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Abstract

We study the impact of the COVID-19 crisis on auto loan origination activity during 2020. We focus on the dynamic impact of the crisis across lending channels, Equifax Risk Score (Risk Score) segments, and relevant geographic characteristics such as urbanization rate. We measure a significant drop in auto loan originations in March–April followed by a near rebound in May–June. Originations remain slightly depressed until October and fall again in November–December. We document the largest drop and the smallest rebound in the subprime segment. We do not find any suggestive evidence that used car loan originations exhibited patterns significantly different from the rest of the market. We also document a more pronounced impact in the Northeast and the Pacific, seemingly influenced by the higher urbanization rate in these regions. Bank-financed originations experienced the largest drop and the smallest rebound, thus resulting in a loss of market share and continuing a 10-year trend of bank share loss in auto lending. We find that the drop in auto loans originated by banks was particularly significant among subprime borrowers. The impact of the COVID-19 crisis across origination channels contrasts with the experience during the Great Recession when banks contributed the largest support to the auto loan origination segment during periods of stress and finance company-originated auto loans were depressed.

Keywords: auto loans, loan originations, COVID-19, consumer credit, bank and non-bank finance
JEL Codes: G01, G21, G23, L62

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1 Introduction

The COVID-19 pandemic generated seismic shocks to the global economy, and these shocks appropriately heightened the attention warranted by the auto loan market. About 60 percent of U.S. adults have an auto loan, and automobiles generally serve as the most expensive durable good for households. The auto lending sector in the U.S., with close to $1.3 trillion in outstanding loan balances, represents a vital segment of consumer finance.[2] By comparison, credit cards represent close to $1 trillion, and student loans represent about $1.7 trillion in outstanding balances. The auto loan market warrants attention for the purpose of closely monitoring household financial health, gaining broader economic insights into household access to credit, and understanding the overall importance of the automobile industry for the economy.

In this paper, we analyze the performance of the auto loan origination market across loan origination channels (i.e., banks, credit unions, and finance companies). We look back at 17 years of data on auto loan originations, with a primary focus on the year 2020 and the disruption generated by the COVID-19 pandemic. Perhaps not surprisingly, we document that the auto loan origination sector was significantly impacted by the pandemic. Our analysis brings into light the heterogeneous impact of the pandemic across different segments of consumers and across loan origination channels. At a high level, auto loan originations were broadly depressed during the initial months of the pandemic across consumer segments and origination channels. However, some origination channels and consumer segments recovered relatively quickly, while others remained depressed for a longer period of time.

The role of automobiles features unique elements in the COVID-19 pandemic context. For instance, on the demand side, the presence of shelter-in-place lockdown orders, remote work, and business shutdowns naturally reduced the household demand for automobiles. On the other hand, heightened fears for public transit (or any public space) and the exodus from cities to the suburbs would correspond to increased demand for automobiles from households. The insights from consumer borrowing in auto purchases can be particularly important for three reasons: (1) these trends speak to one potential major source of the COVID-19 pandemic's real economic impact in the form of durable consumption, (2) these trends may also reveal the changing household preferences for vehicle consumption, as the concepts of isolation, remote work, and social distancing impact how individuals view transit in their daily routine, and (3) the auto loan market provides a space in which we can examine any impairments to credit supply. Our paper primarily directs its attention to the third point, and importantly, we document a relatively quick recovery in the flow of

[2] Mortgages represent the largest consumer lending sector with about $11.5 trillion in outstanding balances (https://fred.stlouisfed.org/).

credit in the nonbank automotive credit sector. This is in sharp contrast to the Great Recession, which featured a long-lasting fragility in the nonbank automotive credit sector.

Our paper relates to several strands of literature. First, our paper naturally joins the rapidly growing literature studying the impact of the COVID-19 pandemic on the economy and on consumer finance in particular. It is now well documented that the pandemic had a dramatic effect in household spending patterns. Baker, Farrokhnia, Meyer, Pagel, and Yannelis (2020a) document a significant increase in certain retail spending in the first weeks of March, followed by a sharp decrease in the following weeks, and other studies using various data sources have reported similar findings. Credit card transactions were significantly depressed in March and April and staged a recovery starting in May 2020 (Horvath, Kay and Wix, 2020). Cox, Ganong, Noel, Vavra, Wong, Farrell, and Greig (2020) and Baker, Farrokhnia, Meyer, Pagel, and Yannelis (2020b) highlight the effect of government assistance programs in limiting the impact of the pandemic on spending.[3] Chetty et al. (2020) report the heterogeneous impact of the COVID-19 pandemic on consumption, with high-income individuals reducing consumption spending most sharply. Undoubtedly, the unprecedented level of government assistance, and the Coronavirus Aid, Relief, and Economic Security (CARES) Act in particular, contributed to the sustainability of consumption. Relevant academic research on the impact of economic stimulus during the last financial crisis, the Economic Stimulus Act (ESA), reports a significant effect on the purchase of durable goods and related services, primarily the purchase of vehicles (Parker et al., 2008). Lee, Park, and Shin (2021) document the heterogeneous impact of COVID-19 on unemployment across demographic and socioeconomic groups, with the largest impact on women, minorities, the less educated, and the young. Han, Meyer, and Sullivan (2020) observe that government policies effectively contained the effect of the pandemic leading to a fall in poverty and an increase in income across a range of demographic groups and geographies. In addition to direct government cash assistance and extensions in unemployment, the level of loan forbearances during the pandemic were unprecedented in mortgages, student loans, and auto lending, which contributed to much less financial stress among borrowers (Cherry, Jiang, Matvos, Piskorski, and Seru, 2021). Lambie-Hanson, Vickery, and Akana (2021) analyze information from a Survey of Consumers conducted by the Federal Reserve Bank of Philadelphia's Consumer Finance Institute and report that about three-quarters of households in mortgage forbearance had experienced some form of job or income loss. An, Cordell, Geng, and Lee (2021) report that mortgage non-payment rates, including forbearance, were significantly higher among lower-income and minority borrowers.

Our paper also contributes to a growing literature analyzing the auto finance market. Several papers in recent years have focused their attention to relevant features of this market. Recent research on the growth

[3] See also Dong, Gozgor, Lu, and Yan (2020).

of long-term auto loans highlights potential risks associated with the growth in this segment (Brevoort et al., 2017; Verma, 2017; Guo et al., 2020; An et al., 2021). Attanasio, Goldberg, and Kyriazidou (2008) investigate the significance of borrowing constraints in auto loan contracts and document that consumers are more responsive to maturity than to interest rate terms. In related research, Argyle, Nadauld, and Palmer (2020) observe that borrowers focus more on payment size and loan maturity over the corresponding interest rate. They interpret their findings as evidence of mental accounting and monthly budgeting on the part of the borrowers. The authors highlight the rapid growth in auto debt since the Great Recession. Our paper also documents this rapid growth in auto lending in recent years, particularly among nonbank lenders, and contributes an historical analysis of the evolution of auto finance across lending channels. Most relevant to our work is research on the performance of auto loan originations across lending channels during periods of economic stress. Naturally, the primary setting of this kind of research prior to the COVID-19 crisis was the Great Recession. Auto loan originations decreased significantly during the Great Recession, and this decrease in auto lending was particularly severe among finance companies. This dramatic collapse was reflected as a decrease in auto asset-backed securitization (ABS) issuances of more than 50 percent. Benmelech, Meisenzahl, and Ramcharan (2017) study auto loan originations during the Great Recession and document that regions where households depended more on nonbank lenders for auto loans experienced a larger drop in auto sales after the collapse of the asset-backed commercial paper market.

Our paper describes how the impact of the COVID-19 crisis on auto loan originations across lending channels is remarkably different from the experience during the Great Recession. We quantify the drop in the auto loan origination activity around the early months of the COVID-19 pandemic by comparing the 2020 trend with prior years' trends. Specifically, based on the observation that auto loan origination trends were extremely consistent in the years 2017–2019 and that the first two months of 2020 aligned with these prior years, we conjecture that the 2020 origination trend was on track to repeat the prior years' trajectory as well. Thus, we estimate the drop in 2020 auto loan originations *relative* to the 2019 level to quantify the impact of the COVID-19 period on auto loan origination activity. Using the credit bureau data from the FRBNY Consumer Credit Panel/Equifax (CCP), we find a significant aggregate drop in loan originations during March and April 2020 followed by an immediate near rebound by May and June. Importantly, we also document the heterogeneity in the drop-and-recovery patterns across financing sources and borrower Risk Score[4]. We find that auto loan originations initially fell similarly between bank

[4] The Equifax Risk Score is a proprietary credit score that estimates the likelihood that an individual will pay his or her debts without defaulting. A variety of factors that relate to loan performance contribute to credit scores, including previous payment history, outstanding debts, length of credit history, new accounts opened, and types of credit used (Federal Reserve Board 2007; Fair Isaac Corporation 2015); delinquency, large increases in one's debt, and events of public record (e.g., bankruptcy or foreclosure) often lead to low credit scores (Anderson 2007). The scores range from 280 to 850, with higher scores representing greater financial health and advantage.

borrowers and nonbank borrowers, but the subsequent rebound was remarkably stronger for nonbank borrowers. Examining the COVID-19 effect across borrower Risk Score, we find that subprime borrowers experienced a substantially larger drop at the beginning of the pandemic, which subsequently persisted while prime borrowers recovered. Motivated by the narrative evidence for a substantial geographic variation in the reaction to the pandemic (e.g., government responses such as lockdowns, health-care support, vaccine distribution, public attitude such as mask-wearing, and aversion to in-person shopping), we further examine whether geographic factors related to the drop in the auto loan origination activity because of the COVID-19 pandemic. We document that the COVID-19-induced loss in auto loan originations was more substantial in the Northeast and Pacific regions. Additionally, we show that much of the geographic heterogeneity in the COVID-19 shock can be explained by the differential urbanization rate and mobility across regions.

Our analysis also reveals that bank-financed auto loan originations fell substantially, even for prime borrower groups, when compared with other nonbank financing sources. We naturally find that the bank share of the auto loan market fell by a substantial amount during the COVID-19 period. We show that this decrease is an accelerated continuation of a pre-pandemic trend rather than being an isolated event. Specifically, we illustrate a significant fall in the bank share of the auto loan market during 2010–2019 and an acceleration of this trend during the COVID-19 period, especially for nonprime borrowers.

The rest of the paper is organized as follows. Section 2 describes our data and sample construction and provides a descriptive analysis that highlights auto loan origination trends since the early 2000s. We present our econometric framework and baseline results in Section 3, and Section 4 discusses the heterogeneity of the COVID-19 effect across regions and across financing sources. Section 5 concludes.

2 Data Description and Historical Auto Loan Origination Patterns

In this section, we describe our data sources and discuss patterns of auto loan originations over time and across segments of consumers and lending channels. In Section 2.1, we provide a broad-level description of our data sources and the main variables of interest and explain how the relevant variables and data segments are constructed. In Section 2.2, we look back at 17 years of data and conduct a descriptive analysis of auto loan origination trends over time, across origination channels, and across Risk Score segments. Our analysis of the historical data corroborates the findings from existing academic research on auto loan originations during the Great Recession. In addition, our analysis expands on prior findings by conducting a detailed descriptive analysis of loan origination trends over a larger time span, both before and after the

crisis. Finally, Section 2.3 graphically documents the recurrence of consistent seasonal patterns of auto loan originations within the typical calendar year for the 2018–2020 period. This analysis provides important insights that guides our econometric framework introduced in Section 3.

2.1 Data Description and Sample Construction

The main source of information for our analysis is the FRBNY Consumer Credit Panel/Equifax (CCP) and the associated Auto Tradeline panel data. The CCP is a quarterly panel data set comprising a selection of information from anonymized individual credit bureau reports starting with the first quarter of 1999. Starting with January 2020, the data transitioned into a monthly panel to allow for more frequent monitoring of the effects of COVID-19.[5] The CCP data collection is the result of a joint collaborative project among the Board of Governors, the Federal Reserve Bank of New York, and the Federal Reserve Bank of Philadelphia. An in-depth description of the project objectives and sample design can be found in Lee and Van der Klaauw (2010). The panel data comprise a nationally representative 5 percent random sample of individuals who have a credit history.[6] The Auto Tradeline panel data associated with the FRBNY CCP was initially the result of a project originated by the Federal Reserve Bank of Philadelphia with the objective of complementing the CCP data with additional tradeline-level (or loan specific) data on auto and credit card loans associated with the individuals in the CCP data set. Eventually, both projects were combined into one.

The combination of consumer level and tradeline level information in the CCP allows us to access a nationally representative data set of auto loans, with the associated loan and consumer information available in the credit bureau file reported in the Equifax credit bureau databases.[7] Each auto loan in the CCP is reported with loan-specific information, such as origination date, initial balance and term, and additional consumer-specific information, such as Risk Score and geographic area of residency. Importantly, the data further identify the financing source of each loan. While we aggregate these lender categories into three broad groups (banks, finance companies, and credit unions), this variable is available at a highly disaggregated level. For example, we can separate used automobile dealers from new automobile

[5] Using the variable *Origination Date*, we can construct a historical series of monthly vintages regardless or reporting frequency.

[6] In addition, for each primary individual in the sample, the CCP includes credit files for all additional individuals residing in the same households, but our focus is on the primary sample.

[7] To get a better understanding of the auto lending market, we complement our data with aggregated auto securitization origination data from Intex Solutions (a leading provider of information and valuation software on structured finance securities).

dealers or identify truck dealers, automotive repair shops, and tire dealers. We use U.S. Census data for various county-level and state-level economic variables, such as urban population percentage and county-level mobility data from the Google Mobility series from Opportunity Insights.[8] Additionally, our data are complemented with data on COVID-19 cases and deaths from the COVID-19 Data Repository by the Center for Systems Science and Engineering (CSSE) at Johns Hopkins University[9]. Relevant variables and classification schemes are described in Table 1.

We aggregate our loan-level observations to the county-Risk Score segment-financing source-level. We consider four Risk Score segments: (1) <620, (2) 620–660, (3) 660–720, and (4) >720. The first group captures the subprime borrower population, while the next two groups represent the middle-tier borrowers, and the last group includes prime borrowers. There is no widely accepted credit score segmentation. Thus, our choice of these thresholds is somewhat arbitrary, but the findings of our paper are robust to experimentation with alternative segmentation schemes. We further segment our data into three groups of financing sources: (1) banks, which also include savings and loan institutions; (2) finance companies, which include car dealerships, auto company financing, and sales financing; and (3) credit unions. This level of disaggregation results in 12 different partitions for each county-month. In robustness exercises, we explore models at different levels of aggregation whenever possible, including state-level, national-level, as well as borrower-level models.[10] For all of our main results, the findings are remarkably consistent across the different levels of aggregation. We default to county-level for our main analysis to leverage geographic variables with county-level variation.

2.2 Historical Perspective on Auto Loan Originations

We begin our descriptive data analysis with the examination of historical loan origination trends across lending channels and across relevant Risk Score segments for the period 2004–2020, depicted in Figure 1. This time span encompasses several years of economic expansion (2004–2007), the Great Recession (2008–2009), as well as the subsequent years of recovery in the auto loan originations market (2010–2019), and finally the first year of the COVID-19 crisis. This analysis over a large time frame contributes new insights into the evolution of the auto loan origination market after the Great Recession and complements prior work

[8] See Chetty et al. (2020) and https://opportunityinsights.org/.

[9] Available at https://github.com/CSSEGISandData/COVID-19.

[10] Loan-level models consider a borrower's propensity to originate a new auto loan, while segment-level models consider the number of new auto loans at the segment level.

on this area. It also allows us to contrast the performance of the auto loan origination market during the 2008 Financial Crisis with its performance during the COVID-19 pandemic.

Prior work by Benmelech, Meisenzahl, and Ramcharan (2017) studies auto loan originations during the Great Recession and concluded that lending originated from finance companies and financed through the securitization channel were significantly impacted by the Great Recession. They also find evidence of substitution from nonbank to bank financing. The authors conclude that funding disruptions in short-term credit markets during the financial crisis contributed significantly to a contraction in car sales. Their analysis of auto loan originations encompasses the period 2006–2010, although their focus is primarily on a comparison of auto loan originations between 2008 and 2009. Our historical description of auto loan originations over a long horizon offers additional insights about the performance of auto loan originations before and after the Great Recession.

Figure 1 follows the evolution of auto loan originations across lending channels and Risk Score segments. Finance company auto loan originations represented around 50 percent of overall originations over the period 2004–2006, with an oversized concentration in subprime. Figure 2 complements Figure 1 and provides a more granular depiction of auto loan originations across Risk Scores, over time, and across lending channels. Both figures show that finance company auto loan originations decreased precipitously over the period 2008–2009. Auto Asset-Backed Securitization (ABS), the main funding source for finance companies, also experienced a significant drop during the 2008–2010 period, as illustrated in Figure 3. From Figures 1 and 2, we can closely follow the evolution of auto loan origination over time across the whole Risk Score range. The decrease in auto loan originations in 2008–2009 was most dramatic in the finance channel and was most noticeable for Risk Scores below 650. We also find a significant drop in banks originating loans to consumers with Risk Scores below 720 primarily, and to a lesser extent a drop in loans originated by credit unions. Auto loan originations for Risk Scores above 720 did not reflect a significant drop through the bank or credit union channels, thus assisting with sustaining the auto lending market. The information conveyed in Figures 1–3 for the period 2006–2010 is broadly consistent with Benmelech, Meisenzahl, and Ramcharan (2017).

Starting with 2010, auto loan originations by finance companies began a five-year period of vigorous growth. In contrast, loan originations by banks grew more moderately for about three years following the Great Recession but stalled afterward. Looking across Risk Score segments, auto loans for Risk Scores below 660 have grown rapidly since 2010, primarily in the finance lending channel, while growth in the bank and credit union lending channels was comparatively moderate. Auto lending for Risk Scores below 660 remained stable after 2016 for finance companies but decreased in the recent years for the bank and credit union lending channels. Auto loan originations for Risk Scores above 660 experienced

significant growth, primarily through the finance and credit union lending channels. The observed differences in lending growth across loan origination channels naturally corresponded a 10-year decrease in auto loan origination market share for banks. In 2019, finance companies originated roughly 60 percent of auto loans, while banks and credit unions originate the remaining 40 percent, with credit unions surpassing banks in recent years across all Risk Score segments. Consistent with the growth in the finance company lending channel, auto ABS securitizations experienced a long period of growth since 2011 (Figure 3).

2.3 Auto Loan Seasonal Origination Patterns in 2020 versus Previous Years

The previous subsection focused on the evolution of auto loan originations from the onset of the Great Recession up until 2019 before the COVID-19 pandemic in 2020. In this subsection, we focus our attention on monthly originations of auto loans during 2020 and compare it with previous years' trends.

In Figure 4, we report monthly auto loan originations across Risk Scores and loan origination channels for 2020 along with years 2017–2019.[11] Aggregate trends in 2017–2019 are largely consistent across months and years. Each year's trend exhibits a slow start in the first two months, then a significant jump in March, followed by a pattern of small fluctuations for the rest of the year. In addition to the recurrent pattern, the level of originations is also similar across the three years. Based on the first two months of 2020 before the pandemic disrupted the market, we find that the origination trend in 2020 appears to be on track to repeat the previous years' trend as well. Loan originations for the first two months of 2020 are broadly in line with originations in 2017–2019. A dramatic relative drop is apparent when the COVID-19 pandemic begins to affect the economy in March 2020. The aggregate auto loan market reports a loss of roughly 30 percent in March and April 2020, relative to prior years' levels before experiencing a recovery. The recovery in auto loan originations from the initial impact of the pandemic observed in May and subsequent months is heterogeneous across Risk Score segments and loan origination channels, with most segments experiencing a quick rebound.

Looking at the specific segments reported in Figure 4, we can gain a better understanding of the heterogeneity underlying the loan origination trends. We observe reasonably consistent trends across financing sources in 2017–2019, with the exception of credit-union financed loan originations, which exhibit some volatility in the prevalent pattern across years.[12] The first two months of 2020 appear to track

[11] These data are normalized by the 2020 January level.

[12] Figure A2 shows no significant difference between captive versus non-captive finance companies.

the previous years' pattern closely. In contrast, starting with March 2020, we observe significant differences with respect to prior years. We also observe significant differences in both the drop and recovery in loan originations across the three financing channels considered. Bank-financed loans exhibit the most dramatic drop and weakest recovery. On the other hand, finance companies display a quick and strong recovery, with loan originations even exceeding the 2019 level of originations as early as May 2020. The recovery in credit union-financed loan originations appear to be somewhere in between banks and finance companies. The lower Risk Score segments for bank originations still remained depressed by December 2020 with respect to their 2019 level, primarily for the bank lending channel, while all other segments reverted over time to loan origination levels comparable to previous years.

The graphical descriptive discussion in this section illustrates two key features of the raw data. First, we observe consistent monthly trends across years 2017–2019, and the first two months of 2020 were on track to repeat previous years' trends as well. The second important feature relates to the significant differences in trends across financing sources and Risk Score segments during the pandemic months, particularly between banks and finance companies and for the subprime versus other risk segment groups. The next section introduces a stylized econometric framework that takes advantage of the observed consistency in monthly trends highlighted in this subsection.

3 Econometric Framework and Empirical Results

The econometric framework described in this section offers a more formal quantitative measure of impact of the COVID-19 pandemic on auto loan originations. In Section 2, we highlighted the consistency in monthly auto loan origination trends across years prior to the onset of the COVID-19 pandemic. Based on that evidence, we argue that the 2019 origination series can serve as an appropriate counterfactual for the 2020 series, absent the pandemic, and use this assumption to identify differences in auto loan origination trends resulting from the pandemic.

3.1 Econometric Framework

Our main econometric specification intuitively compares the realized 2020 auto loan origination trend with year 2019 trends, after controlling for small differences in loan originations in January and February 2020. The modeling approach is motivated by our observation that within-year auto loan origination patterns are reasonably consistent across recent years. Specifically, we select the 2019 observations as our de facto

control group and the 2020 observations as our treated group. We focus on 2019 as our control group as opposed to 2017 or 2018 because the economic environment of 2019 is naturally closest to the first two months of 2020. Our baseline specification can be written as

$$\log\left(Origination_{it}+1\right)=\delta(X_{it})\,Y2020_{t}+\beta(X_{it})\,COVID_{t}+\delta Z_{it}+FE_{it}, \qquad (1)$$

with the dependent variable of interest representing the auto loan origination rate in a particular segment of accounts in the credit bureau data for a specific geography and for a specific risk profile, indexed by *i* and *t* representing monthly observations. Because the loan originations rate can, in some cases, take the value zero in segments with a small number of accounts, or in specific months with low loan-origination activity, we follow standard practice and consider the analysis of "*origination + 1*" as the dependent variable in a log-linear regression specification. Our specifications include fixed effects "FE_{it}" for segment-specific characteristics such as state or county, Risk Score segment, financing source, or calendar-month. *Y2020* is an indicator variable that is equal to 1 for all months in 2020, and *COVID* is an additional indicator variable that takes the value of 1 for the months of March–December 2020. In some specifications, we consider specifying the *COVID* indicator variable separately across months, or for three time subperiods: (1) March–April, (2) May–October, and (3) November–December. This breakdown across time allows for examining broad dynamics by grouping together similar periods. We also include additional time-varying county-level control variables Z_{it} in more general specifications. Intuitively, *Y2020* estimates the average 2020 effect on auto loan originations for the pre-COVID-19 months of January and February, while *COVID* estimates the "additional" 2020 effect that manifests starting in March because of COVID-19. It is important to note that our estimate of the COVID-19 effect captures all elements related to the pandemic that impair economic activity. In other words, our analysis does not aim to isolate a particular effect (e.g., lockdown effects, health shocks, preference shocks, monetary or fiscal policy), but rather, it evaluates the compounded effect. Naturally, our main coefficient of interest is β. Another important focus of our analysis is on the potential sources of the heterogeneous impact of the pandemic, represented in the above equation as X_{it}. Of particular interest will be the analysis of the impact across financing sources, risk segments, and geographic regions. We cluster standard errors at the state-level and weigh each observation by the county's population.

For robustness checks, we consider a variety of model specifications with different levels of aggregation and different econometric model specifications. Overall, our results are broadly consistent across model specifications. Specifically, we analyzed models with varying levels of geographic aggregation at the county, state, and national level. We also consider a Poisson Pseudo Maximum Likelihood (PPML) specification for the number of loan originations, following the suggestion in Ciani and Fisher (2018) that OLS may produce biased difference-in-difference estimates for log-linearized continuous outcome variables, if the treatment effect can be more appropriately modeled in multiplicative form. In

practice, the PPML specification can be simply implemented using non-transformed origination as the outcome variable and specifying each county's population of credit-user households as the weight variable. Finally, we have estimated similar model specifications using account level information; in this case, the focus is on whether a customer originates an auto loan or not in a particular month.

3.2 The Impact of COVID-19 on Auto Loan Originations

Column 1 in Table 2 presents the initial results from the baseline specification of the econometric model in equation (1).[13] The results indicate that, after accounting for the first two months of 2020 and controlling calendar-month fixed effects, the COVID-19 period (i.e., 2020m3-m12) is associated with an average monthly drop in auto loan originations of roughly 15.2 percent from March to December 2020. This coefficient is statistically and economically significant. The estimated *Y2020* coefficient shows that the months of January and February 2020 are associated with 1.7 percent higher auto loan originations per month compared with 2019. In Columns 2–5, we report the results of equation (1) estimated separately for four Risk Score segments. While we estimate the average effect of COVID-19 to be -0.152 in the full sample, we find a substantial variation in the COVID-19 coefficient across Risk Score segments. For the subprime borrower group (Column 2), we find that the January–February 2020 average effect on auto loan originations is roughly -2.2 percent when compared with 2019. The average monthly drop in auto loan originations associated with the COVID-19 period is roughly -21.7 percent. The estimated effect of the COVID-19 pandemic is notably different for other borrower groups. Specifically, for Risk Scores between 620 and 660, the estimated January–February effect is -0.012 and the COVID-19 effect is -0.099. For Risk Scores between 660 and 720, the estimated January–February effect is a small increase of 3.2 percent, and the COVID-19 effect is -0.127. For Risk Scores greater than 720, the estimated January–February effect is a large increase of 0.071, and the COVID-19 effect is -0.164. In summary, while we find a dramatic drop in auto loan origination activity during the COVID-19 period for all borrower groups, the subprime group reports the most substantial drop. The prime group also experiences a significant drop during the COVID-19 period, but, in this case, it can be partially explained by a large increase in their January–February 2020 average monthly effect with respect to 2019.

Table 3 provides additional insights on the heterogeneity of the COVID-19 impact across Risk Score segments. The table considers the dynamic monthly changes in auto loan origination activity during the COVID-19 period. Aggregate auto loan origination activity experienced a dramatic drop associated

[13] The aggregated impact of the COVID-19 pandemic shows consistent estimates across model specifications with incrementally fuller fixed effects structures.

with the beginning of the pandemic. The drop in auto loan origination associated with the months of March and April 2020 is roughly 28.2 percent and 48 percent, respectively. These estimates are both statistically and economically significant. The drastic drop in auto loan originations during the initial two months of the pandemic is followed by a quick and substantial recovery in subsequent months. The associated coefficient in May 2020 is a much less dramatic -0.150 and the associated coefficient in June 2020 of -0.024 is statistically indistinguishable from zero. The subsequent months from July to October 2020 are again associated with statistically significant drops in the aggregate origination activity, but the drop is much smaller compared with the initial effect of the COVID-19 impact in the early months of the pandemic. In November and December, which coincides with a new dramatic wave of COVID-19 cases, we find suggestive evidence for a corresponding second contraction in the auto loan market with coefficient estimates of -0.140 and -0.130, respectively.

Table 3 also reports results separately for the four Risk Score segments. While the initial drop in auto loan originations does not differ dramatically across the Risk Score groups (Columns 2–5), the recovery paths prove notably different across the four borrower groups. The subprime borrower group continues to suffer from a persistent negative effect of COVID-19, following the initial drop in March and April. In contrast, we find a strong recovery starting May for the three higher Risk Score borrower groups. We even find a positive coefficient estimate for June, which ranges between 0.011 and 0.023 across the three higher Risk Score groups.

Motivated by the common narrative that subprime borrowers may be more susceptible to disruptions in the used car market, we also explore how used car loan origination trends differed from new car loan originations. Although we are unable to directly identify in our data whether a loan was originated for a used car or a new car, we are able to observe whether the loan was originated by a used car dealership. Using this information, we examine the dynamics of the COVID-19 effect on auto loans originated by used car dealers and report the results in Table 4. The results indicate that the general trends mimic the aggregate market. The table shows the dramatic drop in originations in the early months of the COVID-19 effect, followed by an immediate near rebound. Breaking down this trend by Risk Score segments, we find that the subprime borrower group experiences a persistent loss during the later months of 2020, while the other borrower groups exhibit a strong recovery starting in May. Investigating the coefficient for *Y2020*, we also document an unusually high 2020 effect (ranging across 0.11–0.38), suggesting that originations by used car dealerships were significantly higher in 2020 compared with their 2019 level before the pandemic. However, we caution that this may not amount to an economically meaningful quantity; used car dealers identified in our sample originate only around 1 percent of the loans in our sample, and naturally, this quantity fluctuates more compared with the larger lender categories we study in other parts of the paper.

We should point out that our sample does not include used car loans originated by other types of lenders; thus, this result should be interpreted with caution. We are unable to speak to any conclusive evidence either in favor or against the claim that the market for used cars was more or less active than the new car market as a result of the pandemic.

4 Heterogeneity of the COVID-19 Impact Across Geographic Characteristics and Lending Channels

In this section, we explore the cross-section of the COVID-19 impact across two important dimensions: geographic region and financing source. Section 4.1 discusses the heterogeneity in the COVID-19 effect across census regions and the characteristics that drive this variation. Section 4.2 describes the differential COVID-19 impact across lending channels, and Section 4.3 focuses the discussion on the declining bank share in the auto loan market.

4.1 Geographic Heterogeneity of the COVID-19 Impact on Auto Loan Originations

Narrative evidence suggests that, while the pandemic initially disrupted economic activities across the globe, the heterogeneous direct impact of the pandemic, the public attitude, and the local government management generated a wide range of economic impacts throughout the pandemic. In this section, we formally compare the differential regional effects on auto loan originations and illustrate how the geographic variation in the COVID-19 effect is related to other variables.

Specifically, we capture the baseline geographic variation by modifying equation (1) to interact the *COVID* indicator variable with the categorical variable representing the county's census division classification. Furthermore, we explore how much of this geographic variation survives with additional control variables of urbanization rate, the COVID-19 death rate, and household mobility. It is natural to posit that urban auto loan markets reacted to the COVID-19 crisis differently compared with rural auto loan markets. Car ownership is smaller in urban areas due to the density of amenities and availability of public transportation. Therefore, as the aversion to public transportation grows because of the pandemic, the demand for first-time car ownership could increase in urban areas. On the other hand, denser areas generally experienced a more severe halt in economic activity during the COVID-19 pandemic, and a growing body of evidence also documents migration away from cities to the suburbs (Gupta, Mittal, Peeters, and Van

Nieuwerburgh, 2021).[14] The COVID-19 death rate captures the state of the local economy's public health and impacts households' ability to engage in economic activities and household mobility variables provide additional information on how much time households are spending away from home. Finally, we estimate the following resulting equation:

$$\log\left(Origination_{it}+1\right)=\alpha\ Census\ Region_i\times Y2020_t+\beta\ Census\ Region_i\times COVID_t+\delta\ Urban_i\times COVID_t$$
$$+\delta\ Mobility_{it}\times COVID_t+\delta\ COVID\ Death\ Rate_{it}+FE_{it}\,. \qquad (2)$$

Our main interest from the results of this regression is β, the vector of coefficients on the interaction terms between the census division indicator variables and the *COVID* indicator variable. We restrict our sample here to the January–May period and focus on the early months of the pandemic when the impact was at its peak. *COVID* takes the value 1 for the months March–May 2020, capturing the period of the pandemic that is both early and long enough to allow for regional variation in the covariate variables. Intuitively, these coefficients illustrate the differential regional loss in auto loan originations during the COVID-19 period. *Urban* is defined as the percentage of the county's population that reside in an area classified as *urban* by the U.S. Census. The mobility variables are derived from the Opportunity Insights GPS data and report the changes in how much time households spend at their home and on public transit. *COVID Death Rate* is defined as the seven-day moving average of COVID-19 deaths in the county per 100,000 people.

In Figure 5, we report how these coefficients vary for incrementally richer set of covariates.[15] First, the top left subfigure shows the distribution of census division-specific coefficients without any control variables. It shows significant differences across these divisions, with the Northeast (i.e., mid-Atlantic and New England) and the Pacific regions shown to be significantly more impacted. These regions report initial COVID-19 effect coefficient estimates in the neighborhood around -0.2 and -0.3. In contrast, the census divisions in the South and the Midwest proved significantly less impacted by the early COVID-19 months, with an estimated initial impact in the neighborhood of -0.1. This finding strengthens the common narrative that the coastal regions in the U.S. generally experienced more dramatic economic disruptions from the pandemic.

The subsequent subfigures suggest that a strong portion of the geographic variation in the COVID-19 effect comes from the variation in urbanization rate and mobility rate. After accounting for the differences in each county's urbanization rate and household mobility, most of the COVID-19 effect attributable to the census region indicator becomes statistically indistinguishable from zero, and there

[14] In Table A1 in the Appendix, estimating our baseline specification for varying degrees of urbanization rates suggests that the COVID-19 effect was more severe in counties with higher urbanization rates.

[15] We report the rest of the regression results in Table A2 in the Appendix. We also provide an alternative specification with separate subsamples across census divisions and dynamic coefficients in Table A3.

remains almost no region-specific interaction with the common COVID-19 effect. Moreover, perhaps unsurprisingly, we do not find that controlling for the regional differences in the COVID-19 death rate affects the differential region effects. While the death rate may represent a proxy for the intensity of the county's exposure to the pandemic, likely inducing a stronger community response to stay home and suspend business activities, it could also imply that the county resumed business activities prematurely and thus reported an increasing death rate. Therefore, it is unclear whether counties with a higher death rate should concurrently have more or less activity in the auto market. The only regional effect that survives can be found for the mid-Atlantic region, suggesting that this region may have experienced a unique auto market reaction to the pandemic beyond urbanization rate and mobility.

4.2 Heterogeneity on Auto Loan Originations Across Lending Channels

To examine the heterogeneity in the COVID-19 impact across financing sources, Panel A of Table 6 reports the estimates from equation (1) separately across different financing sources. First, it shows that originations by finance companies started 2020 with the strongest growth. The coefficients of *Y2020* indicate that finance companies originated roughly 5.4 percent more loans in January and February 2020, relative to their 2019 levels, while banks and credit unions experienced negative or neutral (i.e., statistically indistinguishable from zero) growth. Column 1's coefficient estimate of *COVID,* -0.241, suggests that bank-financed originated auto loans experienced a substantial drop associated with COVID-19. In contrast, columns 2–3 show a much less dramatic COVID-19 impact on auto loan origination activity for finance company-financed and credit union-financed auto loans. The estimates of *COVID* show that the effect of the COVID-19 pandemic on the average monthly drop in auto loans for finance companies and credit unions was around 12.6 percent and 8.9 percent during March–December 2020, respectively.

Panel B of Table 6 decomposes the dynamics of the COVID-19 impact separately across financing sources during the March–December time frame of the pandemic. In Columns 1–3, we break down the sample by financing source. At a high level, the estimated results reveal the heterogeneity of impact over time and across financing sources. Bank-financed originations experienced the strongest drop in auto loan originations related to the COVID-19 impact across all months. Banks exhibit the largest initial drop in originations during March and April, with a coefficient estimate of -0.467, and a persistent negative effect of COVID-19 throughout the following months of the pandemic. On the other hand, finance companies and credit unions report a much stronger recovery between May and December, despite a notable drop in the final two months of the year for finance companies, and despite the fact that finance companies are more likely to serve the subprime segment of consumers.

In Table 7, we examine the impact of COVID-19 auto loan originations across financing sources and Risk Score segments and observe significant differences in the estimated impact across segments. Specifically, we focus our attention on each financing source separately and interact both *Y2020* and *COVID* with the Risk Score segment variable to estimate each group–specific coefficient. We furthermore decompose the *COVID* indicator variable into two sub-variables to separately denote the period of the initial shock (March and April) and the recovery period (May–December). Two features stand out from this table. First, across all financing sources, the subprime borrower group experiences a significant drop in auto loan originations related to COVID-19, notably larger than the middle- and high-Risk Score borrower groups. Second, the origination activity of banks is most significantly affected by COVID-19 across all Risk Score groups and for the 620–660 group in particular. The differences are stark. For the subprime borrower group, we estimate that bank-originated loans initially fell by roughly 44.7 percent per month due to the COVID-19 pandemic, whereas the corresponding drop was 41.1 percent and 24.3 percent for finance company-originated loans and credit union-originated loans, respectively. The recovery period reveals similarly divergent strengths, during which the subprime borrower group reports a loss of around 31.8 percent per month for bank loans, while 22.9 percent and 8.2 percent for finance companies and credit unions, respectively. For the 620–660 borrower group, the table reports a loss of around 21.0 percent per month for bank loans, while 2.7 percent and 0.0 percent for finance companies and credit unions, respectively, during the May–December period of recovery in economic activity. For the prime borrower group, bank-financed originations recover with strength much closer to those of the finance company and credit union counterparts.

4.3 Origination Channels: Changes to Bank Share of the Auto Loan Market

To understand the full picture of the COVID-19 impact on auto loan originations across financing sources, we also examine how the market share of each lender changed during the pandemic. We examine the bank share among newly originated monthly auto loans as the outcome variable. We focus on this measure of the bank market share to quantitatively understand the substitution from banks to either finance companies or credit unions.

Table 8 formally addresses this question by considering a version of equation (1) with the log of bank share as the dependent variable to estimate the COVID-19 impact on the bank share. In Panel A, we estimate the baseline regression with three separate subsamples to distinguish the dynamic COVID-19 effect throughout (1) the initial drop (March–April), (2) the recovery period (May–October), and (3) the drop corresponding to the second wave of COVID-19 cases (November–December). First, we find that, at

the aggregate level, banks were already losing their market share in 2020 prior to the COVID-19 pandemic. The coefficients for *Y2020* show that this magnitude is also economically significant, representing roughly a 4.4 percent drop relative to the 2019 bank share. The COVID-19 period is associated with a further significant drop; we estimate an average of a further 16 percent relative drop in bank share throughout the early months of the COVID-19 period. This relative drop proves to be milder in the later months, recovering to roughly 13.2 percent in the recovery months of May–October and further to 8.6 percent during the second wave of COVID-19 cases.

Panel B of Table 8 shows the heterogeneity of this bank share change across Risk Score groups. It shows that in the pre-COVID-19 months of 2020, banks had lost their market share for the three lower Risk Score groups. The prime borrower group, however, reports that the bank share actually rose by 3.4–6.4 percent during this period, relative to 2019, depending on the specification. The COVID-19 months of 2020 illustrate a more mixed picture, where the bank market share loss is initially similar for all borrower groups — coefficient estimates for the interacted *COVID* variable ranges between -0.125 and -0.198 for March–April — and the prime borrower group reports a notable recovery in the bank share during the subsequent periods. These results combine to suggest that the effect of the COVID-19 pandemic on the bank market share was negative and significant, which naturally complements our previous section's findings that bank-originated auto loans fell by the largest amount compared with other lending institutions. The drop in bank market share was particularly for the under-660 borrower group. This impact of COVID-19 represents a continuation of a 10-year secular trend of decline in bank market share.

5 Conclusion

Our paper analyzes the impact of the COVID-19 crisis on auto loan origination activity during the first year of the COVID-19 pandemic. Our analysis employs auto loan data from a representative sample from the FRBNY Consumer Credit Panel/Equifax data. We focus on the evolution of the COVID-19 impact of the crisis over time, across Risk Score segments, across geographic regions, and across lending channels. We identify the impact of COVID-19 on auto loan growth by comparing the 2020 trend with previous years' trends, separately for the period before and after the onset of the crisis in the U.S. We complement our analysis with an examination of historical trends in auto lending over a 17-year time frame that encompasses the period of economic growth prior to the Great Recession, the recession, and the 10-year period of growth post-recession. Our analysis of auto loan originations during the Great Recession is consistent with existing research, and a further analysis of the last decade of growth highlights interesting trends in auto lending. Over that period, the finance company channel consolidated its dominant position, in particular for the

subprime borrower group, while credit unions have maintained their level of lending or experienced steady growth for the prime borrower group. In contrast, banks have continued to lose overall market share, especially for the subprime borrower group. The pandemic impact on auto loan originations intensified some of these trends. Specifically, our results point to a significant drop in auto loan originations in March–April 2020 across the board, followed by a near rebound in May–June for most borrower groups. Our analysis highlights significant differences across Risk Score segments in the recovery of auto loan origination volumes from the depressed levels of the initial months of the crisis, with the subprime segment experiencing a more severe loss throughout 2020. Our analysis points to a significant geographic variation on the impact on loan originations, which can largely be explained by the differences in the urbanization rate and household mobility responses to the pandemic. We also observe significant differences in the impact across financing sources, where bank lending contracted more significantly and failed to recover as quickly as lending by financing companies and credit unions. This naturally resulted in a drop in the market share for banks in the auto loan origination space. This trend contrasts with the prior period of distress experienced during the Great Recession, when banks contributed the largest support to the auto loan market while finance companies were highly constrained.

Overall, our paper provides a detailed quantitative assessment of the COVID-19 impact on auto loan originations and contributes to the interpretation of the broad narratives describing the longer-term effects of the pandemic on the economy. Specifically, we highlight a highly asymmetric recovery in auto loan origination activity between subprime and prime borrower groups, and the waning role of banks in the auto loan market. These features of the pandemic-induced disruption on the economy can produce significant long-lasting implications on consumer credit and highlight the importance of continued monitoring of consumer credit markets by academicians and industry practitioners.

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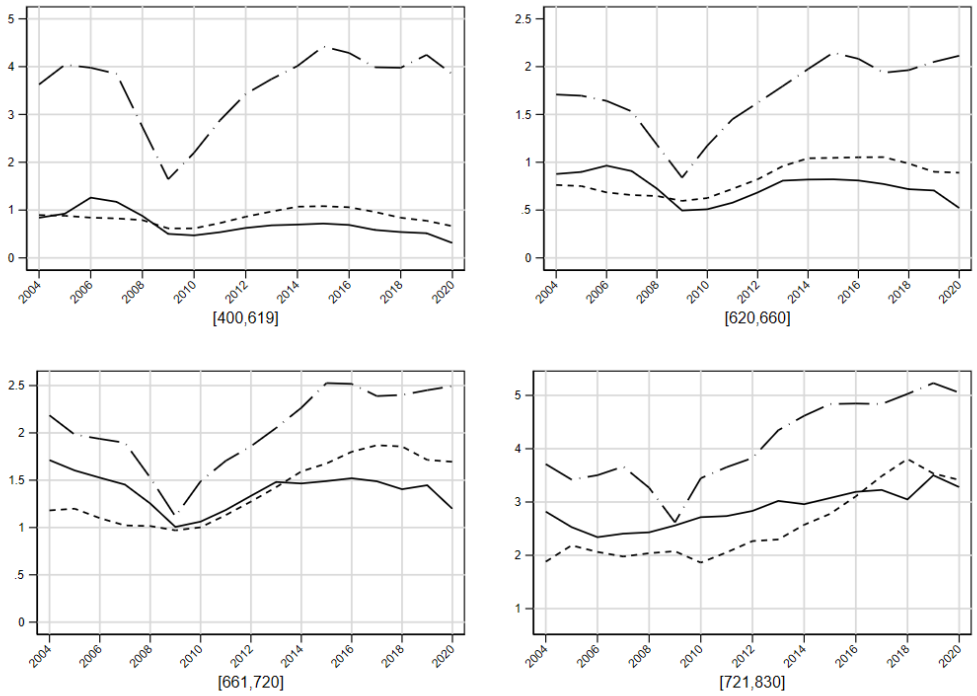
Table 1: Variables and Definitions

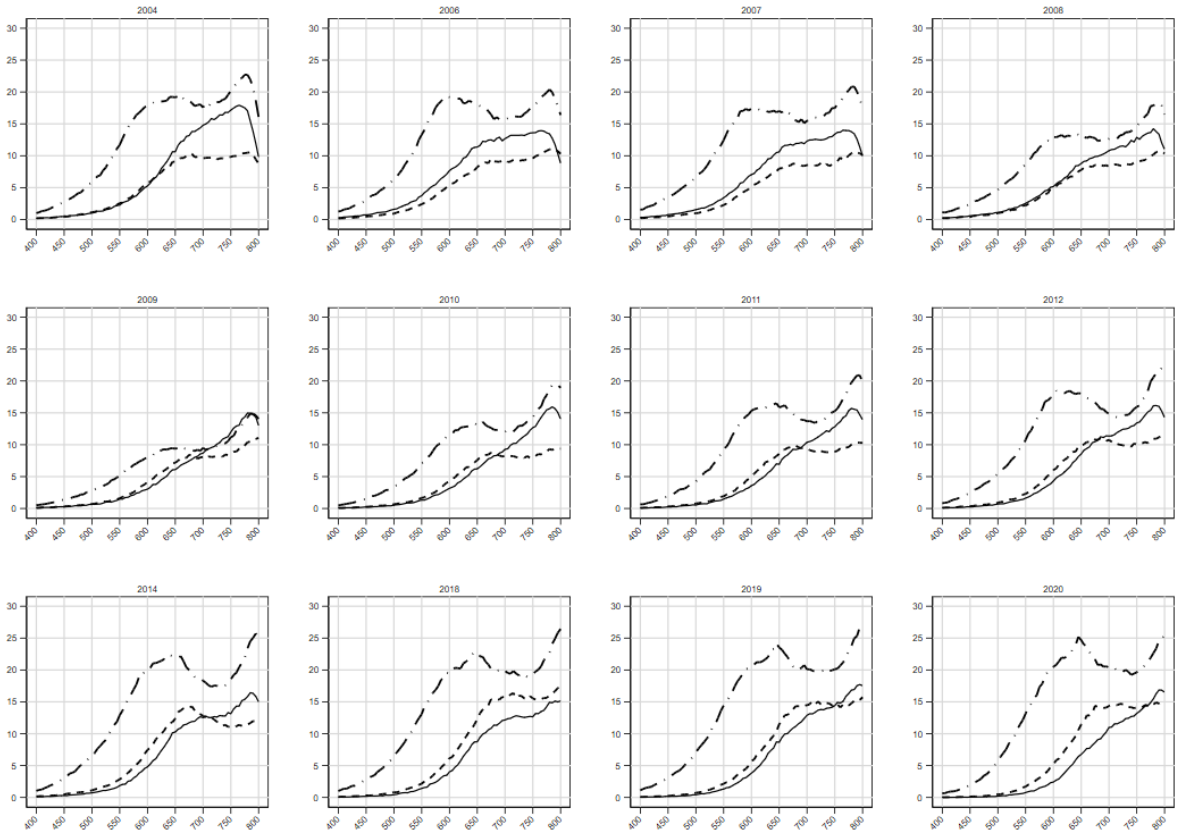
	Definition
CCP Variables	
Risk Score	Borrower Equifax Risk Score at observation time
Origination Date	The month that the reported loan is originated
Segmentation	
Risk Segment 1	Borrowers with Risk Score < 620 (i.e., subprime)
Risk Segment 2	Borrowers with Risk Score between 620 and 660
Risk Segment 3	Borrowers with Risk Score between 660 and 720
Risk Segment 4	Borrowers with Risk Score > 720
Banks	Banks and Savings & Loans
Finance companies	Dealers (used and new), auto and sales financing
Credit Union	Credit Unions (Equifax classification)
Mobility Variables	
Time away from home	Time spent outside of home based on GPS mobility data from Google COVID-19 Community Mobility Reports
Time at public transit	Time inside transit stations based on GPS mobility data from Google COVID-19 Community Mobility Reports
Urban	Percentage of county population residing in an urban area according to census classifications
COVID-19	
COVID death rate	COVID-19 deaths per 100,000 people; 7-day moving average
U.S. Census Regions	
Northeast	
New England	Connecticut, Maine, Massachusetts, New Hampshire, Rhode Island, Vermont
Mid-Atlantic	New Jersey, New York, Pennsylvania
Midwest	
East North Central	Illinois, Indiana, Michigan, Ohio, Wisconsin
West North Central	Iowa, Kansas, Minnesota, Missouri, Nebraska, North Dakota, South Dakota
South	
South Atlantic	Delaware, District of Columbia, Florida, Georgia, Maryland, North Carolina, South Carolina, Virginia, West Virginia
East South Central	Alabama, Kentucky, Mississippi, Tennessee
West South Central	Arkansas, Louisiana, Oklahoma, Texas
West	
Mountain	Arizona, Colorado, Idaho, Montana, Nevada, New Mexico, Utah, Wyoming
Pacific	Alaska, California, Hawaii, Oregon, Washington

Figure 1: Auto Lending over Time Across Lending Channels and Risk Score



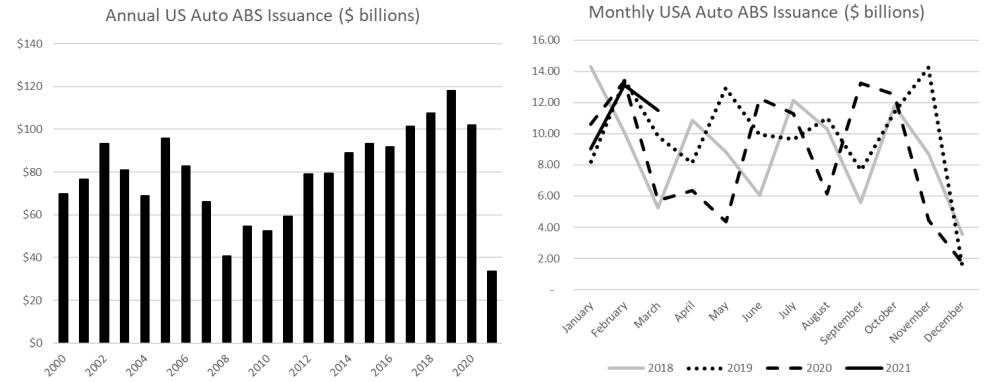
Note: The graphs represent number of annual originations in millions across four Risk Score segments for banks (solid line), finance companies (long dash dot), and credit unions (short dash).
Source: FRBNY Consumer Credit Panel/Equifax (CCP)

Figure 2: Auto Lending over Time Across Lending Channels and Risk Score



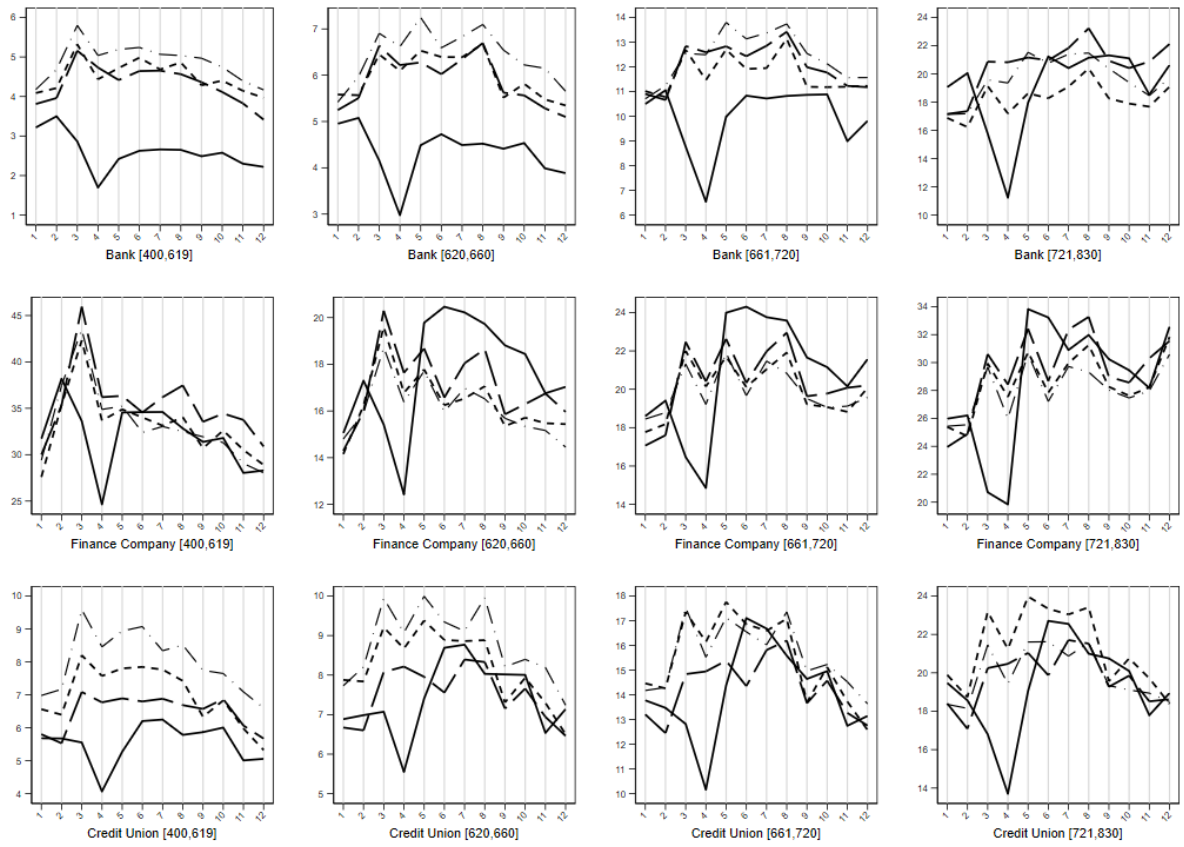
Note: The graphs represent number of annual originations over five Risk Score unit intervals in tens of thousands of loans, across Risk Score and years for banks (solid line), finance companies (long dash dot), and credit unions (short dash). Years 2015–2017 were very stable and are not included. The graphs have been created using the overall sample of primary members in the FRBNY Consumer Credit Panel/Equifax (CCP) multiplied by 20, but weight correcting for joint auto loans, to obtain a representative picture of auto loan originations in the overall CCP.

Figure 3: Auto ABS Deals from January 2000 to March 2021



Note: Based on Auto ABS deals modeled by Intex Solutions. Includes only U.S. deals backed by USD-denominated collateral. Includes the following deal types: auto loan, auto lease, rental fleet, and motorcycle. Issued amount excludes deal tranches not offered to investors. Issued amount includes offered tranches of synthetic securitization deals, or credit-linked notes, referencing pools of bank-owned auto loans.

Figure 4: Monthly Auto Lending Evolution in 2017–2020 for Banks, Finance Companies, and Credit Unions



Note: The graphs represent number of monthly originations in tens of thousands across Risk Score segments for banks, finance companies, and credit unions, for the years 2020 (solid line), 2019 (long dash), 2018 (short dash), and 2017 (dash dot).
Source: FRBNY Consumer Credit Panel/Equifax (CCP)

Table 2: COVID-19 and Auto Loan Origination Growth

This table reports the estimates of equation 1. The dependent variable in all columns is *log(Originations+1)*. The indicator variable *Y2020* is equal to 1 for the calendar year 2020 and 0 otherwise, and *COVID* is equal to 1 for the months March–December 2020. Observations are weighted by the county population. Standard errors, which are clustered by state, are reported in parentheses. *, **, and *** indicate significance of 10%, 5%, and 1% level, respectively.

	(1) All	(2) Risk Score <620	(3) Risk Score 620–660	(4) Risk Score 660–720	(5) Risk Score >720
Year 2020	0.017***	-0.022**	-0.012	0.032***	0.071***
	(0.005)	(0.010)	(0.010)	(0.006)	(0.006)
COVID	-0.152***	-0.217***	-0.099***	-0.127***	-0.164***
	(0.009)	(0.013)	(0.014)	(0.010)	(0.011)
Observations	884,640	217,848	218,880	222,984	224,928
R-squared	0.834	0.853	0.837	0.871	0.906
County FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Risk Segment FE	Yes	No	No	No	No
Financing Source FE	Yes	Yes	Yes	Yes	Yes

Table 3: Monthly Dynamics of the COVID-19 Effect

This table reports the estimates of equation 1 with *COVID* interacted with each calendar month's dummy indicator variable. The dependent variable is *log(Originations+1)*. The indicator variable *Y2020* is equal to 1 for the calendar year 2020 and 0 otherwise, and *COVID* is equal to 1 for the months March–December 2020. Observations are weighted by the county population. Standard errors, which are clustered by state, are reported in parentheses. *, **, and *** indicate significance of 10%, 5%, and 1% level, respectively.

	(1) All	(2) Risk Score <620	(3) Risk Score 620-660	(4) Risk Score 660-720	(5) Risk Score >720
Year 2020	0.017***	-0.022**	-0.012	0.032***	0.071***
	(0.005)	(0.010)	(0.010)	(0.006)	(0.006)
Month 3 # COVID	-0.282***	-0.279***	-0.217***	-0.288***	-0.346***
	(0.017)	(0.020)	(0.023)	(0.022)	(0.021)
Month 4 # COVID	-0.480***	-0.498***	-0.408***	-0.476***	-0.539***
	(0.054)	(0.049)	(0.048)	(0.063)	(0.063)
Month 5 # COVID	-0.150***	-0.225***	-0.095***	-0.121***	-0.160***
	(0.017)	(0.023)	(0.017)	(0.019)	(0.025)
Month 6 # COVID	-0.024	-0.150***	0.021	0.023	0.011
	(0.017)	(0.023)	(0.020)	(0.018)	(0.018)
Month 7 # COVID	-0.078***	-0.144***	-0.030	-0.043***	-0.096***
	(0.014)	(0.016)	(0.026)	(0.014)	(0.012)
Month 8 # COVID	-0.124***	-0.183***	-0.081***	-0.102***	-0.129***
	(0.016)	(0.021)	(0.023)	(0.016)	(0.015)
Month 9 # COVID	-0.052***	-0.169***	0.010	-0.013	-0.037***
	(0.011)	(0.013)	(0.022)	(0.012)	(0.011)
Month 10 # COVID	-0.060***	-0.145***	-0.004	-0.039***	-0.055***
	(0.010)	(0.016)	(0.017)	(0.012)	(0.011)
Month 11 # COVID	-0.140***	-0.202***	-0.091***	-0.113***	-0.153***
	(0.012)	(0.019)	(0.016)	(0.010)	(0.015)
Month 12 # COVID	-0.130***	-0.179***	-0.099***	-0.103***	-0.140***
	(0.010)	(0.017)	(0.019)	(0.013)	(0.013)
Observations	884,640	217,848	218,880	222,984	224,928
R-squared	0.835	0.854	0.839	0.873	0.908
County FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Risk Segment FE	Yes	No	No	No	No
Financing Source FE	Yes	Yes	Yes	Yes	Yes

Table 4: COVID-19 and Used Car Dealership Loans

This table reports the estimates of equation 1 only for originations financed by a used car dealership at the state-level. The dependent variable is *log(Originations+1)*. The indicator variable *Y2020* is equal to 1 for the calendar year 2020 and 0 otherwise, and *COVID* is equal to 1 for the months March–December of 2020. Furthermore, *COVID* is interacted with each calendar month's dummy indicator variable. Observations are weighted by the county population. Standard errors, which are clustered by state, are reported in parentheses. *, **, and *** indicate significance of 10%, 5%, and 1% level, respectively.

	(1) All	(2) Risk Score <620	(3) Risk Score 620–660	(4) Risk Score 660–720	(5) Risk Score >720
Year 2020	0.234***	0.156**	0.113	0.387***	0.280***
	(0.052)	(0.073)	(0.082)	(0.079)	(0.084)
Month 3 # COVID	-0.313***	-0.424***	-0.166*	-0.348***	-0.312**
	(0.058)	(0.055)	(0.097)	(0.100)	(0.128)
Month 4 # COVID	-0.496***	-0.533***	-0.305***	-0.544***	-0.601***
	(0.048)	(0.077)	(0.077)	(0.116)	(0.130)
Month 5 # COVID	-0.037	-0.234***	-0.020	0.098	0.007
	(0.052)	(0.061)	(0.087)	(0.118)	(0.117)
Month 6 # COVID	-0.031	-0.188***	0.156*	-0.017	-0.074
	(0.056)	(0.051)	(0.082)	(0.123)	(0.165)
Month 7 # COVID	-0.110**	-0.190***	0.144	-0.328***	-0.066
	(0.046)	(0.040)	(0.101)	(0.082)	(0.137)
Month 8 # COVID	-0.085	-0.367***	0.080	-0.096	0.043
	(0.055)	(0.069)	(0.089)	(0.142)	(0.098)
Month 9 # COVID	0.004	-0.300***	0.124	0.050	0.141
	(0.044)	(0.053)	(0.108)	(0.119)	(0.094)
Month 10 # COVID	-0.080	-0.339***	0.047	-0.040	0.010
	(0.056)	(0.051)	(0.096)	(0.124)	(0.109)
Month 11 # COVID	-0.176***	-0.457***	-0.078	-0.193*	0.023
	(0.036)	(0.053)	(0.082)	(0.103)	(0.127)
Month 12 # COVID	-0.058	-0.290***	0.032	-0.160	0.186*
	(0.051)	(0.061)	(0.098)	(0.112)	(0.107)
Observations	4,848	1,224	1,224	1,200	1,200
R-squared	0.884	0.956	0.880	0.837	0.805
State FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Risk Segment FE	Yes	Yes	Yes	Yes	Yes

Figure 5: COVID-19 Effect Across Census Divisions with Covariates

This figure reports the coefficient estimates for the interaction terms between census region indicator variables and *COVID* in equation 2. The title of each subfigure denotes the control variables included in the specification. The band around the point estimate represents the 95% confidence interval.

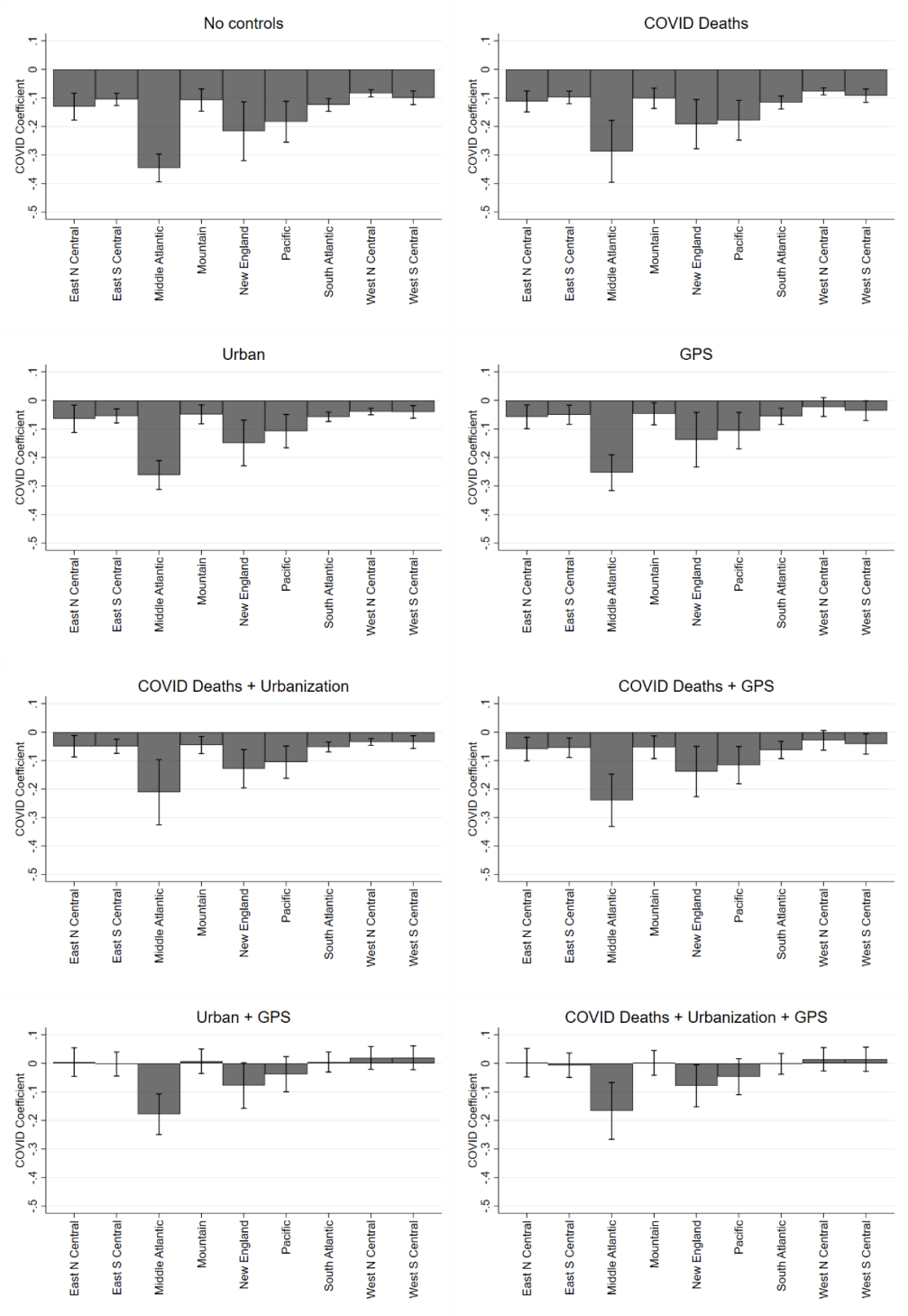


Table 6: Heterogeneity Across Financing Sources

This table reports the estimates of equation 1 separately across financing sources. The dependent variable is *log(Originations+1)*. For column (1), the indicator variable *Y2020* is equal to 1 for the calendar year 2020 and 0 otherwise. For Panel A, *COVID* is equal to 1 for the months March–December 2020. For Columns Panel B, *COVID* is further divided into three indicator variables denoting three distinct subperiods: (1) March–April, (2) May–October, and (3) November–December. Observations are weighted by the county population. Standard errors, which are clustered by state, are reported in parentheses. *, **, and *** indicate significance of 10%, 5%, and 1% level, respectively.

Panel A: Average COVID Effect in 2020m3-2020m12

	(1) Banks	(2) Finance Companies	(3) Credit Unions
Year 2020	-0.014*	0.054***	0.012
	(0.008)	(0.006)	(0.011)
COVID	-0.241***	-0.126***	-0.089***
	(0.014)	(0.009)	(0.011)
Observations	294,168	298,008	292,464
R-squared	0.652	0.900	0.729

Panel B: Dynamic COVID Effect

	(1) Banks	(2) Finance Companies	(3) Credit Unions
Year 2020	-0.014*	0.054***	0.012
	(0.008)	(0.006)	(0.011)
COVID 2020m3-m4	-0.467***	-0.396***	-0.281***
	(0.037)	(0.048)	(0.024)
COVID 2020m5-m10	-0.183***	-0.026***	-0.035***
	(0.015)	(0.007)	(0.011)
COVID 2020m11-m12	-0.193***	-0.154***	-0.059***
	(0.014)	(0.009)	(0.013)
Observations	294,168	298,008	292,464
R-squared	0.653	0.902	0.730
County FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Risk Segment FE	Yes	Yes	Yes

Table 7: COVID-19 and Auto Loan Growth by Risk Score and Financing Source

This table reports the estimates of equation 1 separately across financing sources. The dependent variable is *log(Originations+1)*. The indicator variable *Y2020* is equal to 1 for the calendar year 2020 and 0 otherwise, and the indicator variable *COVID* is further divided into two indicator variables denoting two distinct subperiods: (1) March–April, and (2) May–December. Furthermore, *Y2020* and *COVID* are interacted with each Risk Score segment's indicator variable. Observations are weighted by the county population. Standard errors, which are clustered by state, are reported in parentheses. *, **, and *** indicate significance of 10%, 5%, and 1% level, respectively.

	(1) Banks	(2) Finance Companies	(3) Credit Unions
Score<620 # 2020	-0.073***	0.087***	-0.020
	(0.019)	(0.010)	(0.023)
Score 620–660 # 2020	-0.034**	0.067***	0.010
	(0.014)	(0.009)	(0.017)
Score 660–720 # 2020	-0.010	0.061***	0.039***
	(0.007)	(0.008)	(0.009)
Score>720 # 2020	0.060***	0.003	0.019*
	(0.009)	(0.011)	(0.011)
Score<620 # COVID 2020m3-m4	-0.447***	-0.411***	-0.243***
	(0.040)	(0.039)	(0.030)
Score 620–660 # COVID 2020m3-m4	-0.425***	-0.363***	-0.202***
	(0.043)	(0.048)	(0.024)
Score 660–720 # COVID 2020m3-m4	-0.475***	-0.383***	-0.313***
	(0.041)	(0.050)	(0.031)
Score>720 # COVID 2020m3-m4	-0.519***	-0.426***	-0.367***
	(0.039)	(0.057)	(0.033)
Score<620 # COVID 2020m5-m12	-0.318***	-0.229***	-0.082***
	(0.029)	(0.009)	(0.020)
Score 620–660 # COVID 2020m5-m12	-0.210***	-0.027***	-0.003
	(0.017)	(0.007)	(0.021)
Score 660–720 # COVID 2020m5-m12	-0.134***	-0.006	-0.035**
	(0.015)	(0.009)	(0.014)
Score>720 # COVID 2020m5-m12	-0.080***	0.030**	-0.044***
	(0.013)	(0.012)	(0.013)
Observations	294,168	298,008	292,464
R-squared	0.883	0.942	0.891
County FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Risk Segment FE	Yes	Yes	Yes

Table 8: COVID-19 Effect on Bank Share Loss

This table reports the effect of the COVID-19 period on the bank share of auto loan originations. The dependent variable is the log of the bank share in all columns. The indicator variable *Y2020* is equal to 1 for the calendar year 2020 and 0 otherwise, and *COVID* is equal to 1 for the months March–December of 2020. Each column corresponds to one of three distinct subperiods: (1) March–April, (2) May–October, and (3) November–December. In Panel B, *Y2020* and *COVID* are interacted with each Risk Score segment's indicator variable. Observations are weighted by the county population. Standard errors, which are clustered by state, are reported in parentheses. *, **, and *** indicate significance of 10%, 5%, and 1% level, respectively.

Panel A: Average COVID-19 Effect

	(1) M3-M4	(2) M5-M10	(3) M11-M12
Year 2020	-0.045***	-0.044***	-0.044***
	(0.008)	(0.008)	(0.008)
COVID-19	-0.160***	-0.132***	-0.086***
	(0.013)	(0.008)	(0.011)
Observations	77,930	158,247	77,236
R-squared	0.417	0.422	0.423

Panel B: Heterogeneity of COVID-19 Effect Across Risk Scores

	(1) M3-M4	(2) M5-M10	(3) M11-M12
Score<620 # Year 2020	-0.108***	-0.110***	-0.088***
	(0.015)	(0.017)	(0.019)
Score 620–660 # Year 2020	-0.089***	-0.087***	-0.076***
	(0.014)	(0.015)	(0.015)
Score 660–720 # Year 2020	-0.049***	-0.044***	-0.050***
	(0.010)	(0.009)	(0.010)
Score>720 # Year 2020	0.064***	0.059***	0.034***
	(0.010)	(0.008)	(0.008)
Score<620 # COVID-19	-0.167***	-0.148***	-0.097***
	(0.016)	(0.014)	(0.017)
Score 620–660 # COVID-19	-0.198***	-0.182***	-0.157***
	(0.025)	(0.014)	(0.017)
Score 660–720 # COVID-19	-0.152***	-0.117***	-0.067***
	(0.016)	(0.013)	(0.018)
Score>720 # COVID-19	-0.125***	-0.082***	-0.027*
	(0.019)	(0.013)	(0.016)
Observations	77,930	158,247	77,236
R-squared	0.420	0.426	0.425
County FE	Yes	Yes	Yes
Month FE	Yes	Yes	Yes
Risk Segment FE	Yes	Yes	Yes

Appendix

Table A1: COVID-19 Effect by Urbanization Rate

This table reports the estimates of equation 1 separately across counties by their urbanization rate. *Urbanization rate* is defined as the percentage of the county's population that reside in an area classified as urban by the U.S. Census. The dependent variable is *log(Originations+1)*. The indicator variable *Y2020* is equal to 1 for the calendar year 2020 and 0 otherwise, and *COVID* is equal to 1 for the months March–December of 2020. The indicator variable *COVID* is further divided into three indicator variables denoting three distinct subperiods: (1) March–April, (2) May–October, and (3) November–December. Observations are weighted by the county population. Standard errors, which are clustered by state, are reported in parentheses. *, **, and *** indicate significance of 10%, 5%, and 1% level, respectively.

	(1) Urban 0%	(2) Urban 0–30%	(3) Urban 30–50%	(4) Urban 50–75%	(5) Urban 75–100%
Year 2020	0.021***	0.017***	0.010**	0.032***	0.015**
	(0.005)	(0.005)	(0.005)	(0.006)	(0.006)
COVID-19 2020m3-m4	-0.080***	-0.154***	-0.165***	-0.270***	-0.466***
	(0.013)	(0.018)	(0.017)	(0.033)	(0.034)
COVID-19 2020m5-m10	-0.025***	-0.029***	-0.025***	-0.056***	-0.101***
	(0.006)	(0.006)	(0.007)	(0.008)	(0.011)
COVID-19 2020m11-m12	-0.051***	-0.061***	-0.074***	-0.117***	-0.157***
	(0.009)	(0.009)	(0.009)	(0.012)	(0.011)
Observations	184,440	145,920	192,840	197,184	163,872
R-squared	0.175	0.291	0.462	0.594	0.815
County FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Risk Segment FE	Yes	Yes	Yes	Yes	Yes
Financing Source FE	Yes	Yes	Yes	Yes	Yes

Table A2: COVID-19 and Regional Effects with Covariates

This table reports the estimates of equation 2. Columns (1)-(5) incrementally add the covariates of the specification. The dependent variable in all columns is *log(Originations+1)*. The sample period includes 2019m1-2019m5 and 2020m1-2020m5. The indicator variable *Y2020* is equal to 1 for the calendar year 2020 and 0 otherwise, and *COVID* is equal to 1 for the months March–May 2020. The interaction terms between *Y2020* and Census Division indicator variables are omitted in the reported table. Standard errors, which are clustered by state, are reported in parentheses. *, **, and *** indicate significance of 10%, 5%, and 1% level, respectively.

	(1)	(2)	(3)	(4)	(5)
E S Central # COVID	-0.105***	-0.050***	-0.055***	-0.002	-0.007
	(0.011)	(0.017)	(0.013)	(0.022)	(0.022)
Mid-Atlantic # COVID	-0.346***	-0.253***	-0.261***	-0.178***	-0.167***
	(0.025)	(0.032)	(0.026)	(0.036)	(0.051)
Mountain # COVID	-0.108***	-0.047**	-0.049***	0.007	0.002
	(0.020)	(0.020)	(0.017)	(0.022)	(0.022)
New England # COVID	-0.217***	-0.138***	-0.149***	-0.078*	-0.079**
	(0.053)	(0.049)	(0.041)	(0.041)	(0.038)
Pacific # COVID	-0.183***	-0.106***	-0.108***	-0.038	-0.047
	(0.037)	(0.033)	(0.030)	(0.031)	(0.032)
S Atlantic # COVID	-0.124***	-0.056***	-0.058***	0.005	-0.002
	(0.011)	(0.014)	(0.008)	(0.018)	(0.019)
W N Central # COVID	-0.084***	-0.023	-0.039***	0.019	0.014
	(0.006)	(0.017)	(0.006)	(0.020)	(0.021)
W S Central # COVID	-0.100***	-0.036**	-0.040***	0.020	0.014
	(0.012)	(0.018)	(0.011)	(0.021)	(0.022)
COVID-19 # Urban			-0.152***	-0.147***	-0.146***
			(0.020)	(0.019)	(0.019)
COVID-19 # GPS Away		0.464*		0.494**	0.446*
		(0.233)		(0.226)	(0.235)
COVID-19 # GPS Transit		0.010		-0.016	-0.024
		(0.073)		(0.072)	(0.071)
COVID-19 # Death Rate					-0.023
					(0.029)
Observations	371,420	371,420	368,600	368,600	368,600
R-squared	0.211	0.211	0.442	0.442	0.442
State FE	Yes	Yes	Yes	Yes	Yes
Month FE	Yes	Yes	Yes	Yes	Yes
Risk Segment FE	Yes	Yes	Yes	Yes	Yes
Financing Source FE	Yes	Yes	Yes	Yes	Yes

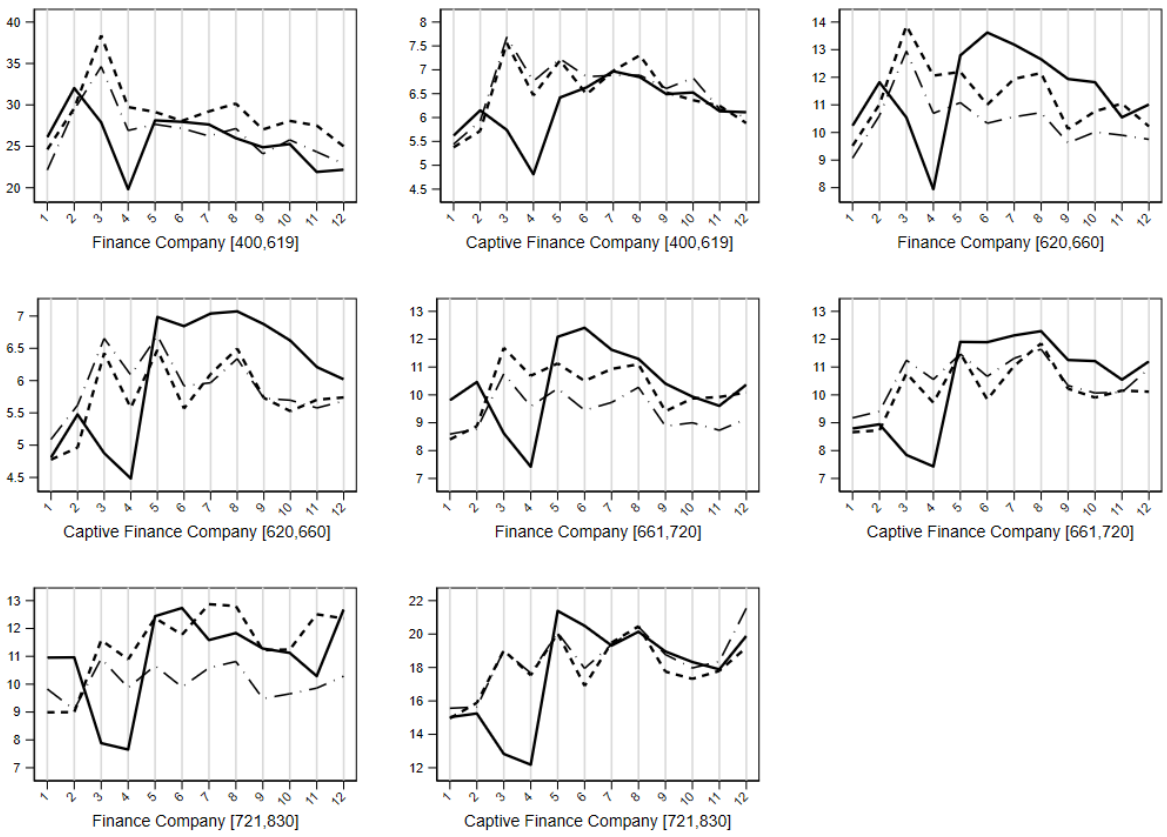
Table A3: COVID-19 Regional Effect Across Census Divisions

This table reports the estimates of equation 1 separately across census regional divisions. The census regional classifications are reported in Table 1. The dependent variable is *log(Originations+1)*. The indicator variable *Y2020* is equal to 1 for the calendar year 2020 and 0 otherwise, and *COVID* is equal to 1 for the months March–December 2020. The indicator variable *COVID* is further divided into three indicator variables denoting three distinct subperiods: (1) March–April, (2) May–October, and (3) November–December. All regressions include county, month, risk segment, and financing source fixed effects. Observations are weighted by the county population. Standard errors, which are clustered by state, are reported in parentheses. *, **, and *** indicate significance of 10%, 5%, and 1% level, respectively.

	South			**Midwest**	
	East S Central	**South Atlantic**	**West S Central**	**West N Central**	**East N Central**
Year 2020	0.014	0.015**	0.028**	0.011	0.018
	(0.013)	(0.005)	(0.007)	(0.011)	(0.009)
COVID-19 2020m3-m4	-0.196***	-0.280***	-0.245***	-0.210***	-0.397***
	(0.014)	(0.025)	(0.030)	(0.020)	(0.064)
COVID-19 2020m5-m10	-0.038*	-0.079***	-0.111***	-0.050***	-0.072***
	(0.015)	(0.013)	(0.019)	(0.010)	(0.008)
COVID-19 2020m11-m12	-0.091**	-0.101***	-0.146***	-0.141***	-0.147***
	(0.023)	(0.013)	(0.016)	(0.016)	(0.023)
Observations	104,016	168,384	132,888	169,584	125,352
R-squared	0.198	0.398	0.293	0.190	0.267

	West		**Northeast**	
	Mountain	**Pacific**	**Mid-Atlantic**	**New England**
Year 2020	0.041**	-0.000	0.005	0.071**
	(0.016)	(0.009)	(0.020)	(0.025)
COVID-19 2020m3-m4	-0.305***	-0.515***	-0.669***	-0.587***
	(0.046)	(0.033)	(0.053)	(0.056)
COVID-19 2020m5-m10	-0.102***	-0.104***	-0.040	-0.157***
	(0.020)	(0.012)	(0.031)	(0.019)
COVID-19 2020m11-m12	-0.174***	-0.140***	-0.123*	-0.223***
	(0.030)	(0.015)	(0.041)	(0.011)
Observations	76,992	45,048	43,128	19,248
R-squared	0.499	0.407	0.541	0.611

Figure A1: Monthly Auto Lending Evolution for 2018–2020 Across Captive and Non-Captive Finance Companies



Note: The graphs represent number of monthly originations in tens of thousands across Risk Scores for captive and non-captive finance companies, for the years 2020 (solid line), 2019 (short dash), and 2018 (dash dot).