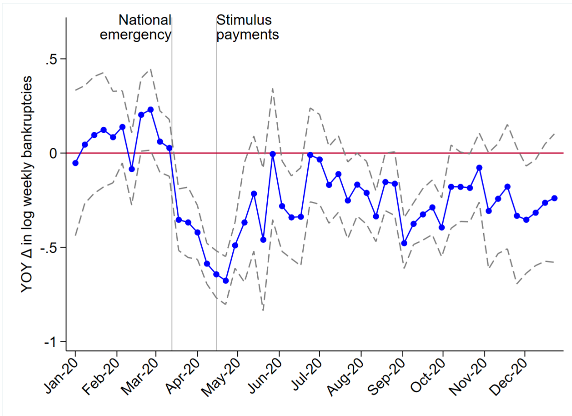
(f) Business Chapter 11



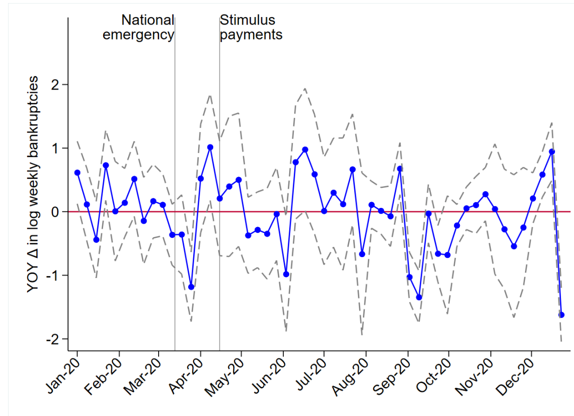
Notes: The sample consists of bankruptcy filings reported by the FJC database. The points represent estimates of the β_τ coefficients in equation (2.1). The dashed lines provide the 95-percent confidence interval for each point estimate. The dependent variable in each panel is log weekly bankruptcy filings for the specified type of filing. The vertical lines represent the dates of the declaration of a national emergency (March 13) and the date most of the CARES Act stimulus payments were deposited (April 15).

Figure 3.9: Year-over-Year Change in Weekly Bankruptcy Filings (2019-2020) - Small and Large Businesses

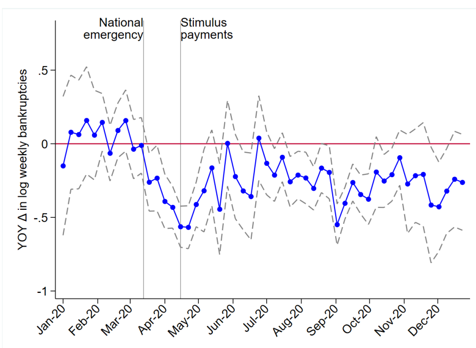
(a) Small Businesses



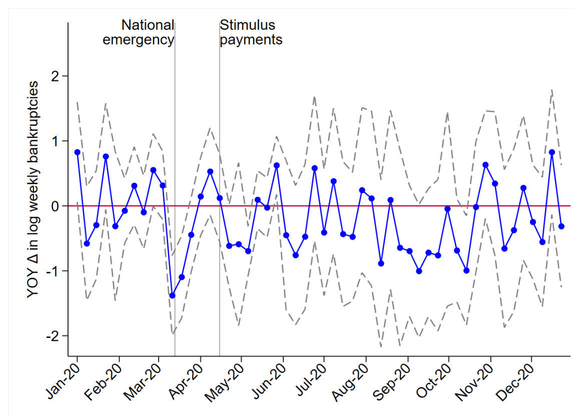
(b) Large Business



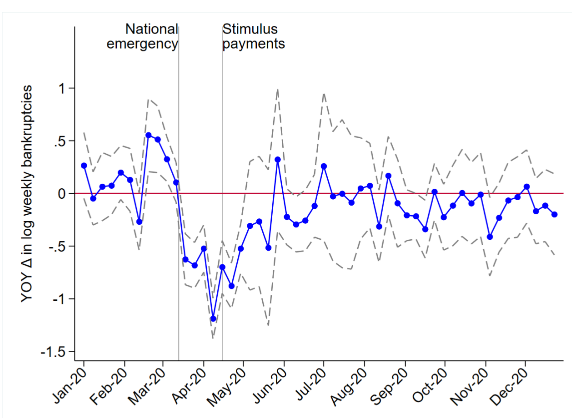
(c) Small Business - Ch. 7



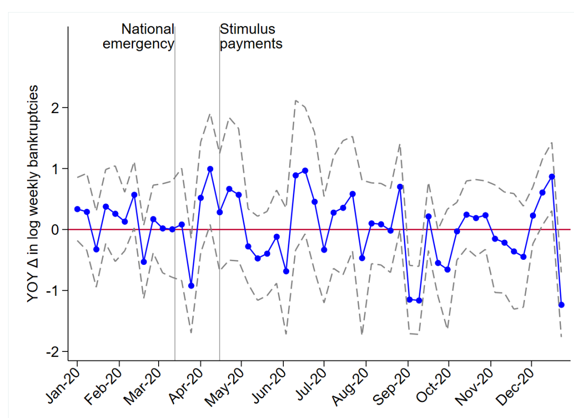
(d) Large Business - Ch. 7



(e) Small Business - Ch. 11

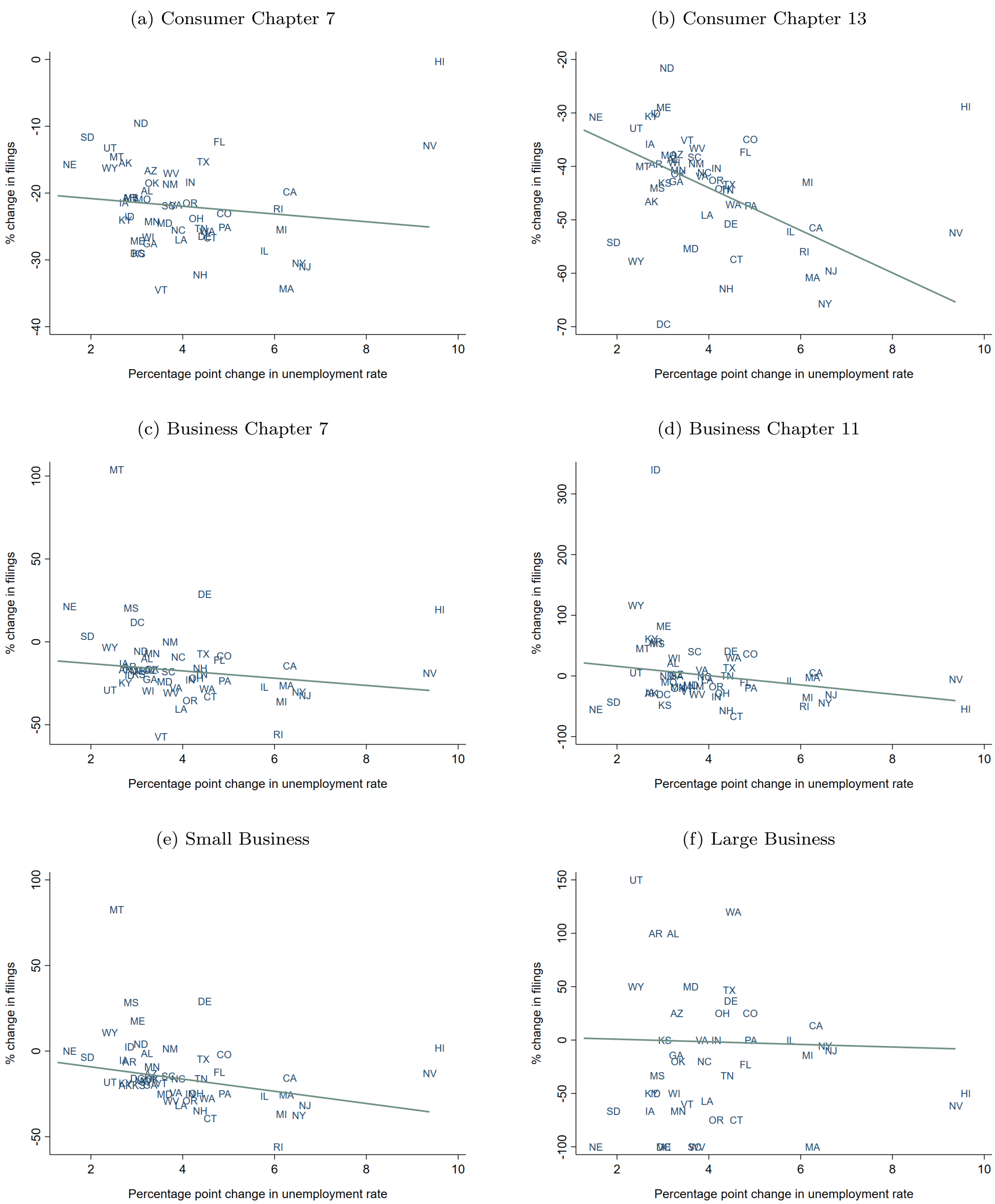


(f) Large Business - Ch. 11



Notes: The sample consists of business bankruptcy filings reported by the FJC. The points represent estimates of the β_τ coefficients in event study coefficients comparing 2019 and 2020 as shown in equation (2.1). The last six weeks are excluded from the sample as some filers don't report sufficient information on their financial condition in initial petitions and provide their financial information during bankruptcy process. The dashed lines provide the 95-percent confidence interval for each point estimate. The dependent variable in each panel is log weekly bankruptcy filings for small businesses and large businesses, where small businesses are those with less than $10 million in assets at the time of filing. All business filings are consolidated at the lead case level to remove subsidiary filings.

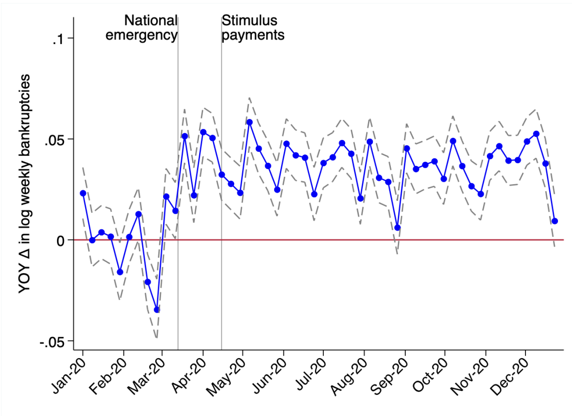
Figure 3.10: State-level Unemployment and Bankruptcy Filings



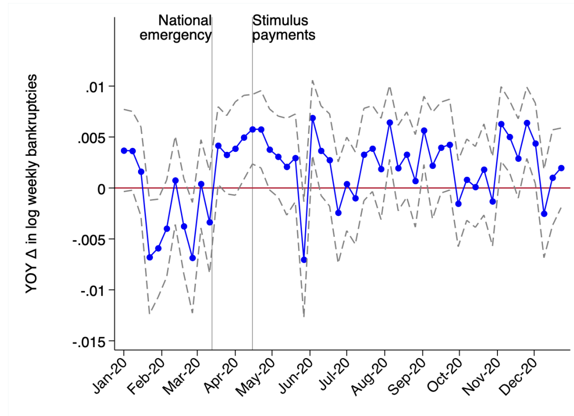
Notes: The figure shows year-over-year changes in bankruptcy filing rates and unemployment levels between 2019 and 2020. To calculate unemployment rate changes, monthly unemployment rates in each quarter are averaged for each state. Then, quarterly percentage point differences in state unemployment rates between 2019 and 2020 are used to obtain year-over-year changes. Year-over-year changes in bankruptcy rates are calculated for each state and quarter. Small business is a firm with total assets less than $10 million. Fitted lines are weighted by state population. Bankruptcy data come from FJC. Unemployment data come from BLS.

Figure 3.11: Bankruptcy Filings in High-income Zip Codes

(a) Consumer Bankruptcies

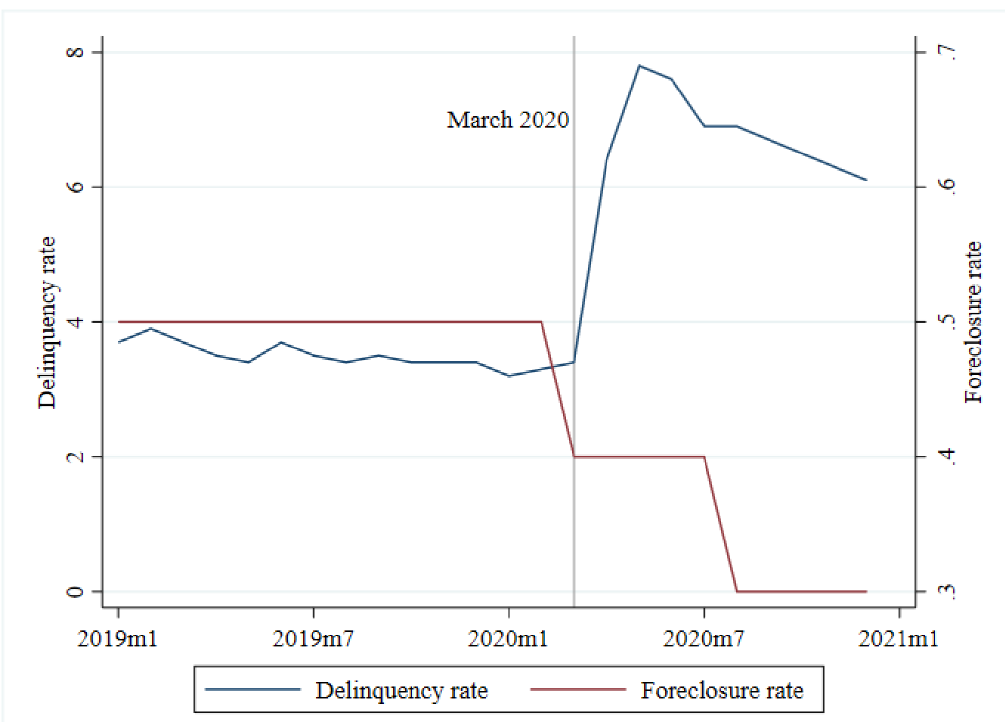


(b) Business Bankruptcies



Notes: This figure shows the evolution of bankruptcy filings in high-income zip codes, relative to low-income zip codes. The points represent estimates of the coefficient on an interaction of a *high income* indicator variable with the week fixed effect, thereby showing how bankruptcy filings evolved in high-income zip codes relative to low-income zip codes. The dependent variable in each panel is log weekly bankruptcy filings for the specified type of filing, at the zip code level.

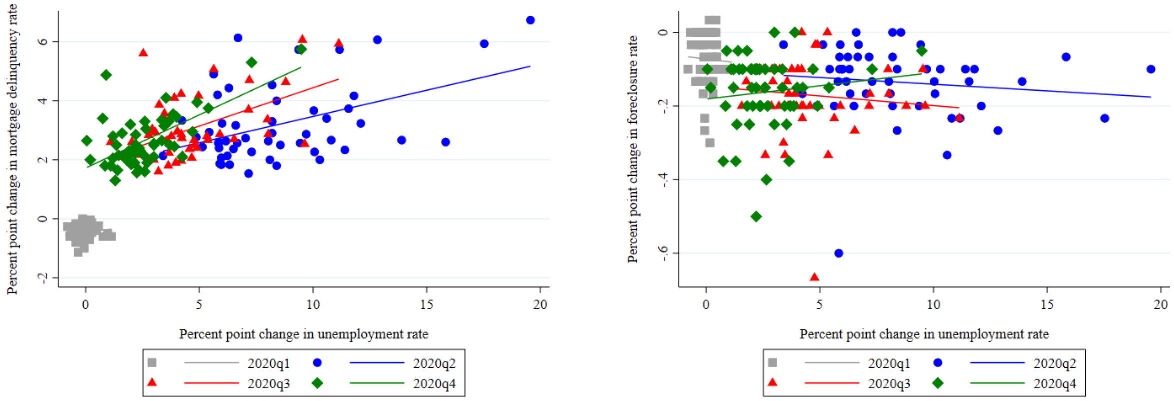
Figure 3.12: Time Series of Mortgage Delinquency and Foreclosure Rates



Notes: The figure presents the time-series of mortgage delinquency and foreclosure rates in the U.S. Source: Black Knight/McDash monthly Mortgage Monitor reports.

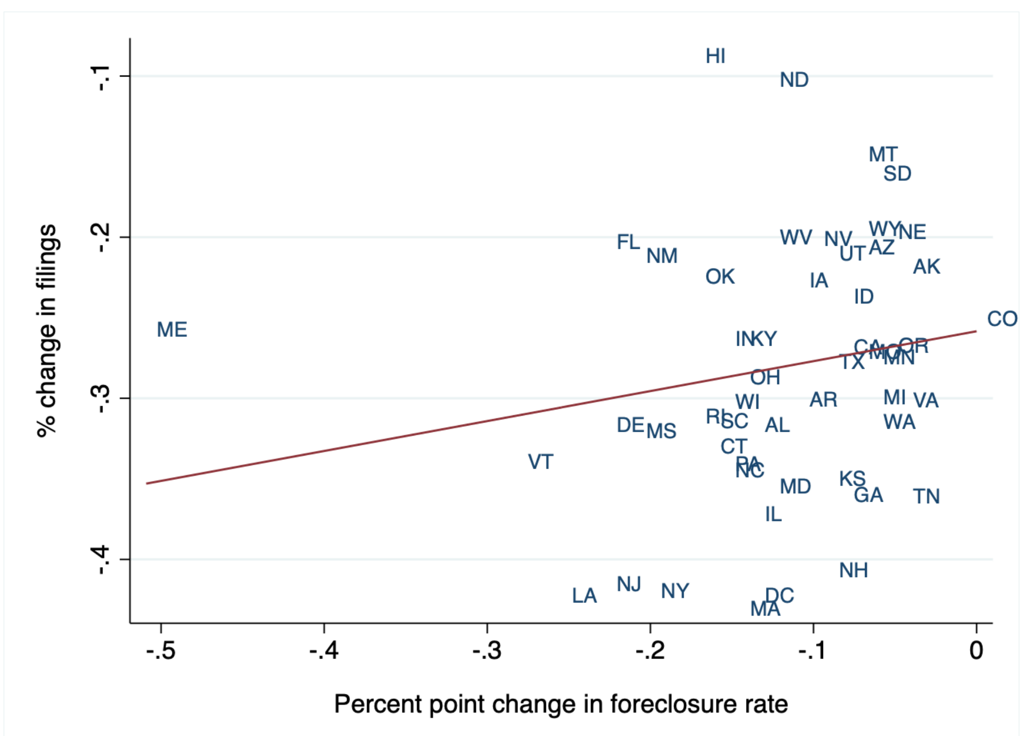
Figure 3.13: State-level Mortgage Performance and Unemployment

(a) Mortgage Delinquencies (b) Mortgage Foreclosures



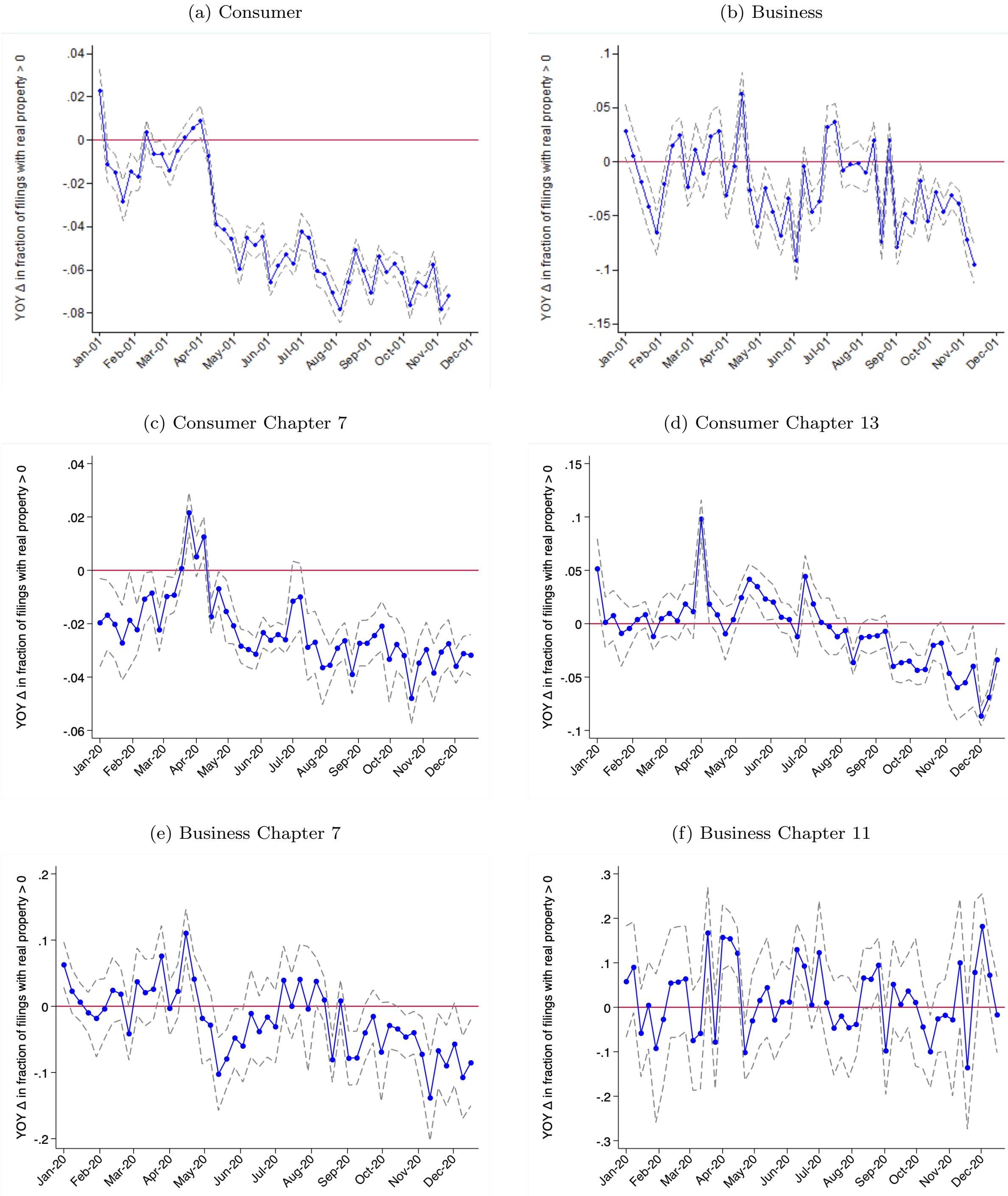
Notes: This figure shows correlations between year-over-year changes in unemployment rates and mortgage performance during 2020. In Panel (a), the y-axis plots year-over-year percentage point changes in state-level mortgage delinquency rates. Panel (b) displays year-over-year percentage point changes in state-level mortgage foreclosure rates. Unemployment rate changes are displayed on the x-axis. We calculate unemployment rate changes by first averaging monthly unemployment rates in each state within a quarter, and then taking the difference from 2019 and 2020. Mortgage data come from Black Knight Mortgage Monitor reports available at https://www.blackknightinc.com/data-reports/. Unemployment data come from BLS.

Figure 3.14: State-level Foreclosures and Bankruptcy Filings



Notes: The figure shows year-over-year changes in mortgage foreclosure rates and bankruptcy filings between 2019 and 2020, weighted by state population. Source: Black Knight/McDash monthly Mortgage Monitor reports (foreclosure rate) and FJC (bankruptcy filings).

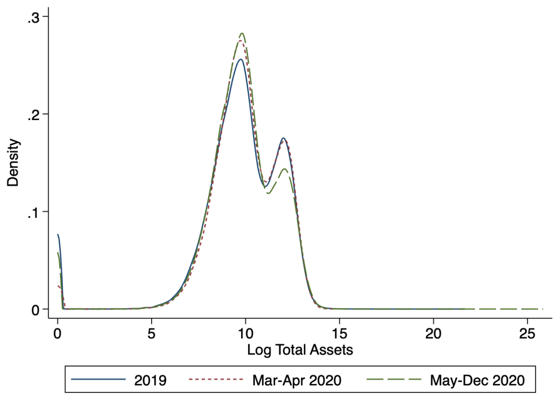
Figure 3.15: Bankruptcy Filings by Property Owners



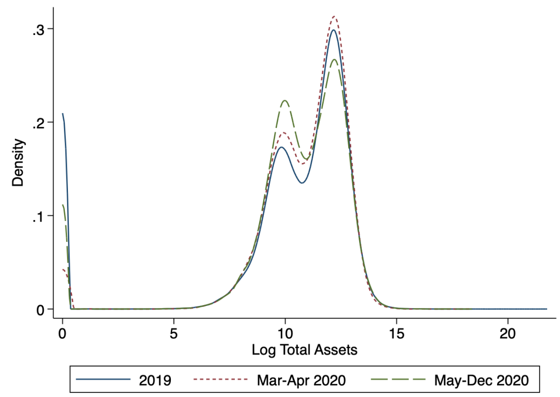
Notes: The figure shows regression coefficients for changes in the fraction of bankruptcy filings by property owners between 2019 and 2020. Property ownership is classified based on those who report real property greater than zero. Data are from the FJC database.

Figure 3.16: Changes in Filer Wealth (2019-2020)

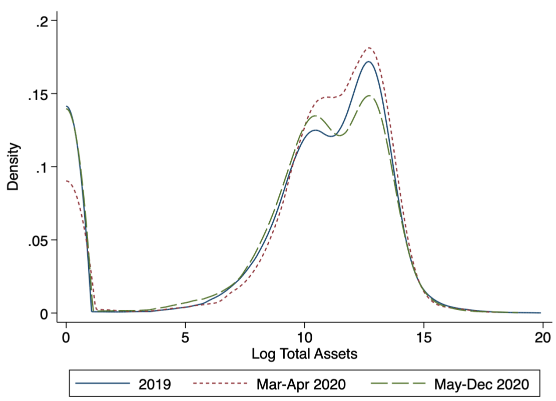
(a) Consumer Chapter 7



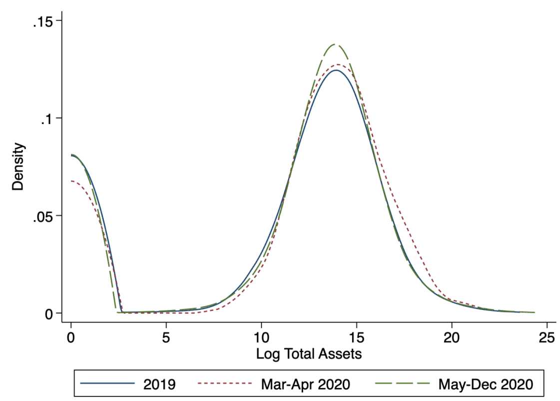
(b) Consumer Chapter 13



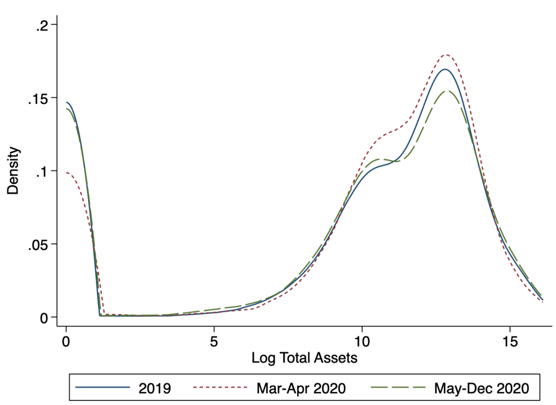
(c) Business Chapter 7



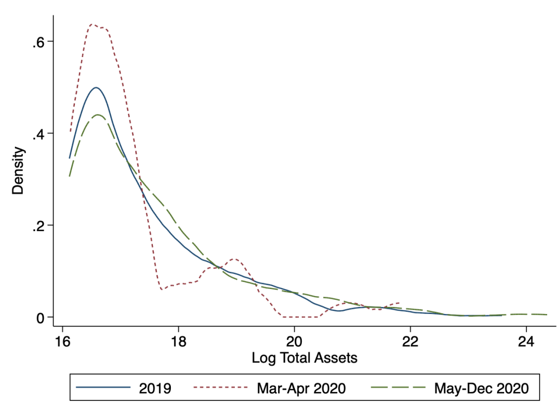
(d) Business Chapter 11



(e) Small Business



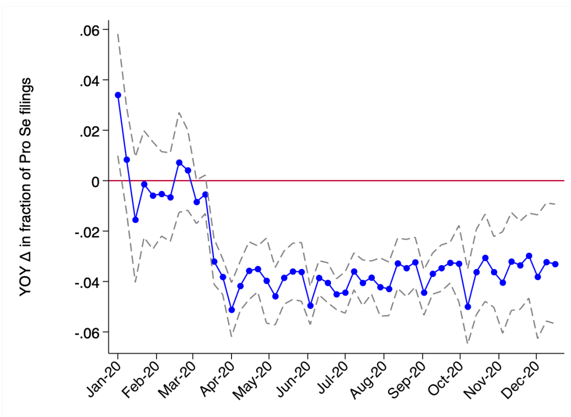
(f) Large Business



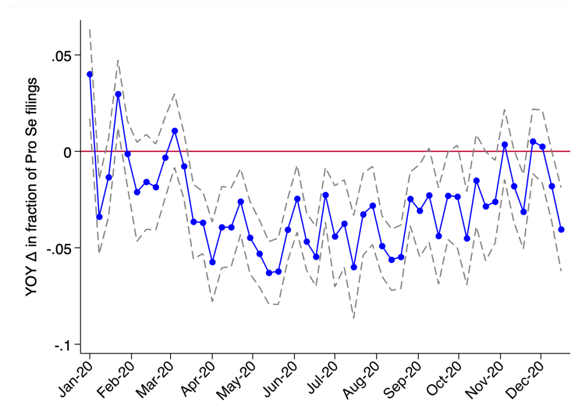
Notes: The figure shows the distributions of log total assets of bankruptcy filers for those filings in 2019, March-April in 2020, and May-December in 2020. Small business is a firm with total assets less than $10 million. Data come from the FJC database.

Figure 3.17: Changes in Pro Se Filings

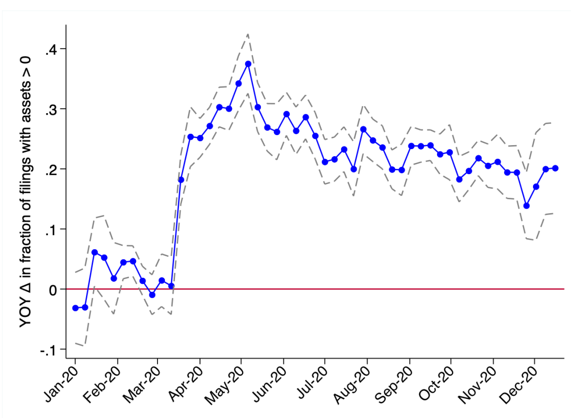
(a) Fraction Pro Se - Consumer



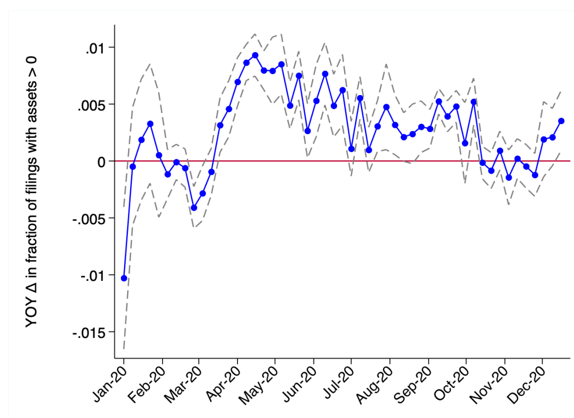
(b) Fraction Pro Se - Business



(c) Fraction with Non-Zero Assets - Pro Se



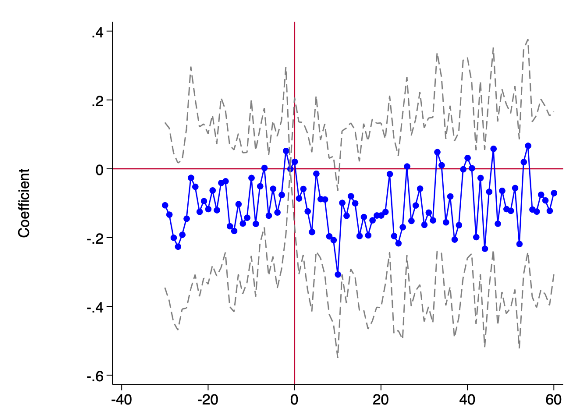
(d) Fraction with Non-Zero Assets - Non Pro Se



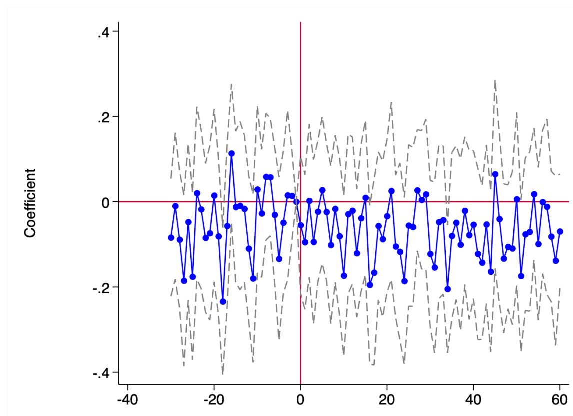
Notes: The figure shows regression coefficients for changes in the fraction and composition of pro se filings between January and December of 2019 and 2020. Panels (a) and (b) present changes in the fraction of pro se filings among all filings between 2019 and 2020, for consumer and business bankruptcies. Panel (c) and (d) present changes in the fraction of filings with non-zero assets conditional on filing pro se or filing non-pro se, including all types of bankruptcy filings. Data are from the FJC database.

Figure 3.18: Effects of Eviction Moratoria on Bankruptcy Rates

(a) Eviction Moratoria - Consumer



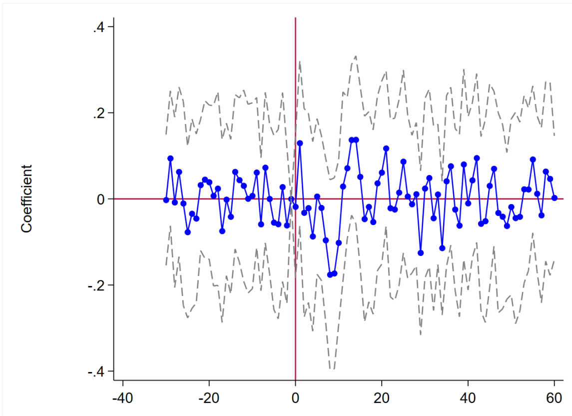
(b) Eviction Moratoria - Businesses



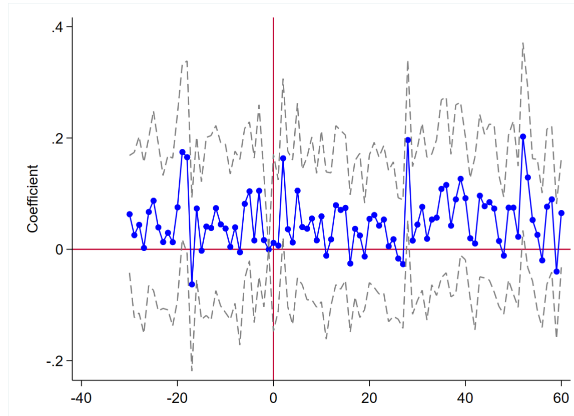
Notes: The figures show the impact of eviction moratoria on the frequency of bankruptcy filings, using the event study framework. During the pandemic, 43 states implemented eviction moratoria, while 7 states did not. Data for bankrtuptcy filing rates are from the FJC.

Figure 3.19: Effects of Mobility Restrictions on Bankruptcy Rates

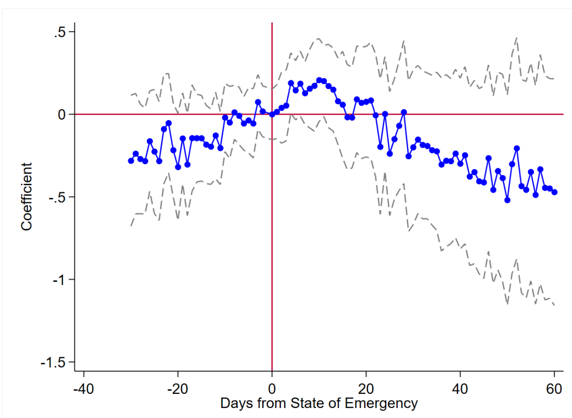
(a) Court Closure - Consumer



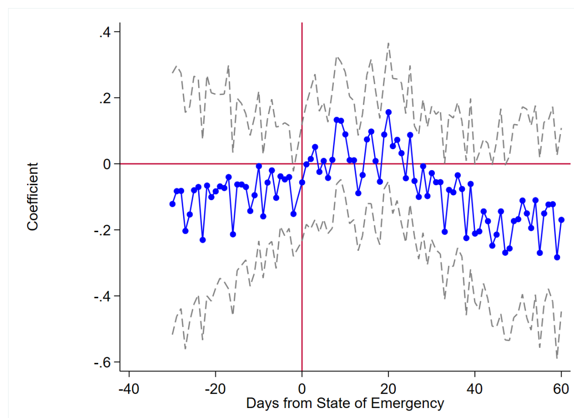
(b) Court Closure - Businesses



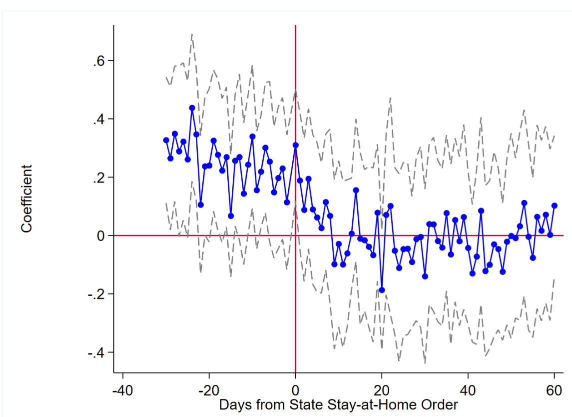
(c) State Emergency - Consumer



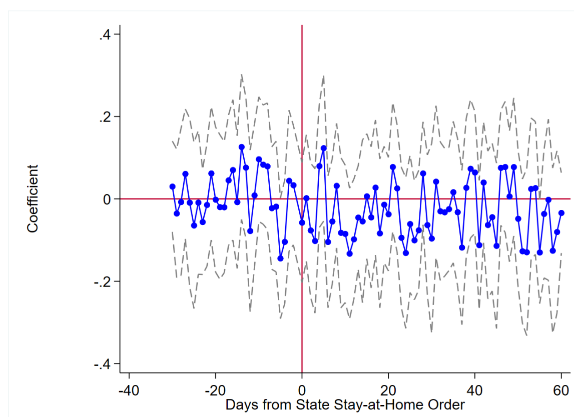
(d) State Emergency - Business



(e) Stay-at-Home Order - Consumer



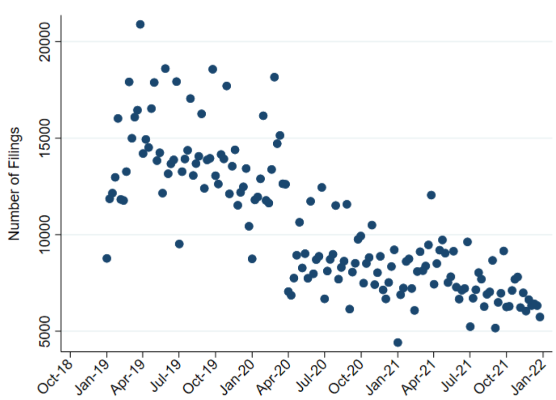
(f) Stay-at-Home Order - Business



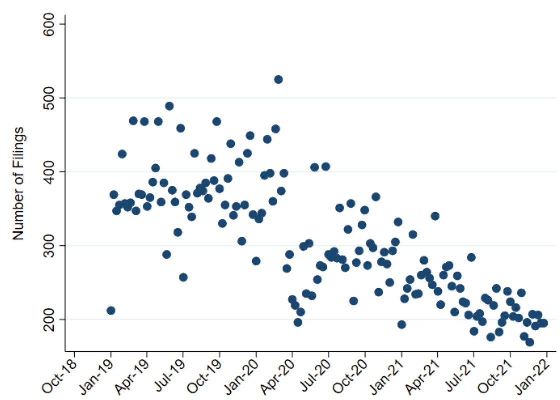
Notes: The figures show the impact of court closure, state-of-emergency declarations and stay-at-home orders on the incidence of bankruptcy filings, using the event study framework. Throughout the pandemic, 51 bankruptcy courts closed while 39 remained open. In addition, all states declared a state of emergency at varying times. In terms of stay-at-home orders, 42 states implemented such orders, while 8 states did not. The closure dates of the courts are from their websites, and the filing rates come from the FJC.

Figure 3.20: Weekly Bankruptcy Filings (January 2019 - December 2021)

(a) Total Consumer



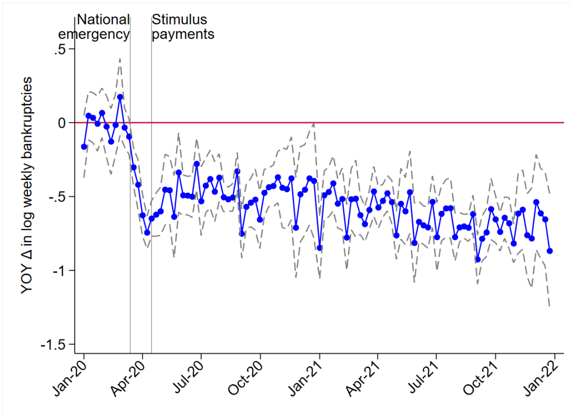
(b) Total Business



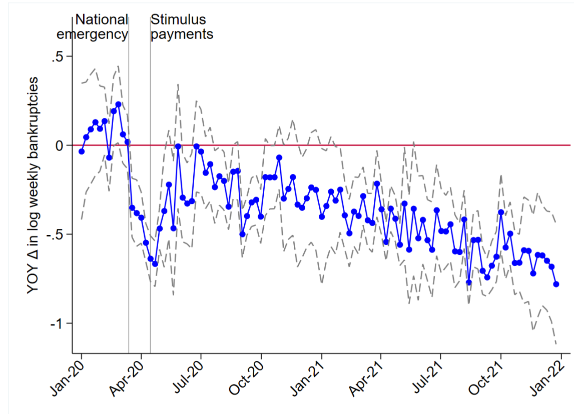
Notes: The figures show the number of weekly nationwide bankruptcies for consumers and businesses, including all bankruptcy chapters. The data come from the FJC database.

Figure 3.21: Year-over-Year Change in Weekly Bankruptcy Filings (2019-2021)

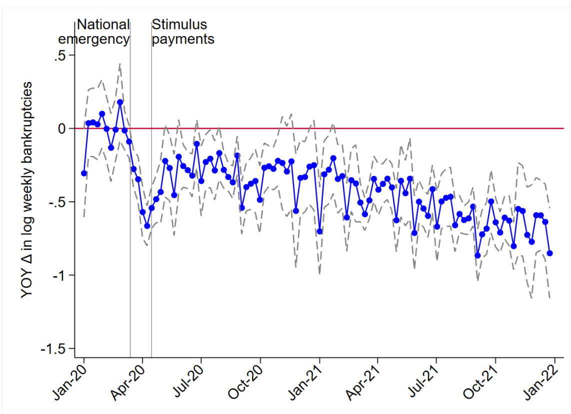
(a) Consumer



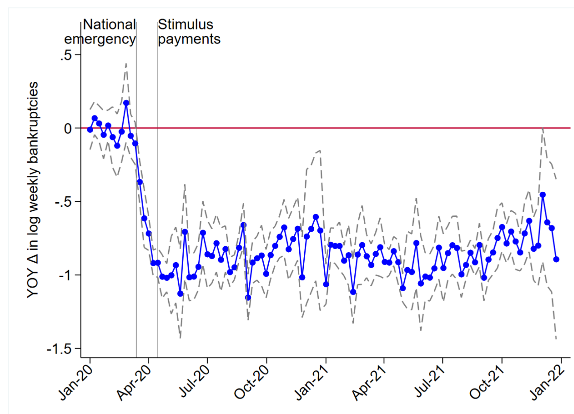
(b) Business



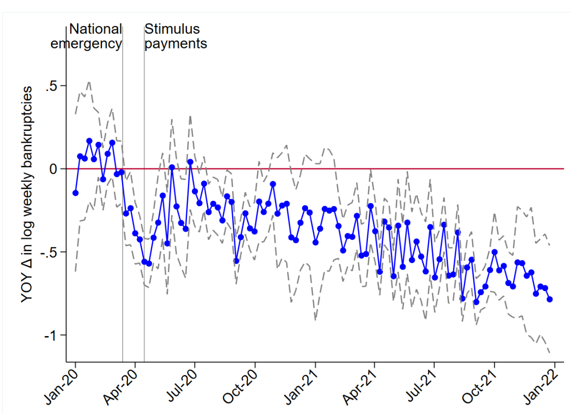
(c) Consumer Chapter 7



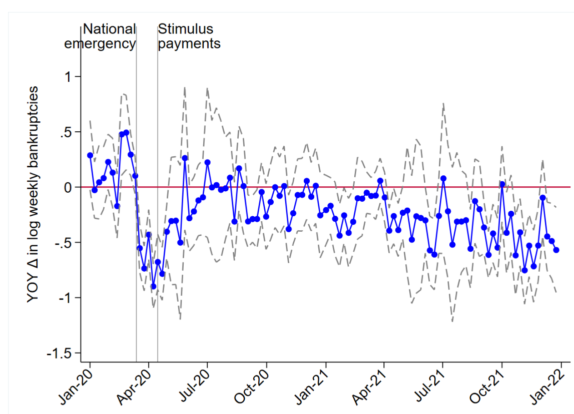
(d) Consumer Chapter 13



(e) Business Chapter 7

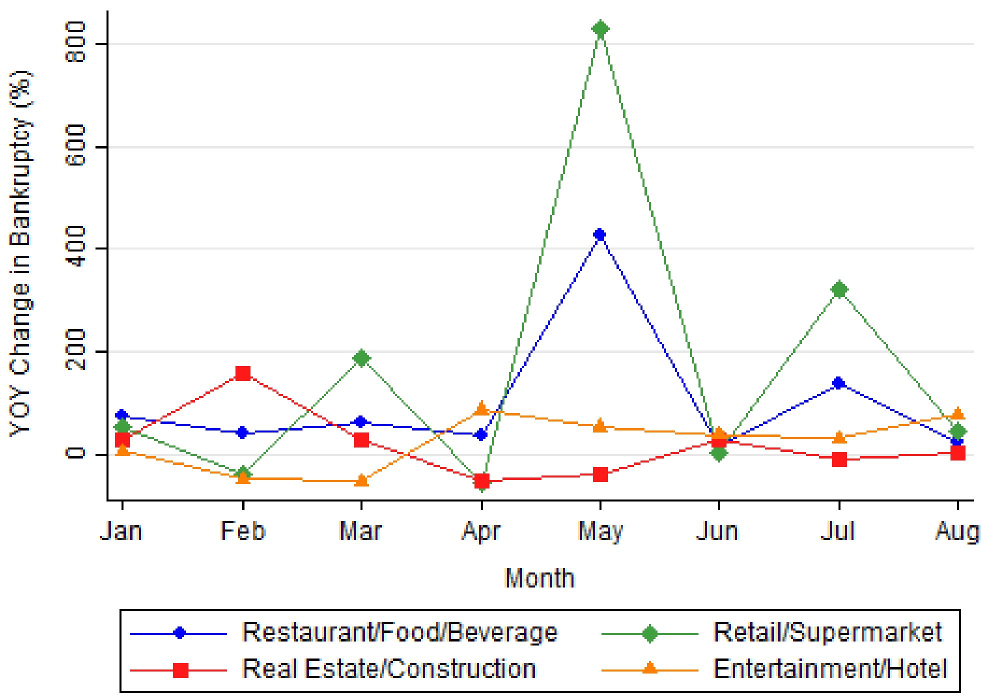


(f) Business Chapter 11



Notes: The sample consists of bankruptcy filings reported by the FJC database in 2020 and 2021. The points represent estimates of the β_τ coefficients in equation (2.1). The dashed lines provide the 95-percent confidence interval for each point estimate. The dependent variable in each panel is log weekly bankruptcy filings for the specified type of filing. The vertical lines represent the dates of the declaration of a national emergency (March 13) and the date most of the CARES Act stimulus payments were deposited (April 15).

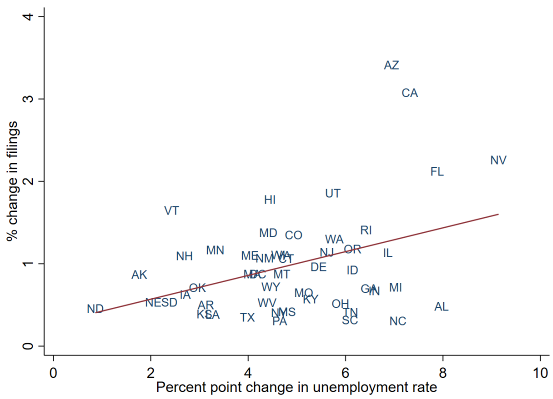
Figure 3.22: Large Business Bankruptcies by Industry



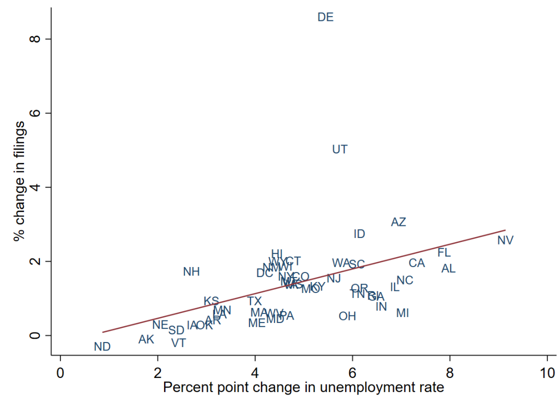
Notes: The figure presents year-over-year percentage changes in business Chapter 11 bankruptcies for selected industries between 2019 and 2020. The data come from NGR, which excludes bankruptcies filed by sole proprietorships.

Figure 3.23: Unemployment Rates and Bankruptcy Filings from 2007-2010

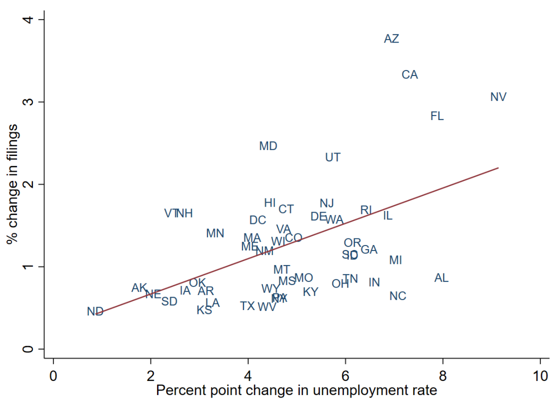
(a) Consumer



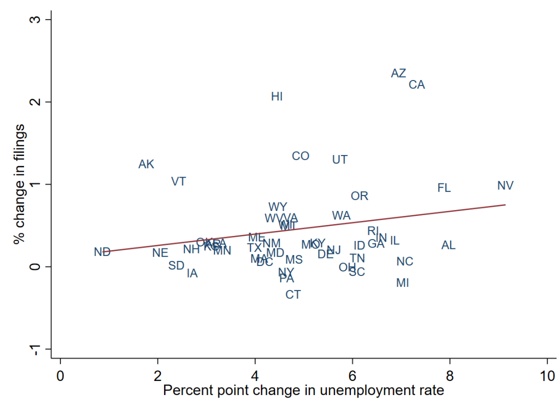
(b) Business



(c) Chapter 7



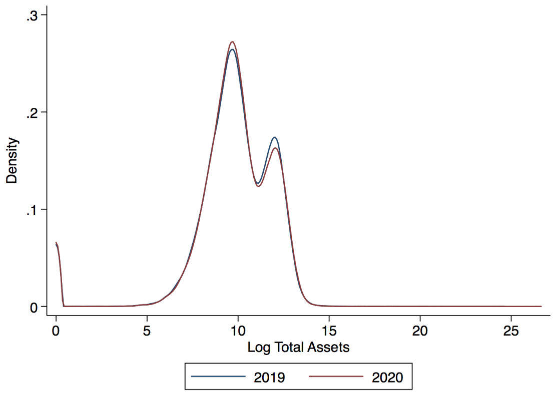
(d) Chapter 13



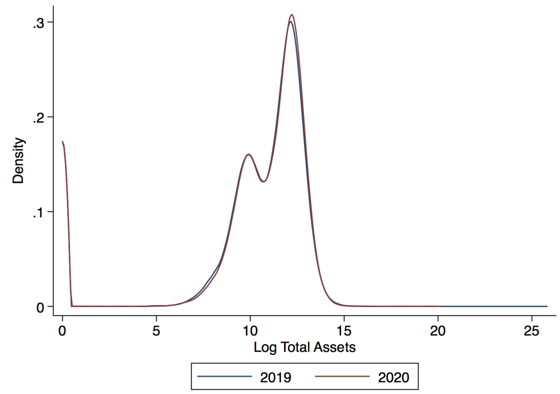
Notes: These figures show the cross-sectional relationship between increases in unemployment and bankruptcy filings during the 2007-9 financial crisis. The sample periods are from January to March 2007 and January to March 2010. The percent change in the number of filings is derived by comparing the number of bankruptcy filings in the first quarter of 2010 with the first quarter of 2007. To calculate unemployment rate changes, monthly unemployment rates in the same period are averaged for each bankruptcy district. Then, percent point differences in state unemployment rates between 2007 and 2010 are used to obtain year-over-year level changes. Source: AOUSC; BLS

Figure 3.24: Pre-Pandemic Changes in Filer Wealth (2019-2020)

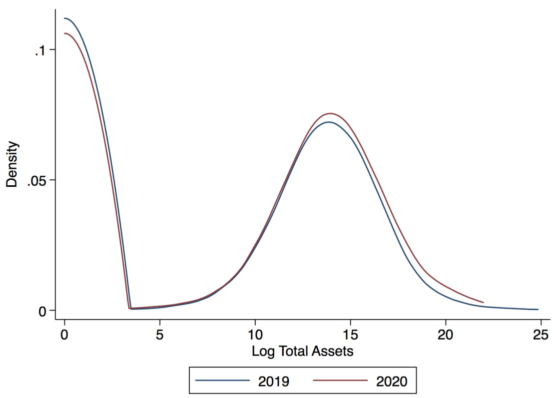
(a) Consumer Chapter 7



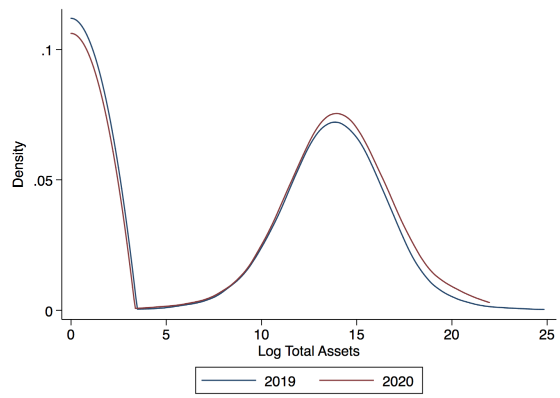
(b) Consumer Chapter 13



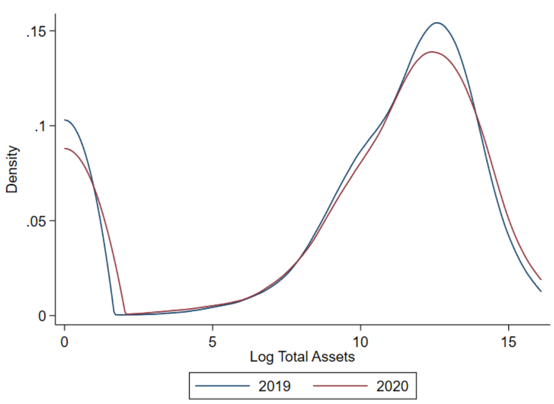
(c) Business Chapter 11



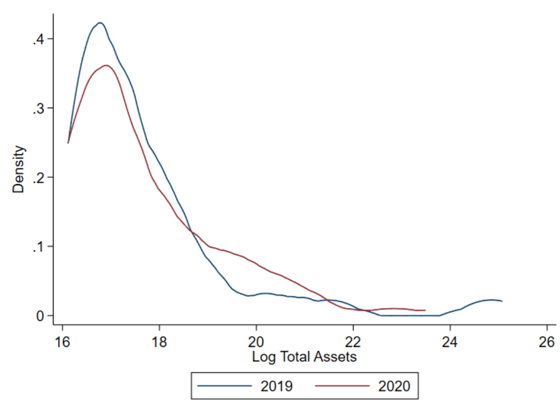
(d) Business Chapter 11



(e) Small Business

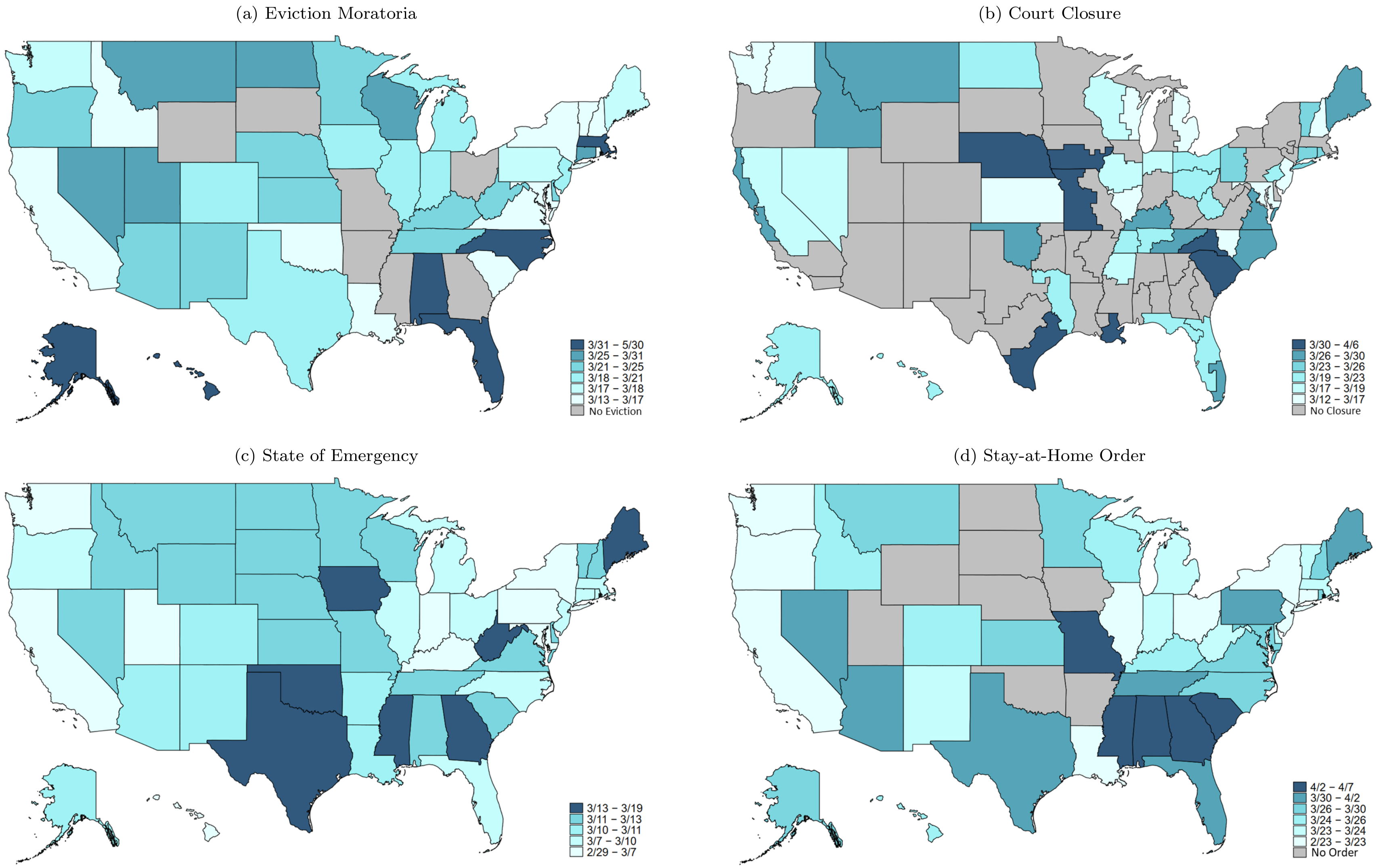


(f) Large Business



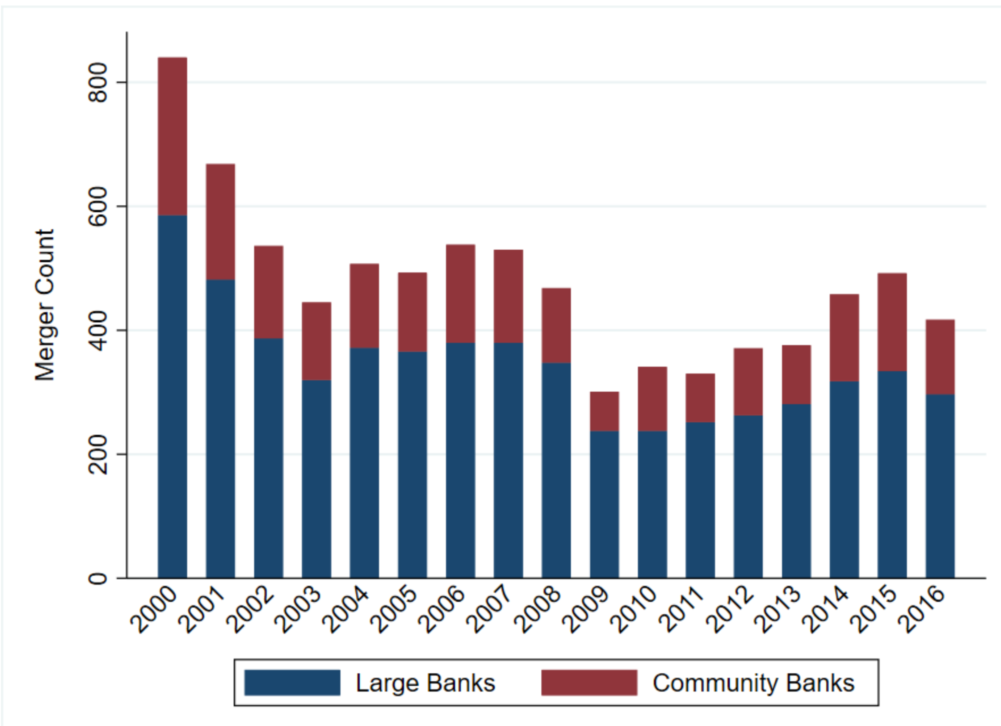
Notes: The figure shows the distributions of log total assets of bankruptcy filers for those filing between January 1st and March 14th of 2019 and 2020. Small businesses are those with less than $10 million in assets at the time of filing. Data come from the FJC database.

Figure 3.25: Dates of Eviction Moratoria and Mobility Restrictions



Notes: The maps presents the dates of the issuance of eviction moratoria and social distancing policies in response to the Covid-19 pandemic. The brightness of each state indicates the timing of those policies, with brighter-colored states having implemented their policy earlier than darker-colored ones.

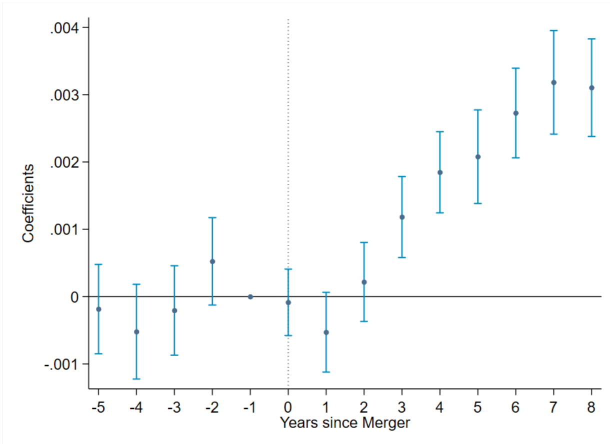
Figure 3.26: The Number of Mergers in the Banking Industry



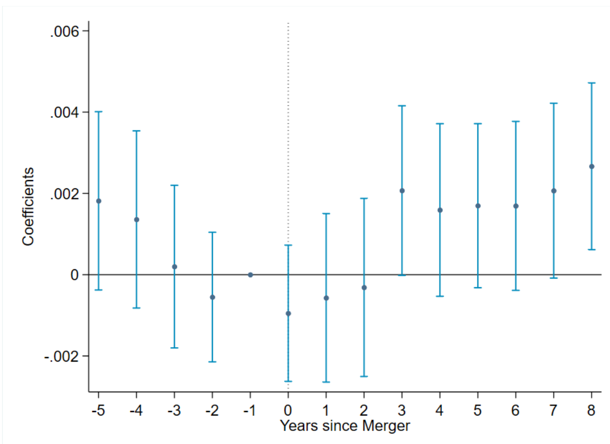
Notes: The chart presents the number of bank merger events from 2000 through 2016. Community banks are defined as banks with less than \$1 million in assets. Data come from the FDIC Report of Changes.

Figure 3.27: The Share of Affected Industries around Bank Merger Events

(a) Small Business

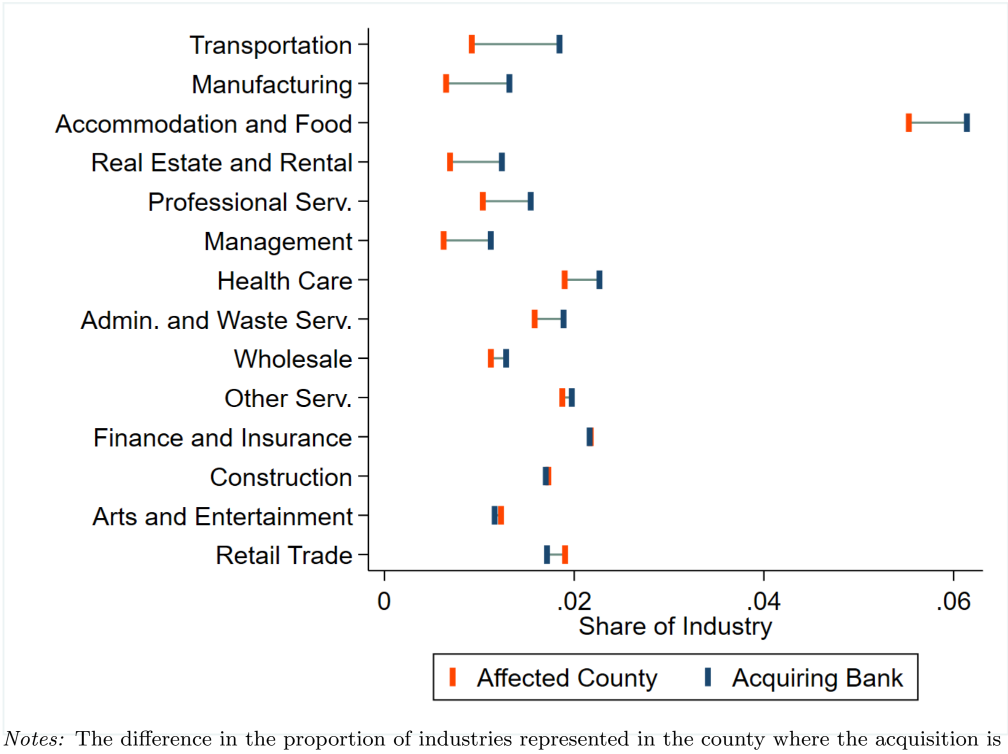


(b) Large Business



Notes: The figures show changes in regional industry structure after bank mergers. Panel (a) uses the event study framework and (b) uses the distributed lags model. I sort industries into two groups by acquiring bank: one includes a set of 4-digit NAICS codes to which the acquiring bank is mostly exposed throughout its branch network. The other group contains remaining industries that the bank has little exposure. In both plots, regression models compare changes in the share of exposed industries against non-exposed ones.

Figure 3.28: The Difference in the Share of Industries between the Affected County and the Acquiring Bank



Notes: The difference in the proportion of industries represented in the county where the acquisition is taking place compared to the industries represented by the acquiring bank. The indusrties are defined by using 2-digit NAICS codes.

Table 3.1: Adoption Dates of the Electronic Filing Sytem

Bankruptcy Court	Adoption Date	Bankruptcy Court	Adoption Date	Bankruptcy Court	Adoption Date
NYS	11/15/1996	KYE	8/1/2002	OKN	12/1/2003
AZ	10/1/1997	MT	8/19/2002	WIE	2/24/2004
VAE	10/15/1997	KYW	8/25/2002	OKE	3/1/2004
GAN	11/3/1997	INN	9/3/2002	ILC	4/12/2004
CAS	3/25/1998	LAW	10/15/2002	NCE	5/5/2004
CO	1/17/2000	NYN	12/30/2002	GUAM	5/17/2004
LAM	2/5/2001	SC	1/21/2003	WAE	6/4/2004
MOW	3/1/2001	SD	1/21/2003	ND	8/2/2004
NCW	3/5/2001	TXN	2/13/2003	TNM	10/4/2004
TXW	3/5/2001	WIW	2/15/2003	INS	10/12/2004
WAW	3/16/2001	FLM	2/18/2003	VAW	10/12/2004
DE	7/27/2001	MOE	2/23/2003	ID	1/1/2005
AK	10/15/2001	RI	4/15/2003	PR	2/22/2005
OHN	10/1/2001	WVS	4/15/2003	MSS	3/14/2005
UT	10/15/2001	MD	4/7/2003	TNE	5/17/2005
LAE	12/10/2001	OHS	4/13/2003	MIE	6/29/2005
ARE	12/17/2001	MA	4/16/2003	ILN	7/1/2005
ARW	12/17/2001	PAM	5/5/2003	GAS	8/1/2005
ME	1/15/2002	NYW	6/15/2003	CAE	8/16/2005
NE	1/1/2002	TNW	6/3/2003	VI	10/15/2005
NV	1/1/2002	HI	6/6/2003	GAM	10/3/2005
PAW	2/3/2002	MIW	7/13/2003	FLS	10/17/2005
ILS	3/1/2002	IAS	8/1/2003	MN	10/17/2005
IAN	3/1/2002	CAN	9/8/2003	OKW	1/3/2006
TXE	3/1/2002	DC	10/6/2003	NM	6/13/2006
TXS	3/15/2002	NCM	10/13/2003	CAC	8/15/2006
NJ	4/1/2002	CT	11/15/2003	PAE	10/7/2006
VT	4/1/2002	OR	11/15/2003	NH	10/16/2006
WY	4/1/2002	MSN	11/9/2003	NYE	10/16/2006
ALS	5/1/2002	FLN	11/12/2003	WVN	10/16/2006
ALM	7/22/2002	KS	12/1/2003	ALN	10/17/2006
				NMI	5/4/2009

Source: PACER

Table 3.2: State Garnishment, Homestead and Property Exemptions in 2000

State	Garnishment	Homestead	Property	State	Garnishment	Homestead	Property
AK	Fed	$54,000	$8,000	MT	Fed	$40,000	$5,700
AL	Fed	$5,000	$6,925	NC	0%	$10,000	$5,000
AR	Fed	Unlimited	$1,400	ND	Fed	$80,000	$7,425
AZ	Fed	$100,000	$9,250	NE	15%	$10,000	$2,550
CA	Fed	$50,000	$ 8,350	NH	0%	$30,000	$11,350
CO	Fed	$30,000	$4,800	NJ	10%	$15,000	$12,200
CT	Fed	75,000	$7,100	NM	Fed	$30,000	$8,050
DE	15%	$0	$5,000	NV	Fed	$95,000	$4,500
FL	Fed	Unlimited	$2,000	NY	10%	$10,000	$7,400
GA	Fed	$5,000	$5,400	OH	Fed	$5,000	$2,900
HI	19%	20,000	$2,000	OK	Fed	Unlimited	$10,925
IA	Fed	Unlimited	$10,600	OR	Fed	$25,000	$9,150
ID	Fed	$50,000	$5,750	PA	0%	$15,000	$12,200
IL	15%	$4,500	$7,125	RI	Fed	$15,000	$12,200
IN	Fed	$7,500	$4,000	SC	0%	$15,000	$12,200
KS	Fed	Unlimited	$24,650	SD	20%	Unlimited	$3,250
KY	Fed	$5,000	$6,500	TN	Fed	$5,000	$7,925
LA	Fed	$15,000	$15,125	TX	0%	Unlimited	$30,000
MA	Fed	$15,000	$12,200	UT	Fed	$8,000	$9,925
MD	Fed	$0	$6,000	VA	Fed	$5,000	$14,750
ME	Fed	$12,500	$9,550	VT	0%	$30,000	$9,400
MI	Fed	$15,000	$12,200	WA	Fed	$30,000	$12,675
MN	Fed	$200,000	$13,000	WI	20%	$40,000	$7,200
MO	10%	$8,000	$3,000	WV	20%	$15,000	$12,200
MS	Fed	$75,000	$10,000	WY	Fed	$10,000	$9,675

Note: This table shows exemption levels by state. "Fed" indicates that the federal maximum of 25% garnishment allowable binds. The entry in homestead exemption is higher of state or federal exemptions, if that state allows borrowers to choose federal exemptions. Source: Amanda E. Dawsey and Lawrence M. Ausubel, Informal Bankruptcy , 2001 (unpublished manuscript), availableat http://www.ausubel.com/creditcard-papers/informal-bankruptcy-jan2001.pdf

Table 3.3: Summary Statistics

	All samples	Early Adopted dist.	Late Adopted dist.	p-value
Weekly Cases	299.6	275.1	326.5	0.313
Chapter 7	221.3	206.4	242.8	0.355
Chapter 11	1.7	2.1	1.3	0.343
Chapter 13	76.6	68.7	83.7	0.387
Population	2,776,403	2,638,019	3,081,497	0.373
Filing per 1,000	0.108	0.107	0.116	0.424
Chapter 7	0.081	0.079	0.086	0.242
Chapter 11	0.001	0.001	0.000	0.322
Chapter 13	0.027	0.028	0.029	0.877
Discharge Rates (%)	83.0	82.2	83.6	0.588
Chapter 7	96.8	96.7	96.9	0.683
Chapter 11	42.2	43.5	41.0	0.557
Chapter 13	39.4	39.7	39.3	0.883

Note: This table provides summary statistics for 66 bankruptcy court districts in our sample. Population is computed by summing up the populations of counties in each district. Filings per 1,000 is the number of bankruptcy cases in a district divided by the population of the district and divided again by 1,000 to re-scale. The discharge rate is the number of discharged cases relative to all cases. Source: PACER, CPS

Table 3.4: Changes in Bankruptcy Filings after the Adoption of the E-filing System

	(1) [-52, 26]	(2) [-52, 26]	(3) [-52, 52]	(4) [-52, 52]	(5) [-52, 104]	(6) [-52, 104]
Adoption	-17.30**	-19.73**	-16.67**	-17.13**	-11.67**	-16.61**
	(-6.765)	(-8.433)	(-6.663)	(-7.536)	(-4.517)	(-7.227)
Avg. Filing per District	287.4	287.4	287.4	287.4	287.4	287.4
District FE	Yes	No	Yes	No	Yes	No
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Dist.×Qtr FE	No	Yes	No	Yes	No	Yes
Observations	4,521	4,510	5,912	5,903	8,412	8,403
R-squared	0.9460	0.9551	0.9383	0.9497	0.9273	0.9427

Note: The table presents the β coefficients in equation (3) using bankruptcty data from 66 districts. Column (1) and (2) compare 52 weeks before and 26 weeks after the adoption of the electronic filing system. Column (3) and (4) expand the post period to 52 weeks. Column (5) and (6) further expand the post period to 104 weeks. Standard errors are clustered at the district level.

Table 3.5: Fraction of Filings from Distant Regions

Panel A: Chapter 7

	(1) >5 miles	(2) >10 miles	(3) >15 miles	(4) >20 miles
Adoption	-0.0023	-0.0084**	-0.0092*	-0.0074
	(-0.92)	(-2.19)	(-1.82)	(-1.63)
Observations	5,903	5,903	5,903	5,903
R-squared	0.7572	0.8619	0.8936	0.9173

Panel B: Chapter 11

	(1) >5 miles	(2) >10 miles	(3) >15 miles	(4) >20 miles
Adoption	-0.0241	-0.0241	-0.0132	-0.0625
	(-0.48)	(-0.33)	(-0.20)	(-0.93)
Observations	2,308	2,308	2,308	2,308
R-squared	0.3031	0.3327	0.3494	0.3488

Panel C: Chapter 13

	(1) >5 miles	(2) >10 miles	(3) >15 miles	(4) >20 miles
Adoption	0.0099	0.0085	0.0124	0.0037
	-1.23	-0.61	-0.83	-0.26
Observations	5,829	5,829	5,829	5,829
R-squared	0.3383	0.5124	0.6423	0.7082

Note: The table presents the fraction of bankruptcy filings in distant regions from the court office. For expample, Column (1) shows the fraction of filings in regions further than 5 miles from the court office. The sample is split by bankruptcy chapter Each panel coresponds to each chapter. Standard errors are clustered at the district level.

Table 3.6: Change in Bakruptcy Filings by Chpater

	(1) Ch. 7	(2) Ch. 7	(3) Ch. 11	(4) Ch. 11	(5) Ch. 13	(6) Ch. 13
adoption	-15.97**	-17.28***	-0.122	0.254*	-0.583	-0.102
	(-6.456)	(-6.480)	(-0.185)	(-0.145)	(-1.634)	(-2.330)
Avg. Filing per District	212.7	212.7	1.2	1.2	73.5	73.5
District FE	Yes	No	Yes	No	Yes	No
Week FE	Yes	Yes	Yes	Yes	Yes	Yes
Dist.×Qtr FE	No	Yes	No	Yes	No	Yes
Observations	5,912	5,903	5,912	5,903	5,912	5,903
R-squared	0.9464	0.9622	0.0997	0.1629	0.8396	0.8508

Note: The table presents the β coefficients in equation (3) using subsamples split by bankruptcy chapter. The sample includes bankruptcy data from 61 districts. The estimation window is 52 weeks for both pre-periods and post-periods. Standard errors are clustered at the district level.

Table 3.7: Share of Computer Owners among Chapter 7 filers in Idaho

Panel A: Total Filings

	(1) Number of Samples	(2) Computer Owner	(3) Share of Computer Owner
Pre-Adoption	982	538	54.79%
Post-Adoption	991	502	50.66%
Total	1,973	1,040	52.71%

Panel B: Filers living within 15 miles

	(1) Number of Samples	(2) Computer Owner	(3) Share of Computer Owner
Pre-Adoption	252	123	48.81%
Post-Adoption	244	122	50.00%
Total	496	245	49.40%

Panel C: Filers living within 10 miles

	(1) Number of Samples	(2) Computer Owner	(3) Share of Computer Owner
Pre-Adoption	133	61	45.86%
Post-Adoption	134	71	52.99%
Total	267	132	49.44%

Note: The table presents the share of computer owners among Chapter 7 bankruptcy filers in Idaho. 2,000 bankruptcy petitions are randomly sampled from Chapter 7 bankruptcy filings. 1,000 filings are from 6 months before the adoption of e-filing system, and 1,000 filings are from 6 months after the adoption. Bankruptcy petitions with missing information about personal properties are excluded. Panel B and C uses subsamples split by filer's distances from the court office.

Table 3.8: Year-over-Year Change in Bankruptcy Filings (2019-2020)

	(1) Jan 1 - Mar 14	(2) Mar 15 - Apr 30	(3) May 1 - Jun 30	(4) Jul 1 - Aug 31	(5) Sep 1 - Oct 31	(6) Nov 1 - Dec 31	(7) YTD
Total	274	-43,680	-48,117	-49,037	-49,541	-40,672	-230,773
	(0%)	(-39%)	(-37%)	(-38%)	(-39%)	(-37%)	(-31%)
Consumer	-84	-42,729	-47,393	-48,389	-48,841	-39,868	-227,304
	(0%)	(-39%)	(-37%)	(-38%)	(-39%)	(-38%)	(-31%)
Business	358	-951	-724	-648	-700	-804	-3,469
	(9%)	(-36%)	(-22%)	(-20%)	(-21%)	(-25%)	(-18%)
Consumer Ch7	8	-25,255	-19,521	-20,213	-21,496	-17,387	-103,864
	(0%)	(-34%)	(-24%)	(-25%)	(-28%)	(-27%)	(-23%)
Consumer Ch13	-41	-17,404	-27,804	-28,122	-27,281	-22,425	-123,077
	(0%)	(-49%)	(-61%)	(-59%)	(-57%)	(-54%)	(-45%)
Business Ch7	132	-557	-454	-494	-529	-608	-2,510
	(5%)	(-30%)	(-20%)	(-22%)	(-23%)	(-27%)	(-18%)
Business Ch11	179	-231	-110	-47	-58	-87	-354
	(24%)	(-46%)	(-17%)	(-7%)	(-9%)	(-15%)	(-9%)
Small Business	344	-957	-722	-646	-690	-800	-3,471
	(9%)	(-37%)	(-23%)	(-20%)	(-21%)	(-26%)	(-18%)
Large Business	14	6	-2	-2	-10	-4	2
$Assets > \$10m$	(18%)	(15%)	(-3%)	(-3%)	(-13%)	(-7%)	(1%)
Very Large Business	5	2	8	5	-4	5	21
$Assets > \$50m$	(18%)	(29%)	(30%)	(28%)	(-14%)	(45%)	(18%)

Notes: The table presents year-over-year changes in nationwide bankruptcy filings between 2019 and 2020. Small business is defined as a firm with total assets less than $10 million. Bankruptcy data come from the FJC database
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Table 3.9: Cross-sectional Regressions on YOY Changes in Bankruptcy Filings

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Consumer		Business	
	All	Consumer	Business	Ch 7	Ch 13	Ch 7	Ch 11
Unemployment	- 1.52	- 1.24	- 10.22	- 1.68	- 2.57	- 4.62	- 19.81
	(2.10)	(2.09)	(5.44)	(1.77)	(1.73)	(4.17)	(15.29)
	[0.47]	[0.56]	[0.07]	[0.35]	[0.14]	[0.27]	[0.20]
Foreclosure rate	- 3.9	- 5.1	- 1.7	- 3.3	- 6.4	5.6	- 55.4
	(4.2)	(4.3)	(6.9)	(3.6)	(5.2)	(8.1)	(34.1)
	[0.36]	[0.24]	[0.81]	[0.36]	[0.23]	[0.49]	[0.11]
Fraction pro se	- 6.0	- 9.2	- 110.8	19.5	- 35.7	- 65.5	75.6
	(25.1)	(24.8)	(88.2)	(22.4)	(13.4)	(42.0)	(130.1)
	[0.81]	[0.71]	[0.22]	[0.39]	[0.01]	[0.13]	[0.56]
Fraction property owners	- 25.3	- 10.0	- 140.7	- 3.6	13.8	- 103.6	- 47.4
	(25.8)	(25.1)	(61.2)	(20.8)	(13.1)	(29.0)	(116.2)
	[0.33]	[0.69]	[0.03]	[0.86]	[0.30]	[0.00]	[0.69]
Median assets (000s)	0.13	0.02	0.20	0.20	- 0.03	0.26	0.00
	(0.10)	(0.09)	(0.08)	(0.15)	(0.02)	(0.06)	(0.00)
	[0.19]	[0.83]	[0.02]	[0.20]	[0.28]	[0.00]	[0.64]

Notes: Table shows cross-sectional regressions of 2019 levels of economic indicators and filer characteristics on the YOY change in each type of bankruptcy from 2019 to 2020. Each column represents a single regression across the fifty states and the District of Columbia. Unemployment is the average monthly unemployment rate in 2019 for each state. The foreclosure rate is the average monthly foreclosure rate in 2019 for each state based on data from Black Knight. Fraction pro se, fraction property owners, and median assets are measured across all bankruptcies in 2019 in each state for each bankruptcy type.

Table 3.10: Changes in Bankruptcy Filer Characteristics (2019-2020)

	Consumer Chapter 7			Consumer Chapter 13			Business Chapter 7			Business Chapter 11		
	Diff	2019	2020	Diff	2019	2020	Diff	2019	2020	Diff	2019	2020
Filing characteristics:												
Asset case	-1%	2%	1%	0%	100%	100%	0%	6%	6%	0%	99%	99%
Small Business	0%	0%	0%	0%	1%	1%	-3%	9%	6%	18%	35%	53%
Pro se	-2%	8%	6%	-4%	9%	5%	-2%	7%	4%	-3%	8%	5%
Fee Fully Paid	3%	79%	82%	2%	72%	74%	0%	95%	95%	-1%	96%	95%
Total assets	-$1,604	$62,366	$60,762	$428	$109,612	$110,041	-$2,811	$110,168	$107,357	$9,885	$170,922	$180,807
Has assets	1%	97%	98%	4%	90%	94%	0%	80%	80%	3%	72%	0.75
Real property	-$2,164	$39,913	$37,749	-$1,305	$81,324	$80,019	-$2,845	$64,082	$61,236	$5,145	$86,223	$91,368
Has real	-2%	32%	30%	0%	56%	56%	-2%	35%	33%	2%	40%	42%
Personal property	$594	$18,747	$19,341	$1,569	$22,295	$23,864	$317	$27,700	$28,016	$1,357	$32,495	$33,852
Has personal	1%	97%	98%	4%	90%	94%	1%	79%	80%	4%	65%	69%
Total liability	-$473	$106,003	$105,530	$1,583	$137,846	$139,429	-$529	$225,758	$225,229	$5,726	$229,257	$234,983
Has total liabilities	1%	97%	98%	4%	90%	94%	1%	83%	84%	2%	74%	76%
Secured claims	-$2,210	$45,903	$43,693	-$2,046	$85,565	$83,519	-$4,354	$81,928	$77,575	$5,382	$126,850	$132,232
Has secured	-1%	66%	65%	2%	84%	86%	-2%	58%	56%	3%	62%	65%
Unsecured priority	-$7	$721	$715	$90	$1,457	$1,547	-$130	$1,896	$1,766	-$190	$2,170	$1,981
Unsecured non-priority	$1,826	$51,507	$53,333	$4,322	$39,569	$43,891	$2,165	$92,609	$94,774	$2,651	$71,265	$73,916
Current monthly income	-$16	$3,124	$3,107	$95	$3,972	$4,067	-$56	$362	$306	-$198	$766	$568
Has current income	0%	90%	90%	3%	86%	89%	-1%	9%	8%	-2%	9%	7%

Notes: The table presents mean statistics for bankruptcy filings between 2019 and 2020. Data are from FJC.

Table 3.11: Total Bankruptcy Filings by Quarter

Panel A: AOUSC Statistics

	(1) 2019	(2) 2020	(3) 2020 Q1	(4) 2020 Q2	(5) 2020 Q3	(6) 2020 Q4
Total	774,837	544,099	181,098	124,395	126,243	112,363
Consumer	752,117	522,508	175,146	119,241	120,722	107,399
Business	22,720	21,591	5,952	5,154	5,521	4,964
Consumer Ch7	465,971	366,786	109,180	90,993	89,749	76,864
Consumer Ch13	285,177	155,171	65,757	28,145	30,837	30,432
Business Ch7	14,174	11,884	3,491	2,700	2,902	2,791
Business Ch11	6,045	7,777	1,865	2,047	2,110	1,755

Panel B: FJC Data

	(1) 2019	(2) 2020	(3) 2020 Q1	(4) 2020 Q2	(5) 2020 Q3	(6) 2020 Q4
Total	757,524	529,048	177,298	120,869	121,947	108,934
Consumer	735,973	508,543	171,566	115,977	116,776	104,224
Business	21,551	20,505	5,732	4,892	5,171	4,710
Consumer Ch7	463,965	358,287	107,939	88,810	86,960	74,578
Consumer Ch13	271,314	149,927	63,467	27,126	29,748	29,586
Business Ch7	14,161	11,599	3,486	2,684	2,773	2,656
Business Ch11	5,210	7,295	1,707	1,909	1,998	1,681

Notes: Panel A comes from published statistics from the Administrative Office of the U.S. Courts. Panel B is computed using our analysis dataset using data from FJC.

Table 3.12: Year-over-Year Change in Bankruptcy Filings, Unconsolidated Filings (2019-2020)

	(1) Jan 1 - Mar 14	(2) Mar 15 - Apr 30	(3) May 1 - Jun 30	(4) Jul 1 - Aug 31	(5) Sep 1 - Oct 31	(6) Nov 1 - Dec 31	(7) YTD
Total	492	-43,351	-47,500	-48,621	-49,072	-40,301	-228,353
	(0%)	(-38%)	(-37%)	(-37%)	(-38%)	(-37%)	(-30%)
Consumer	-81	-42,729	-47,396	-48,390	-48,846	-39,869	-227,311
	(0%)	(-39%)	(-37%)	(-38%)	(-39%)	(-38%)	(-31%)
Business	573	-622	-104	-231	-226	-432	-1,042
	(13%)	(-22%)	(-3%)	(-6%)	(-6%)	(-12%)	(-5%)
Consumer Ch7	9	-25,256	-19,520	-20,213	-21,496	-17,386	-103862
	(0%)	(-34%)	(-24%)	(-25%)	(-28%)	(-27%)	(-23%)
Consumer Ch13	-38	-17,403	-27,804	-28,122	-27,285	-22,427	-123,079
	(0%)	(-49%)	(-61%)	(-59%)	(-57%)	(-54%)	(-45%)
Business Ch7	195	-537	-409	-488	-514	-537	-2,290
	(7%)	(-29%)	(-18%)	(-21%)	(-22%)	(-24%)	(-17%)
Business Ch11	326	76	461	360	400	215	1,838
	(25%)	(11%)	(49%)	(40%)	(41%)	(24%)	(32%)
Small Business	521	-634	-129	-300	-237	-437	-1,216
	(12%)	(-23%)	(-4%)	(-9%)	(-7%)	(-13%)	(-6%)
Large Business	52	12	25	69	11	5	174
$Assets > \$10m$	(55%)	(20%)	(22%)	(90%)	(8%)	(7%)	(31%)
Very Large Business	30	7	28	50	2	6	123
$Assets > \$50m$	(86%)	(54%)	(68%)	(278%)	(3%)	(33%)	(66%)

Notes: The table presents year-over-year changes in nationwide bankruptcy filings between 2019 and 2020. Business filings contain both filings from parent companies and those from their affiliates or branches. Small business is defined as a firm with total assets less than $10 million. The sample consists of bankruptcy filings reported by the FJC database.

Table 3.13: State-Level Unemployment and Bankruptcy Filings

	(1) 2020 Q1	(2) 2020 Q2	(3) 2020 Q3	(4) 2020 Q4	(5) YTD
Total	0.0171	-1.077	0.079	0.397	-0.916
	(2.557)	(0.519)	(0.894)	(1.108)	(0.935)
	[0.995]	[0.043]	[0.93]	[0.722]	[0.332]
Consumer	-1.374	-1.134	0.138	0.345	-0.922
	(1.926)	(0.541)	(0.944)	(1.049)	(0.965)
	[0.479]	[0.0413]	[0.884]	[0.743]	[0.344]
Business	16.43	-0.26	-2.276	1.695	-2.412
	(14.84)	(1.465)	(1.899)	(3.245)	(1.532)
	[0.274]	[0.86]	[0.236]	[0.604]	[0.122]
Consumer Ch7	-2.108	-1.406	0.574	1.624	-0.625
	(2.331)	(0.478)	(0.629)	(0.949)	(0.768)
	[0.37]	[0.0050]	[0.367]	[0.0934]	[0.42]
Consumer Ch13	-0.514	-1.919	-2.979	-3.538	-3.619
	(2.879)	(0.576)	(0.84)	(1.414)	(0.895)
	[0.859]	[0.0017]	[0.0009]	[0.0157]	[0.0002]
Business Ch7	-3.3	-1.128	-1.506	-0.0068	-2.381
	(16.47)	(1.502)	(1.24)	(1.86)	(1.411)
	[0.842]	[0.457]	[0.23]	[0.997]	[0.0979]
Business Ch11	82.82	1.259	-10.79	8.474	-3.828
	(32.95)	(6.195)	(6.38)	(9.299)	(4.995)
	[0.0155]	[0.84]	[0.0975]	[0.367]	[0.447]

Notes: The table presents the coefficients from cross-sectional regressions of the year-over-year percentage point change in state bankruptcy filings on changes in state unemployment rates. Monthly state-level unemployment rates are averaged to compute quarterly unemployment rates, and the regressions are weighted by state population. The coefficients in this table correspond to the slopes in Figure 3.10. Standard errors are in parentheses and p-values are in square brackets. The sample consists of bankruptcy filings reported by the FJC (January - September 2019) and PACER (October 2019 - December 2020). Unemployment rates are from BLS.

Table 3.14: The Growth Rates of Establishments and Employments

	Small Establishments		Large Establishments	
	(1) ln(1+est.)	(2) ln(1+emp.)	(3) ln(1+est.)	(4) ln(1+emp.)
Exposure	0.96***	0.56**	0.542***	-0.0292
	(0.168)	(0.22)	(0.13)	(0.195)
County-Industry FEs	Yes	Yes	Yes	Yes
State-Year FEs	Yes	Yes	Yes	Yes
Adjusted R-squared	0.976	0.883	0.936	0.883
Obs.	11,209,103	11,199,013	11,209,103	11,199,013

Note: The table presents the β coefficients in equation 3.3. Small establishments are defined as the establishments with no more than 100 employees and large establishments with 100 or more employees. Data come from the U.S. Census Bureau's County Business Patterns.

Table 3.15: The Growth Rates of Establishments and Employments

	Small Firms		Large Firms	
	(1)	(2)	(3)	(4)
	ln(1+est.)	ln(1+emp.)	ln(1+est.)	ln(1+emp.)
Exposure	6.281***	6.866***	5.968***	5.792***
	(0.358)	(0.406)	(0.938)	(1.219)
Exposure x Job Zone	-1.927***	-2.207***	-1.773***	-1.808***
	(0.121)	(0.150)	(0.13)	(0.401)
County-Industry FEs	Yes	Yes	Yes	Yes
State-Year FEs	Yes	Yes	Yes	Yes
Adjusted R-squared	0.976	0.879	0.941	0.879
Obs.	7,382,885	7,382,820	7,382,885	7,382,820

Note: The table displays the impact of bank consolidations based on Job Zone categories. Job Zone serves as a proxy for industry-specific skill levels of job roles. Job Zone data are sourced from the U.S. Department of Labor's ONET program's occupational classification system.

References

[1] K. Kleiner, N. Stoffman, and S. Yonker, "Friends with bankruptcy protection benefits," *Journal of Financial Economics*, vol. 139, pp. 578–605, 2021.

[2] I. Livshits, J. MacGee, and J. Tertilt, "Accounting for the rise in consumer bankruptcies," *American Economic Journal: Macroeconomics*, vol. 2, no. 2, pp. 165–193, 2010.

[3] A. A. Dick and A. Lehnert, "Personal bankruptcy and credit market competition," *Journal of Finance*, vol. 65, no. 2, pp. 655–686, 2010.

[4] T. Gross, M. J. Notowidigdo, and J. Wang, "Liquidity constraints and consumer bankruptcy: Evidence from tax rebates," *Review of Economics and Statistics*, vol. 96, no. 3, pp. 432–443, 2014.

[5] S. Agarwal, V. Mikhed, and B. Scholnick, "Peers' income and financial distress: Evidence from lottery winners and neighboring bankruptcies," *Review of Financial Studies*, vol. 33, no. 1, pp. 433–472, 2019.

[6] S. Lewellen and E. Williams, "Did technology contribute to the housing boom? evidence from mers," *Journal of Financial Economics*, vol. 141, pp. 1244–1261, 2021.

[7] A. Fuster, M. Plosser, P. Schnabl, and J. Vickery, "The role of technology in mortgage lending," *Review of Financial Studies*, vol. 32, no. 5, pp. 1854–1899, 2019.

[8] J. Bai, T. Philippon, and A. Savov, "Have financial markets become more informative?" *Journal of Financial Economics*, vol. 122, pp. 625–654, 2016.

[9] M. Gao and J. Huang, "Informing the market: The effect of modern information technologies on information production," *Review of Financial Studies*, vol. 33, no. 4, pp. 1367–1421, 2020.

[10] P. Alexander and K. Slone, "Thinking about the private matters in public documents: Bankruptcy privacy in an electronic age," *American Bankruptcy Law Journal*, vol. 75, pp. 437–446, 2011.

[11] A. Goodman-Bacon, "Difference-in-differences with variation in treatment timing," *Journal of Econometrics*, vol. 225, no. 2, pp. 254–277, 2021.

[12] S. F. Cherry, E. X. Jiang, G. Matvos, T. Piskorski, and A. Seru, "Government and private household debt relief during covid-19," *Brookings Papers on Economic Activity*, vol. Fall, 2021.

[13] P. Ganong, P. J. Noel, and J. S. Vavra, "Us unemployment insurance replacement rates during the pandemic," *National Bureau of Economic Research Working Paper #27216*, 2020.

[14] B. H. Meyer, E. Mihaylov, J. M. Barrero, S. J. Davis, D. Altig, and N. Bloom, "Pandemic-era uncertainty," National Bureau of Economic Research, Tech. Rep., 2022.

[15] W. Li, T. Ryotaro, S. H. Tarlin, *et al.*, "Bankruptcy filings in the third district during covid-19," *Economic Insights*, vol. 5, no. 3, pp. 15–22, 2020.

[16] S. Fay, E. Hurst, and M. J. White, “The household bankruptcy decision,” *American Economic Review*, vol. 92, no. 3, pp. 706–718, 2002.

[17] I. Domowitz and R. L. Sartain, “Determinants of the consumer bankruptcy decision,” *The Journal of Finance*, vol. 54, no. 1, pp. 403–420, 1999.

[18] T. Gross, M. J. Notowidigdo, and J. Wang, “Liquidity constraints and consumer bankruptcy: Evidence from tax rebates,” *Review of Economics and Statistics*, vol. 96, no. 3, pp. 431–443, 2014.

[19] S. Indarte, “Moral hazard versus liquidity in household bankruptcy,” *Working Paper*, 2021.

[20] B. Iverson, “Get in line: Chapter 11 restructuring in crowded bankruptcy courts,” *Management Science*, vol. 64, no. 11, pp. 5370–5394, 2017.

[21] P. Mathurin, O. Aliaj, and J. Fontanella-Kahn, “Pandemic triggers wave of billion-dollar US bankruptcies,” *Financial Times*, Aug. 2020. (visited on 08/24/2020).

[22] C. Bialik and D. Gole, “Yelp: Local economic impact report,” Yelp, Tech. Rep., 2020. [Online]. Available: https://www.yelpeconomicaverage.com/business-closures-update-sep-2020 (visited on 03/24/2021).

[23] R. Chetty, J. N. Friedman, N. Hendren, M. Stepner, *et al.*, “How did covid-19 and stabilization policies affect spending and employment? a new real-time economic tracker based on private sector data,” *National Bureau of Economic Research Working Paper #27431*, 2020.

[24] M. J. White, “Small business bankruptcy,” *Annual Review of Financial Economics*, vol. 8, pp. 317–336, 2016.

[25] W. Li, M. J. White, and N. Zhu, “Did bankruptcy reform cause mortgage defaults to rise?” *American Economic Journal: Economic Policy*, vol. 3, no. 4, pp. 123–47, 2011.

[26] U.S. Bureau of Economic Analysis, “Personal saving rate [psavert], retrieved from fred, federal reserve bank of st. louis,” Tech. Rep., Aug. 2020, Available at https://fred.stlouisfed.org/series/PSAVERT. [Online]. Available: https://fred.stlouisfed.org/series/PSAVERT (visited on 08/25/2020).

[27] J. Granja, C. Makridis, C. Yannelis, and E. Zwick, “Did the paycheck protection program hit the target?” National Bureau of Economic Research, Working Paper 27095, May 2020. DOI: 10.3386/w27095. [Online]. Available: http://www.nber.org/papers/w27095.

[28] R. P. Bartlett and A. Morse, “Small business survival capabilities and policy effectiveness: Evidence from oakland,” *Working Paper*, 2020.

[29] T. Gross, R. Kluender, F. Liu, M. J. Notowidigdo, and J. Wang, “The economic consequences of bankruptcy reform,” *American Economic Review*, vol. 111, no. 7, pp. 2309–41, Jul. 2021. DOI: 10.1257/aer.20191311. [Online]. Available: https://www.aeaweb.org/articles?id=10.1257/aer.20191311.

[30] M. J. White, “Why don’t more households file for bankruptcy?” *Journal of Law, Economics, & Organization*, pp. 205–231, 1998.

[31] E. R. Morrison, “Bankruptcy decision making: An empirical study of continuation bias in small-business bankruptcies,” *The Journal of Law and Economics*, vol. 50, no. 2, pp. 381–419, 2007.

[32] P. M. Skiba, D. Jiménez, M. M. Miller, P. Foohey, and S. S. Greene, "Bankruptcy courts ill-prepared for tsunami of people going broke from coronavirus shutdown," *The Conversation*, May 2020. [Online]. Available: https://theconversation.com/bankruptcy-courts-ill-prepared-for-tsunami-of-people-going-broke-from-coronavirus-shutdown-137571.

[33] R. M. Lawless, "Does chapter 13 prop up bankruptcy filing rates?" *Credit Slips: A Discussion on Credit, Finance, and Bankruptcy*, 2013. [Online]. Available: https://www.creditslips.org/creditslips/2013/01/my-entry.html.

[34] H.-L. Q. Nguyen, "Are credit markets still local? evidence from bank branch closings," *American Economic Journal: Applied Economics*, vol. 11, no. 1, pp. 1–32, 2019, ISSN: 1945-7782, 1945-7790. DOI: 10.1257/app.20170543. [Online]. Available: https://pubs.aeaweb.org/doi/10.1257/app.20170543 (visited on 01/13/2021).

[35] E. Asiedu, J. A. Freeman, and A. Nti-Addae, "Access to credit by small businesses: How relevant are race, ethnicity, and gender?" *American Economic Review*, vol. 102, no. 3, pp. 532–537, 2012, ISSN: 0002-8282. DOI: 10.1257/aer.102.3.532. [Online]. Available: https://pubs.aeaweb.org/doi/10.1257/aer.102.3.532 (visited on 01/20/2021).

[36] N. Crouzet and N. R. Mehrotra, "Small and large firms over the business cycle," *American Economic Review*, vol. 110, no. 11, pp. 3549–3601, 2020, ISSN: 0002-8282. DOI: 10.1257/aer.20181499. [Online]. Available: https://pubs.aeaweb.org/doi/10.1257/aer.20181499 (visited on 09/25/2022).

[37] M. Brülhart, J. Gruber, M. Krapf, and K. Schmidheiny, "Behavioral responses to wealth taxes: Evidence from switzerland," *American Economic Journal: Economic Policy*, vol. 14, no. 4, pp. 111–150, 2022, ISSN: 1945-7731, 1945-774X. DOI: 10.1257/pol.20200258. [Online]. Available: https://pubs.aeaweb.org/doi/10.1257/pol.20200258 (visited on 12/10/2022).

[38] J. C. Suárez Serrato and O. Zidar, "Who benefits from state corporate tax cuts? a local labor markets approach with heterogeneous firms," *American Economic Review*, vol. 106, no. 9, pp. 2582–2624, 2016, ISSN: 0002-8282. DOI: 10.1257/aer.20141702. [Online]. Available: https://pubs.aeaweb.org/doi/10.1257/aer.20141702 (visited on 12/10/2022).

[39] C. Fuest, A. Peichl, and S. Siegloch, "Do higher corporate taxes reduce wages? micro evidence from germany," *American Economic Review*, vol. 108, no. 2, pp. 393–418, 2018, ISSN: 0002-8282. DOI: 10.1257/aer.20130570. [Online]. Available: https://pubs.aeaweb.org/doi/10.1257/aer.20130570 (visited on 12/10/2022).

[40] I. Drechsler, A. Savov, and P. Schnabl, "The deposits channel of monetary policy*," *The Quarterly Journal of Economics*, vol. 132, no. 4, pp. 1819–1876, 2017, ISSN: 0033-5533, 1531-4650. DOI: 10.1093/qje/qjx019. [Online]. Available: https://academic.oup.com/qje/article/132/4/1819/3857743 (visited on 12/10/2022).

[41] K. Schmidheiny and S. Siegloch, "On event studies and distributed-lags in two-way fixed effects models: Identification, equivalence, and generalization," *SSRN Electronic Journal*, 2020, ISSN: 1556-5068. DOI: 10.2139/ssrn.3571164. [Online]. Available: https://www.ssrn.com/abstract=3571164 (visited on 12/10/2022).

[42] M. Ghaly, V. Anh Dang, and K. Stathopoulos, "Cash holdings and labor heterogeneity: The role of skilled labor," *The Review of Financial Studies*, vol. 30, no. 10, pp. 3636–3668, 2017, ISSN: 0893-9454, 1465-7368. DOI: 10.1093/rfs/hhx045. [Online]. Available: https://academic.oup.com/rfs/article/30/10/3636/3835431 (visited on 12/10/2022).

[43] F. Belo, J. Li, X. Lin, and X. Zhao, "Labor-force heterogeneity and asset prices: The importance of skilled labor," *The Review of Financial Studies*, vol. 30, no. 10, pp. 3669–3709, 2017, ISSN: 0893-9454, 1465-7368. DOI: 10.1093/rfs/hhx070. [Online]. Available: https://academic.oup.com/rfs/article/30/10/3669/3978889 (visited on 01/31/2023).

[44] M. Ochoa, "Volatility, labor heterogeneity and asset prices," *Federal Reserve Board, Washington*, 2013, ISSN: 19362854. DOI: 10.17016/FEDS.2013.71. [Online]. Available: https://www.federalreserve.gov/econres/feds/volatility-labor-heterogeneity-and-asset-prices.htm (visited on 01/31/2023).

[45] A. Donangelo, "Labor mobility: Implications for asset pricing: Labor mobility: Implications for asset pricing," *The Journal of Finance*, vol. 69, no. 3, pp. 1321–1346, 2014, ISSN: 00221082. DOI: 10.1111/jofi.12141. [Online]. Available: https://onlinelibrary.wiley.com/doi/10.1111/jofi.12141 (visited on 03/03/2023).