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**The COVID-19 Shock and Consumer Credit: Evidence from
Credit Card Data**

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The COVID-19 Shock and Consumer Credit: Evidence from Credit Card Data

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Abstract

We use credit card data from the Federal Reserve Board's FR Y-14M reports to study the impact of the COVID-19 shock on the use and availability of consumer credit across borrower types from March through August 2020. We document an initial sharp decrease in credit card transactions and outstanding balances in March and April. While spending starts to recover by May, especially for risky borrowers, balances remain depressed overall. We find a strong negative impact of local pandemic severity on credit use, which becomes smaller over time, consistent with pandemic fatigue. Restrictive public health interventions also negatively affect credit use, but the pandemic itself is the main driver. We further document a large reduction in credit card originations, especially to risky borrowers. Consistent with a tightening of credit supply and a flight-to-safety response of banks, we find an increase in interest rates of newly issued credit cards to less creditworthy borrowers.

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I. Introduction

The ongoing COVID-19 pandemic and the ensuing public health interventions have severely disrupted economic activity in the United States. Real GDP decreased by more than 30 percent (BEA, 2020), unemployment rose to its highest levels since the Great Depression (Cajner et al., 2020a), and economic uncertainty reached historic heights (Baker et al., 2020b). How does this large economic shock affect the use and availability of consumer credit? Are credit market disruptions driven by the pandemic itself or by the policy responses in the form of restrictive non-pharmaceutical interventions (NPIs)? And how do these effects vary across borrower types?

We investigate these questions using monthly account-level credit card data from the Federal Reserve Board’s FR Y-14M reports and study the impact of the COVID-19 shock on both the use and availability of consumer credit over time. We investigate two potential, non-mutually exclusive channels. First, changes in the use of credit can be driven by the pandemic itself, as measured by the local number of cases. If people are afraid to contract the virus, they go out less, shop less, and shelter at home—even in the absence of an official order. Accordingly, we use the term “pandemic itself” to refer not only to the direct health effects (people falling sick with the virus), but also to voluntary changes in individual behavior in response to the outbreak (“fear of the virus”). Second, policy responses in the form of NPIs, such as shelter-in-place orders or the closure of nonessential businesses, can also disrupt local economies and can have a similar or potentially stronger impact on credit use. Whether economic activity is more disrupted by the pandemic itself or by restrictive NPIs remains an open question with important policy implications. Regarding the supply side, the COVID-19 shock could also negatively affect the availability of consumer credit. If banks expect rising default rates, they may possibly tighten lending standards, either at the extensive margin by originating fewer credit cards, or at the intensive margin by lowering credit limits or raising interest rates of newly issued cards.

We next study how the impact of the COVID-19 shock on the use and availability of consumer credit differs across borrower types. While negative income shocks and heightened economic uncertainty can trigger a reduction in consumption and thus in credit demand, especially risky borrowers may rely on unsecured credit for consumption smoothing to offset unemployment-induced earnings losses (Sullivan, 2008; Herkenhoff, 2019). However, access to credit might be limited for these

households if banks, seeking to adjust their credit exposure in the wake of adverse economic conditions, disproportionately reduce credit supply to less creditworthy borrowers (Benmelech et al., 2017; Ramcharan et al., 2016).

For our analysis, we construct a novel dataset from several sources. We obtain monthly account-level data on consumer credit card lending from the Federal Reserve Board’s FR Y-14M reports; daily county-level data on confirmed COVID-19 cases from the Johns Hopkins Coronavirus COVID-19 Global Cases GitHub repository; and daily county-level data on NPIs from the Coronavirus Intervention Dataset provided by Keystone Strategy. The granularity of the Y-14M data allows for a rich analysis of the credit market response to the COVID-19 shock. The dataset contains, inter alia, account-level information on cardholders’ ZIP codes and FICO scores, the card issuing bank, as well as the account origination and cycle-end dates. Using the latter two variables, we construct a pseudo-weekly panel dataset of credit card outcomes from our monthly data, which allows us to accommodate the fast-paced nature of the crisis. Therefore, we can compare the credit market outcomes of borrowers in the *same county*, in the *same FICO bucket*, borrowing from the *same bank*, at a weekly frequency over the course of the pandemic.

Our main findings are as follows. First, we document a sharp drop in consumer credit use around mid-March, when the pandemic was declared a national emergency. Credit card spending across all borrowers decreased by 50 percent year over year by the end of April and subsequently started to recover in May, especially for the least creditworthy borrowers. Credit card balances decreased by 27 percent until the end of April and remain depressed since. Second, we find that local pandemic severity has a strong negative impact on consumer credit use over nearly the entire course of the pandemic, even after controlling for weekly changes in state-level NPI policies. This impact is largest in April and becomes smaller over time, consistent with the notion of “pandemic fatigue.” A one-standard deviation cross-sectional increase in local pandemic severity is associated with a 5.8 percentage point reduction in credit card transactions in April but only with a 1.9 percentage point reduction in July. Third, we also find that, after controlling for local COVID-19 incidence, local NPI stringency has a negative impact on credit use, which is mostly smaller in magnitude. We conclude that, for most of our sample period, the pandemic itself was the main driver with regard to changes in spending and the use of consumer credit. Fourth, we report a large 60 percent decrease in the origination of new credit cards, especially to less creditworthy

borrowers. While this collapse in credit card originations likely reflects both demand and supply effects, we provide evidence for a reduction in credit availability, especially to riskier borrowers. At the intensive margin, we document a 4 percentage point increase in the annual percentage rate of interest (APR) spreads of new credit cards issued to risky borrowers but no changes in APR spreads for the most creditworthy borrowers.

The finding that banks reduce credit availability to riskier borrowers following an adverse macroeconomic shock is consistent with both the theory (Bernanke, Gertler, and Gilchrist, 1996) and empirical evidence (Ramcharan et al., 2016; Benmelech et al., 2017; Di Maggio et al., 2017) of a flight-to-safety effect. Our findings on the use of consumer credit warrant further discussion. According to the predictions of standard consumption theory and existing empirical evidence (Braxton, Herkenhoff, and Phillips, 2020), borrowers use unsecured consumer credit for consumption smoothing in the face of a negative transitory income shock, which implies countercyclical credit demand (Hundtofte, Olafsson, and Pagel, 2019). By contrast, we find a strong reduction in consumer credit use in the wake of the COVID-19 shock. On the one hand, this negative borrowing response could indicate that households expect the COVID-19 crisis to be a permanent instead of a transitory shock. On the other hand, our findings are also in line with recent empirical evidence that consumer credit demand appears to be procyclical and that households make limited use of credit cards for consumption smoothing, at odds with standard consumption theory (Ganong and Noel, 2019; Hundtofte, Olafsson, and Pagel, 2019; Olafsson and Pagel, 2018). Interestingly, for the riskiest borrowers, we find that the recovery in spending goes together with a continued reduction in balances and thus behavior consistent with a positive income shock. Ganong, Noel, and Vavra (2020) report that the expansion of unemployment insurance under the CARES Act entailed a median wage replacement rate of above 100 percent. Thus, especially newly unemployed workers with low earnings before the pandemic might have experienced an increase in income between April and July.

Moreover, our finding that creditworthy borrowers initially reduced their balances more strongly than risky borrowers is consistent with heterogeneity in the consumer credit response to economic uncertainty shocks (Bloom, 2009). Di Maggio et al. (2017) find that local economic uncertainty is more strongly associated with a reduction in credit card balances for more creditworthy borrowers. The underlying mechanism is heterogeneity in the pecuniary costs of default. Risky borrowers with

limited access to credit have a lower cost of default than creditworthy borrowers (Guiso, Sapienza, and Zingales, 2013), and the latter respond to increased uncertainty by targeting greater financial flexibility to protect their credit reputation and future credit access. Therefore, our findings are also in line with the interpretation of COVID-19 as an economic uncertainty shock (Baker et al., 2020b).

Our paper is related to several strands of literature. First, we add to the rapidly growing literature on the economic effects of the COVID-19 crisis. Previous studies have found that the pandemic strongly affected labor markets (Bartik et al., 2020; Cajner et al., 2020b; Coibion et al., 2020c; Forsythe et al., 2020), stock markets (Baker et al., 2020a), household expectations (Binder, 2020; Coibion et al., 2020a; Hanspal et al., 2020), economic uncertainty (Baker et al., 2020b), and overall economic activity (Lewis, Mertens, and Stock, 2020; Ludvigson, Ma, and Ng, 2020). More specifically, we contribute to the literature on the effects of the COVID-19 shock on households' consumption behavior. Using transaction data from fintech companies (Baker et al., 2020d), private credit card processors (Chetty et al., 2020; Dunn et al., 2020), or individual banks (Cox et al., 2020), previous papers have studied consumer spending during the COVID-19 pandemic in the United States.¹ While most existing papers rely on data from individual banks or fintech companies, our dataset encompasses more than 70 percent of accounts in the U.S. consumer credit card market. Moreover, our paper does not only investigate borrowers' spending response, but also provides novel evidence on the availability of consumer credit in the wake of the COVID-19 shock.

Second, our paper contributes to the ongoing policy debate about whether economic activity is more severely disrupted by the pandemic itself or by the policy responses in the form of restrictive public health interventions. While some studies find large adverse effects of shutdown policies on economic activity (Coibion, Gorodnichenko, and Weber, 2020a; Friedson, McNichols, Sabia, and Dave, 2020), other studies report small or only modest effects (Andersen, Hansen, Johannesen, and Sheridan, 2020b; Baek, McCrory, Messer, and Mui, 2020; Goolsbee and Syverson, 2020). We contribute to this literature by not only investigating the impact of pandemic severity and NPIs at a single point in time, but by tracing out their time-varying relative importance over the course of the pandemic from March to August.

¹Other papers have studied consumer spending in China (Chen, Qian, and Wen, 2020a), Denmark (Andersen et al., 2020a), France (Bouniey, Camaraz, and Galbraith, 2020), Spain (Carvalho et al., 2020), and the United Kingdom (Hacioglu, Känzig, and Surico, 2020; Chronopoulos, Lukas, and Wilson, 2020).

Finally, our paper is related to the empirical literature on households’ consumption and debt response to adverse economic shocks. We provide corroborative evidence that households made limited use of credit cards for consumption smoothing (Ganong and Noel, 2019; Hundtofte, Olafsson, and Pagel, 2019; Olafsson and Pagel, 2018) during the COVID-19 pandemic.

The remainder of the paper is structured as follows. Section II discusses our data sources and presents descriptive summary statistics. We discuss our methodology in Section III. Section IV presents the results for the use of credit and Section V the results for the availability of credit. Robustness checks are provided in Section VI. Section VII concludes.

II. Background and Data

A. *The United States Consumer Credit Card Market*

We obtain account-level data on consumer credit cards from the Federal Reserve Board’s FR Y-14M reports. These reports require large U.S. bank holding companies, with at least \$100 billion in total assets, to report detailed information on individual credit card accounts on a monthly basis. Our data contain information on 21 banks, which cover a large portion of the market and account for 70 percent of outstanding balances on consumer credit cards (CFPB, 2019). To study credit use and availability, we obtain data on cycle-end balances and transaction volumes (use of credit), as well as data on credit limits and annual percentage rates (APRs) (availability of credit).² Our data contain existing credit cards and newly issued credit cards. In each month, existing cards are defined as cards that already existed in the previous month, while new cards are defined as accounts that have been originated in the given month.

To accommodate the fast-paced nature of the pandemic, we convert our monthly data into weekly frequency by utilizing information about the account cycle-end date (for existing cards) and account origination date (for newly issued cards) contained in the dataset. We distinguish between existing cards with an account-cycle end date between the 1st and the 7th (Week 1), the 8th and the 14th (Week 2), the 15th and the 21st (Week 3), and on or after the 22nd (Week 4) day of the month, respectively. Similarly, for new cards, we distinguish cards based on their account origination date

²We define transaction volumes as the sum of purchase volumes and cash advance volumes. We calculate APR spreads as the observed APR less the the bank prime loan rate in the same period.

using the same cutoff days of the month. These weekly observations enable us to study credit market outcomes at a high frequency over the course of the pandemic. To filter out both monthly seasonality and annual growth rates, we measure credit market outcomes as year-over-year changes normalized to January 2020, the month before the onset of the COVID-19 pandemic.

We augment our Y-14M data with monthly information on credit card mailing offers from the Mintel Comperemedia (2020) dataset. Each month, Mintel surveys about 4,000 consumers, which are paid to, inter alia, collect all direct mail credit card offers and send the originals to Mintel. These data are merged externally with TransUnion credit card data to identify the creditworthiness of borrowers. While changes in the quantity and terms of credit observed in the Y-14M data are equilibrium outcomes that reflect both supply and demand effects, the Mintel Comperemedia data helps us to assess changes in credit supply across borrower types more directly. We obtain data on the total number of credit card mailing offers as well as data on the offered APR spread.

B. The Evolution of the COVID-19 Shock in the United States

B.1. The Spread of the COVID-19 Pandemic

Figure 1 illustrates how, starting in March, the pandemic spread rapidly across the United States. On March 13, the COVID-19 outbreak was officially declared a national emergency (White House, 2020). The number of daily new cases rose to 30,000 in early April, decreased to 20,000 by mid-June, and then increased again to more than 70,000 by mid-July.

[Figure 1 about here]

We obtain daily county-level data on confirmed COVID-19 cases from the Johns Hopkins Coronavirus COVID-19 Global Cases GitHub repository (Dong, Du, and Gardner, 2020). As people arguably do not only react to COVID-19 cases in their own county, but also to cases in the surrounding area, we define the variable $Area\ Cases_{c,t}$ as the number of cumulative confirmed cases in the county itself and all adjacent counties. We measure time-varying local pandemic severity

as the number of newly confirmed area cases over the past four weeks t scaled by the combined population in millions of county c and all adjacent counties:

$$\text{Local Pandemic Severity}_{c,t} = \frac{\text{Area Cases}_{c,t} - \text{Area Cases}_{c,t-4}}{\text{Population of Own and Adjacent Counties}_{2019}} \times 1,000,000 \quad (1)$$

Panel A of Table I provides county-level summary statistics on the spread of the COVID-19 pandemic across 3,131 counties in the United States from March to August 2020. While the average number of new cases per 1 million population was effectively zero in almost all counties at the beginning of March, this number quickly rose to 264 by the beginning of April and to 5,063 by the beginning of August. Table I also illustrates the considerable cross-sectional heterogeneity across counties. For example, while the median county had only 862 new area cases per 1 million population as of May 1 (reflecting the course of the pandemic in April), the most affected county (Rockland, New York) had 18,193 new cases per 1 million population. Figure A1 in the Appendix provides map charts that show how the geographical spread of the pandemic shifted from states in the Northeast and Northwest in April to Southern states in July.

[Table I about here]

B.2. Non-Pharmaceutical Interventions (NPIs)

Shortly after the outbreak in March, many states started to enact various non-pharmaceutical interventions (NPIs), such as shelter-in-place orders, aimed at containing the spread of the virus. Local economies may therefore not only be affected by the outbreak of the pandemic itself, but also by the ensuing policy responses in the form of NPIs.

We obtain daily state- and county-level data on NPIs from the Coronavirus Intervention Dataset made available by Keystone Strategy (Keystone, 2020). These data contain information on the start and end dates of various NPIs for all 50 states and the District of Columbia, and additional county-level NPIs for 650 individual counties.³ We focus on the four most restrictive NPIs, which have received the most attention in the literature or have been found to adversely affect economic activity (Friedson, McNichols, Sabia, and Dave, 2020; Chen, Igan, Pierri, and Presbitero, 2020b): shelter-

³While most NPIs are enacted at the state level, some counties impose stricter measures than their state. Thus, using county-level information on NPI policies improves the accuracy of our analysis (Goolsbee and Syverson, 2020).

in-place orders, nonessential business closures, public venue closures, and gathering size limitations of 10 people or less. As NPIs are often enacted jointly, disentangling their effects on economic outcomes is extremely challenging (Kong and Prinz, 2020). Thus, for our baseline analysis, we remain agnostic about which NPI has the most severe impact on consumer credit markets. We construct an NPI stringency indicator defined as the number of days that one or more of these most restrictive NPIs were in place in that county over the past 30 days:⁴

$$\text{NPI Stringency}_{c,t} = \sum_{\tau=0}^{29} \mathbb{I}_{c,t-\tau}^{SNPG} \quad (2)$$

where $\mathbb{I}_{c,t-\tau}^{SNPG}$ is a dummy variable which takes the value of 1 if either one of the four NPIs had been enacted in county c in period $t-\tau$. The minimum value of $\text{NPI Stringency}_{c,t}$ is zero if no NPI was in place over the past 30 days in county c , and a maximum value of 30 if at least one of these four NPIs was in place for every day of the past 30 days. Figure 1 illustrates the average stringency of the policy response across counties over time. Starting in mid-March, following the national emergency declaration, most counties quickly adopted restrictive NPIs. Average NPI stringency peaked at 29.9 between April 25 and May 2, reflecting the shutdown period in April. In May, many states reopened and gradually removed restrictions; with average NPI stringency decreasing to 18 by August.

Panel B of Table I provides county-level summary statistics on NPI stringency across 3,131 counties in the United States from March to August 2020. The standard deviations illustrate increasing heterogeneity in NPI stringency starting in May, when some states reopened, while others maintained their restrictive shutdown policies. Figure A3 in the Appendix provides map charts that illustrate the geographic heterogeneity of our NPI stringency measure. As the map shows, most counties inherited their NPI measures from state legislation and were therefore subject to a high degree of NPI stringency relative to their number of cases. In Section III.B, we discuss how this feature helps us to disentangle the impact of the pandemic itself from the impact of NPIs.

⁴Figure A2 in the Appendix illustrates the strong co-movement of the four individual NPIs over time. In Section VI.A, we provide robustness checks using alternative measures of NPI stringency.

C. Sample Construction

We collect monthly account-level data on consumer credit cards from the Federal Reserve Board’s FR Y-14M reports for the period from January 2018 to August 2020. We convert the monthly Y-14M data into weekly frequency by utilizing information about the account cycle-end date (for existing cards) and account origination date (for newly issued cards) contained in our dataset, as described in Section II.A. We aggregate the data to the County \times Bank \times FICO Bucket \times Week level.⁵ We distinguish between five different FICO buckets: Below 580, 580–669, 670–739, 740–799, and 800–900.⁶ We focus on general purpose and private label (95 percent of all cards in the data), unsecured (99 percent), consumer credit cards (93 percent), with a revolving feature (97 percent), for which the account is unclosed in the current month (88 percent). Furthermore, we exclude corporate credit cards (1 percent) and charged-off accounts (2 percent). This results in a sample of about 100 million existing cards and 0.8 million new cards per week.⁷ We merge county-level data on COVID-19 cases from the Johns Hopkins Coronavirus COVID-19 Global Cases Database and county-level data on NPIs from the Coronavirus Intervention Dataset. Our final *existing cards data* are at the County \times Bank \times FICO Bucket \times Week level and contain about 25 million observations, covering 3,131 counties, 21 banks, 5 FICO buckets, and 124 weeks, over the period from January 2018 to August 2020. Similarly, our final *new cards data* contain about 14 million observations, covering 3,131 counties, 16 banks, 5 FICO buckets, and 120 weeks, over the period from January 2018 to July 2020.⁸

⁵The Y-14M data are originally available at the five-digit ZIP code level. We map ZIP codes into County FIPS codes using the mapping file provided by SimpleMaps (SimpleMaps, 2020).

⁶The Y-14M data report a commercially available credit bureau score, which for roughly 84.5% of the observations is the FICO score, for 15% the Vantage Score, and for 0.5% another credit score. We use the FICO score when available, but otherwise use other credit scores interchangeably. In unreported results, we further replicate our analysis using three instead of five FICO buckets (below 620, 620–740, 740–900) and obtain very similar results.

⁷The number of newly issued cards drops significantly during the pandemic, while the number of existing cards remains roughly constant. These summary figures are as of January 2020.

⁸Due to delayed reporting of newly issued credit cards in the Y-14M data, our *new cards data* contain one month less of data than our *existing cards data*.

III. Empirical Methodology

A. The Impact of Local Pandemic Severity

We assess the impact of local pandemic severity on credit market outcomes over time by estimating the following regression specification:

$$\Delta Y_{c,b,f,t} = \sum_{\tau} \gamma^{\tau} (D_{\tau} \times \text{Log Pandemic Severity}_{c,t-1}) + \alpha_c + \alpha_{b,t} + \alpha_{f,t} + \alpha_{s,t} + \varepsilon_{c,b,f,t} \quad (3)$$

where the outcome variable $\Delta Y_{c,b,f,t}$ is the week t year-over-year change in credit market outcomes Y for borrowers in county c , in FICO bucket f , borrowing from bank b , normalized relative to January 2020. For our analysis of the use of credit, we focus on the sample of existing cards. Our outcome variables of interest are changes in the logarithm of average outstanding credit card balances and changes in the logarithm of average credit card transactions (purchase volumes and cash advances). For our analysis of credit availability, we focus on the sample of newly issued cards, because it is likely easier for banks to tighten lending standards for new originations rather than by adjusting the contractual terms of existing cards. In this analysis, our outcome variables of interest are the changes in the logarithm of the number of newly issued credit cards, changes in the logarithm of average credit limits, and changes in average annual percentage rate (APR) spreads over the bank prime loan rate.

The variables D_t are a set of weekly calendar time dummies, which take the value of 1 for week t , and zero otherwise. The variable $\text{Pandemic Severity}_{c,t}$ is defined as the number of new area cases over the past four weeks scaled by 1 million population, as described in Section II.B.1. We use the logarithm of our pandemic severity measure to account for the fact that, for example, a cross-sectional ten case difference likely had a different impact in the later stages of the pandemic compared with the earlier stages, when overall case levels were much lower. The coefficients γ^t represent the average changes in credit market outcomes Y associated with a 1 percent cross-sectional increase in local pandemic severity in week t . To allow for a delayed response in consumer behavior, we lag the pandemic severity measure by one period. Additionally, we include county fixed effects α_c , bank-week fixed effects $\alpha_{b,t}$, FICO bucket-week fixed effects $\alpha_{f,t}$, and state-week

fixed effects $\alpha_{s,t}$.⁹ Thus, we compare changes in credit market outcomes for borrowers in the *same county*, in the *same FICO bucket*, borrowing from the *same bank*, and further allow for differential time trends by bank and borrowers’ creditworthiness. Importantly, the inclusion of state-week fixed effects absorbs all time-varying variation at the state level. This specification allows us to effectively control for NPI stringency and other time-varying state-level policies, because most counties inherit their local NPI measures from state-level rules.

Changes in the use and availability of credit might differ substantially across borrower types. The COVID-19 shock had heterogeneous effects on consumer spending across different categories of goods and services (Baker, Farrokhnia, Meyer, Pagel, and Yannelis, 2020d). Discretionary spending categories (for example recreation, travel, and entertainment expenses) declined the most, while non-discretionary expenses (e.g., utilities, food, and childcare) declined only modestly (Coibion, Gorodnichenko, and Weber, 2020a). As the latter category of expenses likely makes up a larger share of overall consumption for low-income households, they have potentially less leeway to reduce spending and therefore to reduce their use of consumer credit. Also changes in credit availability might differ substantially across different borrower types. Historically, during contractions, banks tend to reduce credit to the least creditworthy borrowers (Ramcharan et al., 2016; Benmelech et al., 2017; Di Maggio et al., 2017). To investigate this heterogeneity across borrower types, we estimate the following regression specification:

$$\Delta Y_{c,b,f,t} = \sum_f \sum_\tau \gamma^{\tau,f} (D_f \times D_\tau \times \text{Log Pandemic Severity}_{c,t-1}) + \alpha_c + \alpha_{b,t} + \alpha_{s,t} + \epsilon_{c,b,f,t} \quad (4)$$

where we interact our time-varying regressor of interest $D_\tau \times \text{Log Pandemic Severity}_{c,t-1}$ with a battery of FICO bucket dummy variables D_f and where $f \in \{[0-579], [580-669], [670-739], [740-799], [800-900]\}$. This specification allows us to estimate time-varying coefficients for each of the five FICO buckets.

The number of credit cards varies across the observational units in our sample (County \times Bank \times FICO Bucket \times Week). To ensure that our results are not driven by cells with just a few credit cards, we weight all regressions by the number of credit cards per observational unit as of January 2020, the month immediately before our time period of interest.

⁹Note that the inclusion of county-week fixed effects is not feasible, as these would absorb our regressor of interest.

B. The Impact of Local NPI Stringency

We next assess the impact of local NPI stringency on credit market outcomes over time by estimating the following regression specification:

$$\begin{aligned} \Delta Y_{c,b,f,t} = & + \sum_{\tau} \theta^{\tau} (D_{\tau} \times \text{NPI Stringency}_{c,t-1}) \\ & + \sum_{\tau} \gamma^{\tau} (D_{\tau} \times \text{Log Pandemic Severity}_{c,t-1}) \\ & + \alpha_c + \alpha_{b,t} + \alpha_{f,t} + \epsilon_{c,b,f,t} \end{aligned} \tag{5}$$

where the variable $\text{NPI Stringency}_{c,t}$ is defined as in Equation (2) as the number of days that either one of the following four NPIs had been enacted in county c in period t over the past 30 days: shelter-in-place orders, nonessential business closures, public venue closures, or gathering size limitations of 10 people or less. The coefficients θ^t represent the average changes in credit market outcomes Y in week t associated with an NPI being in place an additional day during the past 30 days. Since NPIs are largely enacted at the state level, including state-week fixed effects, as in the previous specification in Equation (3), now becomes infeasible. All remaining variables are defined as in the previous Section III.A.¹⁰

The main identification concern in this specification is that NPIs are conceivably enacted in response to local pandemic outbreaks, which would make it difficult to distinguish their role for credit market outcomes from the role of the pandemic itself. However, since most counties inherited their NPI measures from state legislation (as shown in Figure A3 in the Appendix), local NPI stringency is largely independent of local pandemic severity. Over our sample period, the cross-sectional correlation coefficient between the two variables ranges from 0.02 (on April 15) to only 0.14 (on July 15). This orthogonality of local pandemic severity and local NPI stringency allows us to disentangle the impact of the pandemic itself from the impact of NPIs at the county level.

¹⁰Figure A5 in Appendix VII shows that the estimated coefficients γ^t are similar for the two regression specifications in Equation (3) and Equation (5).

C. Local Pandemic Severity and Local NPI Stringency: Mean Decomposition

We next assess the relative importance of local pandemic severity and local NPI stringency for credit market outcomes over time. To this end, we decompose the overall mean change in credit market outcomes based on our estimation results from Equation (5), evaluated at the sample means:¹¹

$$\text{Avg}_t(\Delta Y_{c,b,f,t}) = \hat{\alpha}^t \tag{6a}$$

$$+ \hat{\gamma}^t \times \text{Avg}_{t-1}(\text{Log Pandemic Severity}_{c,t-1}) \tag{6b}$$

$$+ \hat{\theta}^t \times \text{Avg}_{t-1}(\text{NPI Stringency}_{c,t-1}), \quad \forall t \tag{6c}$$

where $\Delta Y_{c,b,f,t}$ is the week t average year-over-year change in credit market outcomes Y ; $\hat{\gamma}^t$ and $\hat{\theta}^t$ are the estimated coefficients from our regression model in Equation (5); and the terms $\text{Avg}_{t-1}(\cdot)_{c,t-1}$ are the week $t - 1$ sample averages of our regressors of interest, log local pandemic severity, and local NPI stringency. County-, bank-week-, and FICO bucket-week fixed effects are captured in the term $\hat{\alpha}^t$. This approach allows us to decompose the overall mean change in credit market outcomes into time fixed effects (6a), average time-varying local pandemic severity (6b), and average time-varying local NPI stringency (6c), for every week t in our sample. For a county exhibiting average levels of local pandemic severity and local NPI stringency, this decomposition gauges the estimated contributions of the “national” COVID-19 shock, local NPIs, and local case incidence to the observed time variation in credit market outcomes $\Delta Y_{c,b,f,t}$.

IV. Use of Consumer Credit

A. Descriptive Statistics

Panel A of Figure 2 illustrates the mean year-over-year change in credit card transaction volumes relative to January 2020. There was a sharp decrease in spending across all borrower types starting around mid-March, when the pandemic was declared a national emergency. By the end of April, transaction volumes had decreased by 50 percent, as indicated by the black, dashed line. While the initial drop in spending was of similar magnitude across all borrower types, there was considerable

¹¹This approach is similar in spirit to a predictive margins analysis at the means (Williams, 2012).

heterogeneity in the recovery paths by the end of April. Spending recovered most strongly for borrowers in the lowest FICO class and, by the end of August, transaction volumes were up 14 percent for the least creditworthy borrowers relative to 2019. These results are consistent with other studies, that find a particularly strong spending recovery for low-income households, and are likely driven by the stimulus payments of the CARES Act (Cox et al., 2020; Chetty et al., 2020).

[Figure 2 about here]

Panel B of Figure 2 illustrates the mean year-over-year change in outstanding credit card balances relative to January 2020. Similar to the decrease in transactions, there was a strong reduction in outstanding credit card balances. By the end of April, balances had decreased by 27 percent with no sign of substantial recovery by the end of August. This drop in balances was initially driven by the most creditworthy borrowers. By the beginning of April, borrowers in the highest FICO class had reduced their balances by 24 percent, whereas borrowers in the lowest FICO class initially exhibited a slight increase of 4 percent. By mid-April, balances had dropped by 40 percent for the most creditworthy but only by around 10 percent for the riskiest borrowers. Over subsequent months, however, balances again rose for borrowers in the highest FICO class, while risky borrowers continued to reduce their balances. We further elaborate on this finding in Section IV.E. Overall, this figure illustrates a quick and sharp reduction of consumer credit demand at the onset of the pandemic, which persisted in the following months.

B. Local Pandemic Severity and the Use of Consumer Credit

Panel A of Figure 3 illustrates the estimation results for the impact of local pandemic severity on credit card transactions over time. The blue line plots the regression coefficients γ^t from Equation (3) in Section III.A starting on March 15.¹² Through most of our sample period, from March to the beginning of July, we find a strong impact of the pandemic itself on credit card spending. In the week of April 22, a 1 percent cross-sectional increase in local pandemic severity is associated with a 0.053 percentage point (pp) reduction in credit card transaction volumes. Given the large cross-sectional variation in case numbers, the economic magnitude of the impact in April is substantial.

¹²We do not plot the regression coefficients for the period from February 1 to March 8, as they are based on a very low number of cases and are hence estimated imprecisely, with large standard errors.

It implies a 5.8 pp reduction in spending for a one standard deviation increase in pandemic severity. These findings are consistent with other studies that document a close link between local COVID-19 incidence and a reduction in consumer spending (Chetty et al., 2020; Goolsbee and Syverson, 2020). Our findings, however, show that this relation vanishes over time. The magnitude of the coefficient decreases to -0.030 pp by the end of May and to -0.016 pp by the end of June, before becoming insignificant in July. Panel B of Figure 3 shows an overall similar pattern for the impact on outstanding credit card balances.

[Figure 3 about here]

The declining importance of local pandemic severity for credit card spending is consistent with the notion of “pandemic fatigue.”¹³ Figure A4 in the Appendix illustrates the mobility patterns of individuals in the U.S. during the pandemic. At the beginning of the pandemic, people drastically reduced their visits to stores, restaurants, and transit stations, and instead spent more time at home. These patterns reversed by mid-April and individual mobility reached pre-pandemic levels by July, despite a resurgence of cases. Our results show that such a declining “fear of the virus” is associated with a declining sensitivity of consumer credit use to the pandemic itself. Our findings (including Figure 2) also show that aggregate mobility patterns are closely linked to aggregate credit card spending and can serve as a proxy measure for economic activity (Goolsbee and Syverson, 2020; Maloney and Taskin, 2020).

Panel A of Figure 4 illustrates the estimation results for the impact of local pandemic severity on credit card spending across borrower types. The lines plot the regression coefficients $\gamma^{\tau, f}$ from Equation (4) in Section III.A. During the early stages of the pandemic, local pandemic severity was more strongly associated with a reduction in spending for more creditworthy borrowers. This difference can be interpreted as an initial disruption of consumption patterns. There is evidence that the COVID-19 shock had heterogeneous effects on consumer spending across different categories of goods and services (Baker et al., 2020d). Coibion et al. (2020a) and Cox et al. (2020) find that nonessential spending categories (e.g., retail, restaurants, and entertainment) declined the most,

¹³As reported by the New York Times in October 2020, “after a spring characterized by fear and safety [...] fear has really been replaced with fatigue” (Bosman, Mervosh, and Santora, 2020), and “people were searching for less information about the virus, less concerned about the risks and less willing to follow recommended behaviors” (Santora and Kwai, 2020).

while non-discretionary expenses (e.g., utilities and groceries) declined only modestly. As the former category of expenses makes up a larger share of overall consumption for less creditworthy borrowers, they had less leeway to reduce spending in counties severely affected by the pandemic. Thus, our findings are consistent with evidence that a higher pre-shock spending share for nonessential goods and services was initially associated with a larger reduction in total spending in the early stages of the COVID-19 pandemic (Andersen et al., 2020a). By July, however, this pattern reverses, and local pandemic severity is now more strongly associated with a reduction in spending for riskier borrowers.

[Figure 4 about here]

As shown in Panel B of Figure 4, there is also significant heterogeneity in the relation between local pandemic severity and outstanding credit card balances. While higher local pandemic severity is associated with a large and significant reduction in balances for creditworthy borrowers, this relation is much weaker and mostly insignificant for riskier borrowers. The stronger response for creditworthy borrowers is consistent with the interpretation of COVID-19 as an economic uncertainty shock (Baker et al., 2020b). Di Maggio et al. (2017) find that local economic uncertainty is more strongly associated with a reduction in credit card balances for more creditworthy borrowers. The underlying mechanism is heterogeneity in the pecuniary costs of default. Risky borrowers with limited access to credit have a lower cost of default than creditworthy borrowers (Guiso, Sapienza, and Zingales, 2013), and the latter respond to increased uncertainty by targeting greater financial flexibility to protect their credit reputation and future credit access.

Overall, our results show substantial heterogeneity in the consumer credit response to local pandemic severity across different borrower types, with the overall results being driven by the most creditworthy borrowers.

C. NPI Stringency and the Use of Consumer Credit

The use of consumer credit might not only be affected by the COVID-19 pandemic itself, but also by the policy responses in the form of NPIs. Figure 5 illustrates the estimation results for the impact of local NPI stringency on consumer credit use over time. The blue line plots the

regression coefficients θ^t from Equation (5) in Section III.B, starting on March 22.¹⁴ As shown in Panel A, we find a weak and statistically insignificant relation between local NPI stringency and credit card spending in April and May. During this shutdown period, most counties had enacted most of the NPIs. Hence, there is little variation in local NPI stringency across counties and the coefficients are estimated with fairly large standard errors. By mid-May however, when some states had reopened while others maintained their restrictive policies, we find a negative relation between local NPI stringency and credit card spending. In the week of May 15, a restrictive NPI in place an additional day is associated with a 0.77 pp reduction in credit card transactions. This implies a 2.5 pp reduction in spending for a one standard deviation cross-sectional increase in NPI stringency (3.3 days as of May 22). Similar to the declining impact of pandemic severity shown in Figure 3, we also see a weakening relation between local NPI stringency and consumer credit use over time. Panel B shows a qualitatively similar pattern, albeit somewhat smaller in magnitude, for the relation between local NPI stringency and outstanding credit card balances. Overall, the results indicate that local NPI stringency is associated with a significant reduction in consumer credit demand in May, but the results suggest a muted relationship in the later stages of the pandemic. Our May results are consistent with other studies that document an adverse effect of restrictive NPIs on consumer spending and economic activity (Alexander and Karger, 2020; Coibion et al., 2020a; Friedson et al., 2020).

[Figure 5 about here]

D. Local Pandemic Severity and Local NPI Stringency: Mean Decomposition

We next assess the relative time-varying contribution of local pandemic severity and local NPI stringency to the reduction in consumer credit use for the average county over the course of the pandemic. We decompose the average reduction in credit market outcomes into the model-based margins explained by (time) fixed effects, average time-varying local pandemic severity, and average time-varying local NPI stringency for every week t in our sample, as described in Section III.C. Figure 6 illustrates this decomposition for credit card transactions (Panel A) and outstanding credit card balances (Panel B). In each panel, the dashed black line represents the contribution

¹⁴We do not plot the regression coefficients for the period from February 1 to March 15, as almost no counties had NPIs in place at that time and the coefficients are hence estimated imprecisely, with large standard errors.

of weekly time fixed effects and might therefore be interpreted as the nation-wide baseline effect, which can neither be explained by local pandemic severity nor by local NPI stringency. The red area represents the additional average contribution of local pandemic severity and the green shaded area the additional average contribution of local NPI stringency. The dashed red lines represent the average overall reduction in transactions and balances and is identical to the dashed black lines in Figure 2.

[Figure 6 about here]

Panel A shows that there was large drop in transactions already by the end of March, which was also present in counties with no local COVID-19 incidence and without any local NPIs in place. Over April and May, both local pandemic severity and local NPI stringency started to contribute more strongly to the reduction in credit card spending. Except for the week of May 15, the contribution of local pandemic severity exceeds the contribution of local NPI stringency in the average county. Moreover, local pandemic severity also remains a (albeit small) contributing factor in the later stages of the pandemic from June to August, while the contribution of local NPI stringency vanishes over time. We find an overall similar pattern for the mean decomposition of changes in outstanding balances in Panel B. Hence, we conclude that, for most of our sample period, the pandemic itself was the main driver with regard to changes in consumer credit use. Toward the end of our sample period, however, neither cross-county variation in pandemic severity nor in NPI stringency contributes much to the overall observed drop in transactions and balances. During this period, almost all changes can be attributed to the weekly time fixed effects in our model.

E. Transactions versus Balances for High and Low FICO Borrowers

This section explores the differences in the evolution of credit card transactions and outstanding balances between creditworthy and risky borrowers. Figure 7 plots the mean year-over-year changes in transactions and balances from Panels A and B in Figure 2 for both borrowers in the highest and in the lowest FICO class. For the most creditworthy borrowers, the decrease and the recovery in spending goes hand in hand with the decrease and recovery in outstanding balances. In contrast, for the riskiest borrowers, the initial reduction in transactions is much steeper than the initial reduction

in balances (see also Adams and Bord (2020) for a discussion). In April, credit card transactions began to recover strongly for risky borrowers, while their balances continued to decrease. Over this period, these borrowers simultaneously increased their spending and paid off their balances, thus exhibiting behavior consistent with a positive income shock. Ganong, Noel, and Vavra (2020) provide evidence that the expansion of unemployment insurance under the CARES Act entailed a median wage replacement rate of 145%. Thus, especially unemployed workers with low earnings before the pandemic might have experienced an increase in income between April and August. Armantier et al. (2020) report that households used about 30 percent of the stimulus payments to increase consumption and split the remainder between paying down debt and other forms of savings. Moreover, Baker et al. (2020c) and Coibion, Gorodnichenko, and Weber (2020b) find that especially poorer households used the stimulus payments to pay off debt.

[Figure 7 about here]

V. Availability of Consumer Credit

A. Descriptive Statistics

We now turn to the impact of the COVID-19 shock on credit availability in the U.S. consumer credit card market. We investigate both the extensive margin (the number of new credit cards originated) and the intensive margin (APR spreads and credit limits of newly issued cards). Panel A of Figure 8 illustrates the year-over-year change in the number of credit cards originated relative to January 2020. We document a large 60 percent overall drop in the number of newly issued cards by the end of April, as indicated by the dashed black line. For the riskiest borrowers, the credit card market almost froze, with new originations dropping by almost 90 percent and no sign of recovery by the end of July. This reduction in credit card originations could, in principle, reflect both demand and supply effects. While borrowers reduced their demand for consumer credit (as documented in the previous section), banks might also have tightened lending standards in the anticipation of rising default rates. Even though we cannot quantitatively disentangle how supply and demand factors affected card originations, our additional results help us to assess their qualitative, relative importance across borrower types.¹⁵

¹⁵In Section V.C, we further study credit card mailing offers to assess changes in credit supply more directly.

[Figure 8 about here]

Panel B of Figure 8 illustrates the year-over-year change in the average APR spreads of newly issued credit cards. In April, APR spreads increased substantially for riskier borrowers. By June, the average credit card for borrowers in the lowest FICO class had a 4 pp higher APR spread compared with the previous year, but there was no increase in APR spreads for the most creditworthy borrowers.

These findings suggest heterogeneous supply and demand effects across borrower types, similar to the mechanism in Agarwal et al. (2018). While for the most part of the pandemic, riskier borrowers had a higher marginal propensity to borrow (MPB), as indicated by the lower decrease in balances in Figure 2, banks had a lower marginal propensity to lend (MPL) to these borrowers, as indicated by the increase in APR spreads in Figure 8. Conversely, while banks had a relatively higher MPL to more creditworthy borrowers, as suggested by the muted impact on APR spreads, these borrowers had a lower MPB, as indicated by the stronger decrease in balances in Figure 2. Thus, the drastic reduction in card originations to riskier borrowers appears to be more strongly affected by supply effects than the decrease in originations to creditworthy borrowers. In line with this explanation, the recovery in credit card originations to creditworthy borrowers by mid-April in Figure 8 follows a similar path to the recovery of their outstanding balances in Figure 2, suggesting a close link between card originations and consumer demand. Overall, these findings are consistent with a flight-to-safety response of banks in consumer credit lending during the COVID-19 pandemic.

Finally, Panel C of Figure 8 illustrates the year-over-year change in the average credit limits of newly issued credit cards. Consistent with an overall tightening of lending standards, we see a 20 percent year-over-year decrease in average credit limits, as indicated by the dashed black line. The pattern across borrower types is more ambiguous than for average APR spreads. At the end of the sample period, we see the smallest decrease for the riskiest borrowers, followed by the most creditworthy borrowers.

B. Local Pandemic Severity, Local NPI Stringency, and the Availability of Consumer Credit

We next investigate whether there was heterogeneity in the availability of credit across counties associated with either local pandemic severity or local NPI stringency. Figure 9 illustrates the

estimation results for the impact of local pandemic severity on credit card originations (Panel A), average APR spreads (Panel B), and average credit limits (Panel C) over time. In each panel, the blue line plots the regression coefficients γ^t from Equation (3) in Section III.A. Panel A shows that, especially at the beginning of the pandemic, higher local pandemic severity was associated with a reduction in the number of credit card originations. Our further results indicate that this likely reflects a reduction in credit demand, rather than geographic heterogeneity in the reduction of banks' credit supply. In line with the demand interpretation, Panel B and Panel C show little evidence for an impact of local pandemic severity on credit availability at the intensive margin. For most periods, there is no significant relation between local pandemic severity and the APR spreads and credit limits of newly issued cards. Similarly, Figure 10 shows that there was also no impact of local NPI stringency on the intensive margin of credit supply but a negative impact on the number of newly issued cards. Since credit card lending decisions are largely automated (Gross and Souleles, 2002), we would expect local pandemic severity and local NPI stringency to only have an impact on supply if banks incorporated this information in their algorithmic scoring. Our results provide little evidence that this has been the case.

[Figure 9 about here]

[Figure 10 about here]

C. Evidence from Credit Card Marketing

While the decrease in credit card originations, alongside a reduction in credit limits and an increase in APR spreads, observed in the Y-14M data suggest a reduction in credit supply, these data are still equilibrium outcomes. To assess changes in credit supply more directly, we use the Mintel Comperemedia (2020) dataset on credit card mailing offers. Figure 11 illustrates the change in the number of credit card mailing offers (Panel A) and the offered APR spread (Panel B) relative to January 2020 across different borrower types.¹⁶ Panel A shows that credit card mailing offers decreased strongly by up to 80 percent from January to June. Unlike for credit card originations, this decrease is of similar magnitude across all borrower types, suggesting that

¹⁶While the Y-14M data report the FICO score for the large majority of accounts, the Mintel Comperemedia (2020) dataset uses the Vantage Score. To ensure comparability of our results, we still use the same cutoff values for different borrower classes as in our Y-14M analysis.

banks heavily scaled back on credit card marketing across the board. Panel B shows the change in offered APR spreads relative to January 2020. Similar to our findings in Section V.A, we find a particularly strong increase in offered APR spreads to less creditworthy borrowers in the second lowest Vantage Score class and even a reduction for borrowers in the second highest Vantage Score class. For the borrowers in the lowest and highest class, the effects are qualitatively similar but more modest in magnitude. Overall, our analysis of credit card mailing offers is consistent with an overall reduction in credit supply, especially to less creditworthy borrowers.

[Figure 11 about here]

VI. Robustness Checks

A. Alternative NPI Stringency Measure

In our baseline analysis, we measure local NPI stringency as the number of days that *either one* of the most four restrictive NPIs had been in place in a county over the past 30 days: shelter-in-place orders, nonessential business closures, public venue closures, or gathering size limitations of 10 people or less. This measure implicitly assumes, that after having one of these NPIs in place, enacting an additional NPI has no impact on economic activity. In this section, we calculate an alternative measure of local NPI stringency, defined as the total number of days that *each of* these most restrictive NPIs have been enacted over the past 30 days:

$$\text{NPI Stringency}_{c,t} = \sum_{j=1}^5 \sum_{\tau=0}^{29} \text{NPI}_{c,t-\tau}^j \quad (7)$$

where $\text{NPI}_{c,t-\tau}^j$ is a dummy variable which takes on the value of 1 if one of the four NPIs j had been enacted in county c in period $t - \tau$. Using this alternative measure, we re-estimate the regression in Equation (5) for the impact of local NPI stringency on the use of consumer credit. Figure 12 presents the results of this robustness check. As in our baseline analysis, we find a negative impact of local NPI stringency on both credit card transactions (Panel A) and outstanding balances (Panel B), which becomes weaker over time. We also re-calculate the mean decomposition from Section III.C and find a similar overall pattern as in Figure 6. For the most part, local pandemic severity

was the main driver with regard to changes in the use of consumer credit and this finding is robust to how we measure NPI stringency.

[Figure 12 about here]

B. *Disentangling Individual NPI Policies*

As shown in Figure A2 in the Appendix, individual NPIs are often enacted jointly and strongly co-move over time, making it difficult to estimate the impact of each individual NPI due to strong collinearity. In this section, we nonetheless attempt to disentangle their impacts on credit market outcomes. Following Kong and Prinz (2020), we include each NPI separately and estimate the following regression equation:

$$\begin{aligned}
\Delta Y_{cbft} = & + \sum_{\tau} \theta^{\tau, SIP} (D_{\tau} \times \text{Shelter-in-Place}_{c,t-1}) \\
& + \sum_{\tau} \theta^{\tau, NEBC} (D_{\tau} \times \text{Nonessential Business Closure}_{c,t-1}) \\
& + \sum_{\tau} \theta^{\tau, PVC} (D_{\tau} \times \text{Public Venue Closure}_{c,t-1}) \\
& + \sum_{\tau} \theta^{\tau, GSL} (D_{\tau} \times \text{Gathering Size Limitation}_{c,t-1}) \\
& + \sum_{\tau} \gamma^{\tau} (D_{\tau} \times \text{Log Pandemic Severity}_{c,t-1}) \\
& + \alpha_c + \alpha_{bt} + \alpha_{ft} + \epsilon_{cbft}
\end{aligned} \tag{8}$$

where each of the four NPI policy variables is defined as the number of days that the respective NPI had been enacted over the past 30 days. Figure 13 presents the results of this robustness check. We find qualitatively similar patterns for each of the individual NPIs, with shelter-in-place orders having the strongest impact in terms of magnitude.

[Figure 13 about here]

VII. Conclusion

Geographic heterogeneity in the COVID-19 shock provides an opportunity to trace out its impact on the use and availability of consumer credit over time. Using comprehensive regulatory data on individual credit card accounts from the Federal Reserve’s Y-14M reports, we estimate the effect of the local severity of the outbreak and the effect of local policy responses in the form of NPIs. Exploiting the granularity of our dataset, we construct data of weekly frequency, which allows us to compare the credit market outcomes of borrowers in the *same county*, in the *same FICO bucket*, borrowing from the *same bank* at a weekly frequency over the course of the pandemic.

We find that local pandemic severity has a strong negative impact on consumer credit use over almost the entire course of the pandemic, even after controlling for weekly changes in state-level policies. This effect is largest in April and becomes smaller over time, consistent with the notion of “pandemic fatigue.” We also find a negative impact of local NPI stringency on the use of credit, which is, however, mostly smaller in magnitude. Hence, because these effects are robust to a rich set of fixed effects and alternative measurements of NPI stringency, we conclude that, for most of our sample period, the pandemic itself was the main driver with regard to changes in consumer credit use. Thus, we provide evidence that the fear of the virus yields strong negative effects on consumer credit demand, even in the absence of government-mandated restrictions. Moreover, we find a large decrease in the origination of new credit cards, especially to the riskiest borrowers. Consistent with a tightening of credit supply and a flight-to-safety response of banks, we document an increase in APR spreads of newly issued cards to less creditworthy borrowers, and an overall reduction in credit limits.

REFERENCES

- Adams, Robert, and Vitaly Bord, 2020, The effects of the COVID-19 shutdown on the consumer credit card market: Revolvers versus transactors, *FEDS Notes. Washington: Board of Governors of the Federal Reserve System* October 21, 2020.
- Agarwal, Sumit, Souphala Chomsisengphet, Neale Mahoney, and Johannes Stroebe, 2018, Do banks pass through credit expansions to consumers who want to borrow?, *Quarterly Journal of Economics* 133, 129–190.
- Alexander, Diane, and Ezra Karger, 2020, Do stay-at-home orders cause people to stay at home? Effects of stay-at-home orders on consumer behavior, *Federal Reserve Bank of Chicago Working Paper* 2020-12.
- Andersen, Asger Lau, Emil Toft Hansen, Niels Johannesen, and Adam Sheridan, 2020a, Consumer responses to the COVID-19 crisis: Evidence from bank account transaction data, *Covid Economics* 7, 88–114.
- Andersen, Asger Lau, Emil Toft Hansen, Niels Johannesen, and Adam Sheridan, 2020b, Pandemic, shutdown and consumer spending: Lessons from scandinavian policy responses to COVID-19, *Mimeo* .
- Armantier, Olivier, Leo Goldman, Gizem Ko***sar, Jessica Lu, Rachel Pomerantz, and Wilbert van der Klaauw, 2020, How have households used their stimulus payments and how would they spend the next?, *Liberty Street Economics* October 13, 2020.
- Baek, ChaeWon, Peter B. McCrory, Todd Messer, and Preston Mui, 2020, Unemployment effects of stay-at-home orders: Evidence from high frequency claims data, *IRLE Working Paper* 101-20.
- Baker, Scott R., Nicholas Bloom, Steven J. Davis, Kyle J. Kost, Marco C. Sammon, and Tasaneeeya Viratyosin, 2020a, The unprecedented stock market impact of COVID-19, *Review of Asset Pricing Studies* forthcoming.
- Baker, Scott R., Nicholas Bloom, Steven J. Davis, and Stephen J. Terry, 2020b, COVID-induced economic uncertainty, *NBER Working Paper Series* 26983.

- Baker, Scott R., R. A. Farrokhnia, Steffen Meyer, Michaela Pagel, and Constantine Yannelis, 2020c, Income, liquidity, and the consumption response to the 2020 economic stimulus payments, *NBER Working Paper 27097*.
- Baker, Scott R., R.A. Farrokhnia, Steffen Meyer, Michaela Pagel, and Constantine Yannelis, 2020d, How does household spending respond to an epidemic? Consumption during the 2020 COVID-19 pandemic, *Review of Asset Pricing Studies* forthcoming.
- Bartik, Alexander W., Marianne Bertrand, Feng Lin, Jesse Rothstein, and Matt Unrath, 2020, Measuring the labor market at the onset of the COVID-19 crisis, *NBER Working Paper 27613*.
- BEA, U.S. Bureau of Economic Analysis, 2020, Gross domestic product, 2nd quarter 2020 (advance estimate) and annual update, *News release, July 30, 2020* .
- Benmelech, Efraim, Ralf R. Meisenzahl, and Rodney Ramcharan, 2017, The real effects of liquidity during the financial crisis: Evidence from automobiles, *Quarterly Journal of Economics* 132, 317–365.
- Bernanke, Ben, Mark Gertler, and Simon Gilchrist, 1996, The financial accelerator and the flight to quality, *Review of Economics and Statistics* 78, 1–15.
- Binder, Carola, 2020, Coronavirus fears and macroeconomic expectations, *Review of Economics and Statistics* Forthcoming.
- Bloom, Nicholas, 2009, The impact of uncertainty shocks, *Econometrica* 77, 623–685.
- Bosman, Julie, Sarah Mervosh, and Marc Santora, 2020, As the coronavirus surges, a new culprit emerges: Pandemic fatigue, *New York Times* October 17, 2020.
- Bouniey, David, Youssouf Camaraz, and John W. Galbraith, 2020, Consumers’ mobility, expenditure and online-offline substitution response to COVID-19: Evidence from French transaction data, *Mimeo* .
- Braxton, J. Carter, Kyle F. Herkenhoff, and Gordon M. Phillips, 2020, Can the unemployed borrow? Implications for public insurance, *NBER Working Paper 27026*.

- Cajner, Tomaz, Leland D. Crane, Ryan A. Decker, John Grigsby, Adrian Hamins-Puertolas, Erik Hurst, Christopher Kurz, and Ahu Yildirmaz, 2020a, The U.S. labor market during the beginning of the pandemic recession, *NBER Working Paper Series* 27159.
- Cajner, Tomaz, Leland D. Crane, Ryan A. Decker, Adrian Hamins-Puertolas, and Christopher Kurz, 2020b, Tracking labor market developments during the COVID-19 pandemic: A preliminary assessment, *Finance and Economics Discussion Series* 2020-030.
- Carvalho, Vasco M., Juan Ramón García, Stephen Hansen, Álvaro Ortiz, Tomasa Rodrigo, Sevi Rodríguez Mora, and Pep Ruiz, 2020, Tracking the COVID-19 crisis with high-resolution transaction data, *CEPR Discussion Paper Series* DP14642.
- CFPB, 2019, The consumer credit card market, *Report* .
- Chen, Haiqiang, Wenlan Qian, and Qiang Wen, 2020a, The impact of the COVID-19 pandemic on consumption: Learning from high frequency transaction data, *Mimeo* .
- Chen, Sophia, Deniz Igan, Nicola Pierri, and Andrea F. Presbitero, 2020b, Tracking the economic impact of COVID-19 and mitigation policies in Europe and the United States, *IMF Special Series on COVID-19* .
- Chetty, Raj, John N. Friedman, Nathaniel Hendren, Michael Stepner, and The Opportunity Insights Team, 2020, How did COVID-19 and stabilization policies affect spending and employment? A new real-time economic tracker based on private sector data, *NBER Working Paper* 27431.
- Chronopoulos, Dimitris K., Marcel Lukas, and John O.S. Wilson, 2020, Consumer spending responses to the COVID-19 pandemic: An assessment of Great Britain, *Mimeo* .
- Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber, 2020a, The cost of the Covid-19 crisis: Lockdowns, macroeconomic expectations, and consumer spending, *NBER Working Paper* 27141?
- Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber, 2020b, How did U.S. consumers use their stimulus payments?, *NBER Working Paper* 27693.
- Coibion, Olivier, Yuriy Gorodnichenko, and Michael Weber, 2020c, Labor markets during the COVID-19 crisis: A preliminary view, *NBER Working Paper* 27017.

- Cox, Natalie, Peter Ganong, Pascal Noel, Joseph Vavra, Arlene Wong, Diana Farrell, and Fiona Greig, 2020, Initial impacts of the pandemic on consumer behavior: Evidence from linked income, spending, and savings data, *Becker Friedman Institute for Economics Working Paper* 2020-82.
- Di Maggio, Marco, Amir Kermani, Rodney Ramcharan, and Edison Yu, 2017, Household credit and local economic uncertainty, *Federal Reserve Bank of Philadelphia Working Paper* 17-21.
- Dong, Ensheng, Hongru Du, and Lauren Gardner, 2020, An interactive web-based dashboard to track COVID-19 in real time, *The Lancet: Infectious Diseases* 20, 533–534, <https://github.com/CSSEGISandData/COVID-19>, Accessed April 16, 2020.
- Dunn, Abe, Kyle Hood, and Alexander Driessen, 2020, Measuring the effects of the COVID-19 pandemic on consumer spending using card transaction data, *BEA Working Paper Series* WP2020-5.
- Forsythe, Eliza, Lisa B. Kahn, Fabian Lange, and David Wiczer, 2020, Labor demand in the time of COVID-19: Evidence from vacancy postings and UI claims, *Journal of Public Economics* 189.
- Friedson, Andrew I., Drew McNichols, Joseph J. Sabia, and Dhaval Dave, 2020, Did California’s shelter-in-place order work? Early coronavirus-related public health effects, *NBER Working Paper* 26992.
- Ganong, Peter, and Pascal Noel, 2019, Consumer spending during unemployment: Positive and normative implications, *American Economic Review* 109, 2383–2424.
- Ganong, Peter, Pascal J. Noel, and Joseph S. Vavra, 2020, US unemployment insurance replacement rates during the pandemic, *NBER Working Paper* 27216.
- Google LLC, 2020, Google COVID-19 community mobility reports <https://www.google.com/covid19/mobility/> Accessed: June 11, 2020.
- Goolsbee, Austan, and Chad Syverson, 2020, Fear, lockdown, and diversion: Comparing drivers of pandemic economic decline 2020, *Becker Friedman Institute Working Paper* 2020-80.

- Gross, David B., and Nicholas S. Souleles, 2002, Do liquidity constraints and interest rates matter for consumer behavior? Evidence from credit card data, *Quarterly Journal of Economics* Volume 117, 149–185.
- Guiso, Luigi, Paola Sapienza, and Luigi Zingales, 2013, The determinants of attitudes toward strategic default on mortgages, *Journal of Finance* 68, 1473–1515.
- Hacioglu, Sinem, Diego Känzig, and Paolo Surico, 2020, Consumption in the time of Covid-19: Evidence from UK transaction data, *CEPR Discussion Paper Series DP14733*.
- Hanspal, Tobin, Annika Weber, and Johannes Wohlfart, 2020, Exposure to the COVID-19 stock market crash and its effect on household expectations, *Covid Economics* 23, 188–262.
- Herkenhoff, Kyle F., 2019, The impact of consumer credit access on unemployment, *Review of Economic Studies* 86, 2605–2642.
- Hundtofte, Sean, Arna Olafsson, and Michaela Pagel, 2019, Credit smoothing, *NBER Working Paper* 26354.
- Keystone, 2020, <https://www.keystonestrategy.com/coronavirus-covid19-intervention-dataset-model/> Accessed May 7, 2020.
- Kong, Edward, and Daniel Prinz, 2020, Disentangling policy effects using proxy data: Which shutdown policies affected unemployment during the covid-19 pandemic?, *Journal of Public Economics* 189, 104257.
- Lewis, Daniel, Karel Mertens, and James H. Stock, 2020, U.S. economic activity during the early weeks of the SARS-Cov-2 outbreak, *NBER Working Paper* 26954.
- Ludvigson, Sydney C., Sai Ma, and Serena Ng, 2020, Covid 19 and the macroeconomic effects of costly disasters, *NBER Working Paper* 26987.
- Maloney, William F., and Temel Taskin, 2020, Determinants of social distancing and economic activity during COVID-19: A global view, *World Bank Policy Research Working Paper* 9242.
- Mintel Comperemedia, 2020, Mintel credit cards and mortgage & loan databases Accessed: D 11, 2020.

- Olafsson, Arna, and Michaela Pagel, 2018, The liquid hand-to-mouth: Evidence from personal finance management software, *Review of Financial Studies* 31, 4398–4446.
- Ramcharan, Rodney, Stéphane Verani, and Skander J. Van den Heuvel, 2016, From Wall Street to Main Street: The impact of the financial crisis on consumer credit supply, *Journal of Finance* 71, 1323–1356.
- Santora, Marc, and Isabella Kwai, 2020, As virus surges in europe, resistance to new restrictions also grows, *New York Times* October 9, 2020.
- SimpleMaps, 2020, <https://simplemaps.com/data/us-zips> Accessed February 26, 2020.
- Sullivan, James X., 2008, Borrowing during unemployment: Unsecured debt as a safety net, *Journal of Human Resources* 43, 383–412.
- White House, 2020, Proclamation on declaring a national emergency concerning the novel coronavirus disease (COVID-19) outbreak, *Federal Register Presidential Proclamation* 85 FR 15337, 15337–15338, <https://www.whitehouse.gov/presidential-actions/proclamation-declaring-national-emergency-concerning-novel-coronavirus-disease-covid-19-outbreak/>, Accessed on June 21.
- Williams, Richard, 2012, Using the margins command to estimate and interpret adjusted predictions and marginal effects, *Stata Journal* 12, 308–331.

Table I
Pandemic Severity and NPI Stringency

This table reports summary statistics related to the COVID-19 pandemic across 3,131 counties in the United States over time. Panel A reports the number of new area cases over the past four weeks per 1 million population. Area cases are defined as the number of confirmed cases in the county itself and all adjacent counties. These numbers are based on data from the Johns Hopkins Coronavirus COVID-19 Global Cases GitHub repository (Dong, Du, and Gardner, 2020). Panel B reports summary statistics for the stringency of non-pharmaceutical interventions (NPIs) as defined in Equation (2) in Section II.B.2. These numbers are based on daily county-level NPI data from Keystone Strategy (Keystone, 2020).

| Date | Mean | Median | Min | 10% | 90% | Max | SD |
|---|------|--------|-----|------|--------|--------|------|
| <i>Panel A. New Area Cases over the Past Four Weeks per 1 Million Population.</i> | | | | | | | |
| March 1 | 0 | 0 | 0 | 0 | 0 | 3 | 0 |
| April 1 | 264 | 142 | 0 | 36 | 494 | 6520 | 514 |
| May 1 | 1563 | 862 | 0 | 204 | 3651 | 18 193 | 2224 |
| June 1 | 1818 | 1151 | 0 | 170 | 4109 | 24 811 | 2385 |
| July 1 | 2147 | 1532 | 0 | 408 | 4741 | 13 975 | 1882 |
| August 1 | 5063 | 3601 | 0 | 1204 | 10 948 | 27 864 | 4077 |
| <i>Panel B. Non-Pharmaceutical Intervention Stringency Indicator.</i> | | | | | | | |
| March 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| April 1 | 13 | 14 | 2 | 9 | 17 | 25 | 4 |
| May 1 | 30 | 30 | 25 | 30 | 30 | 30 | 1 |
| June 1 | 26 | 30 | 0 | 9 | 30 | 30 | 8 |
| July 1 | 20 | 30 | 0 | 0 | 30 | 30 | 14 |
| August 1 | 18 | 30 | 0 | 0 | 30 | 30 | 15 |

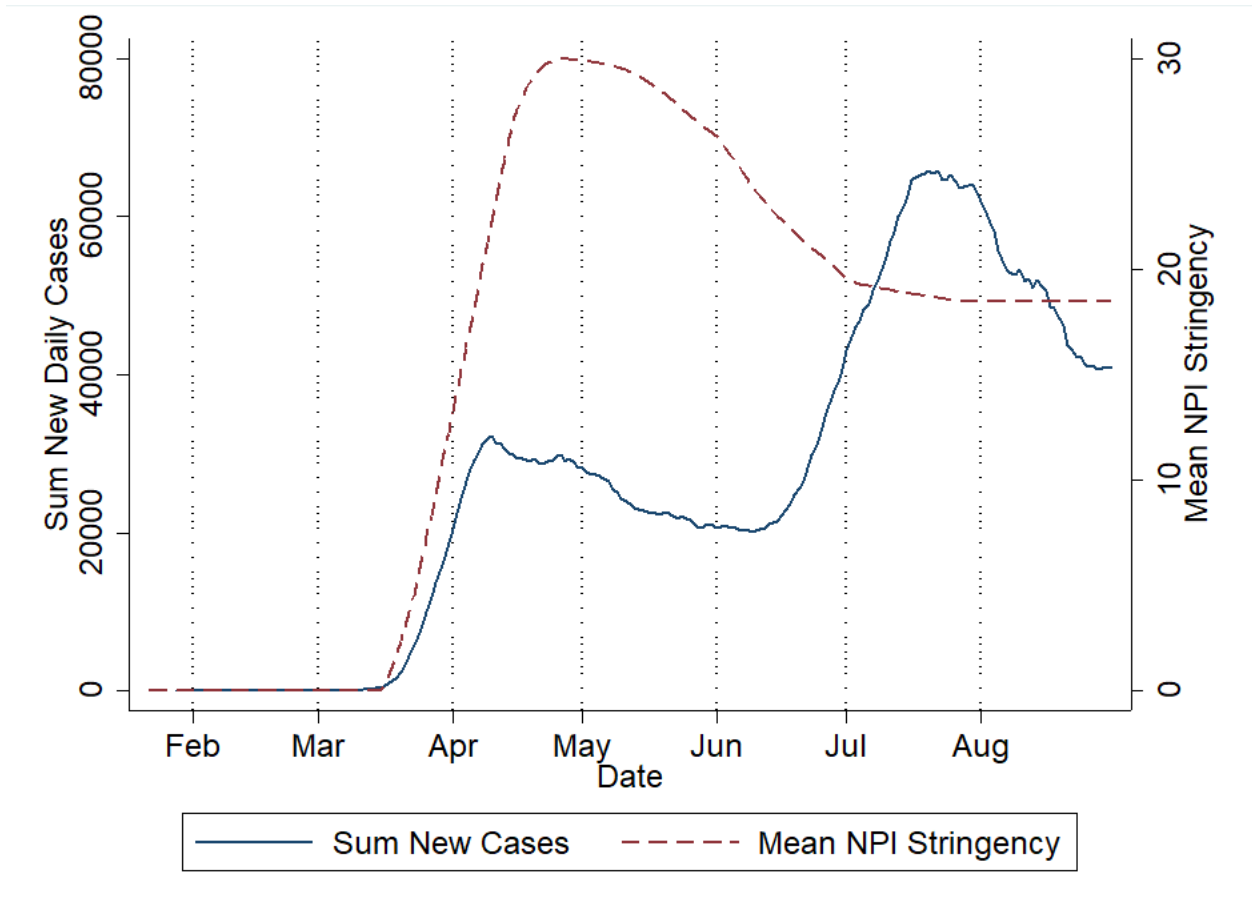
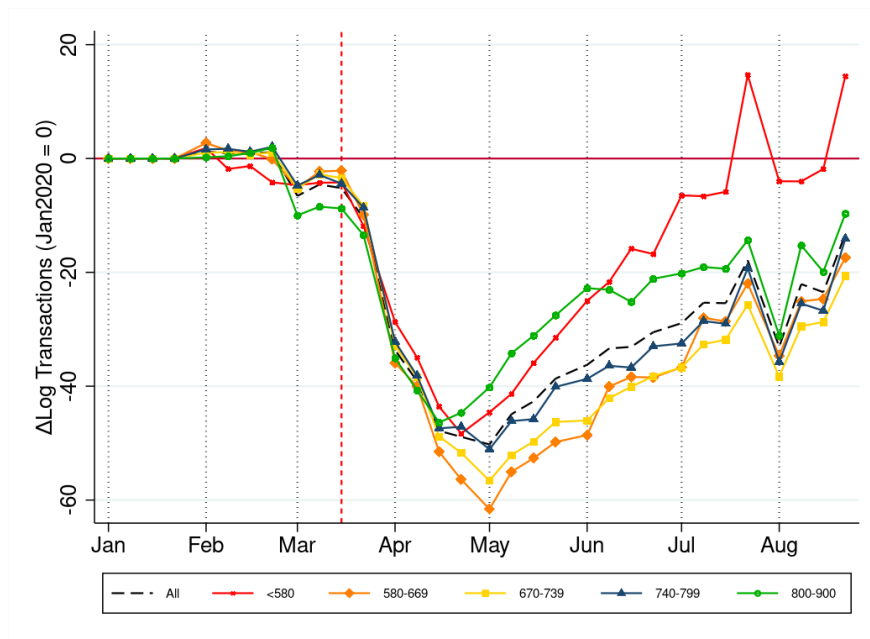


Figure 1. Pandemic Severity and NPI Stringency over Time. This figure illustrates the evolution of new COVID-19 cases and of the policy response in the form of non-pharmaceutical interventions (NPIs) over time. The solid blue line plots the seven-day moving average of daily new cases in the United States, and the dashed red line plots the average NPI stringency indicator as defined in Section II.B.2.

(A) Mean Change in Credit Card Transactions by FICO Classes over Time



(B) Mean Change in Credit Card Balances by FICO Classes over Time

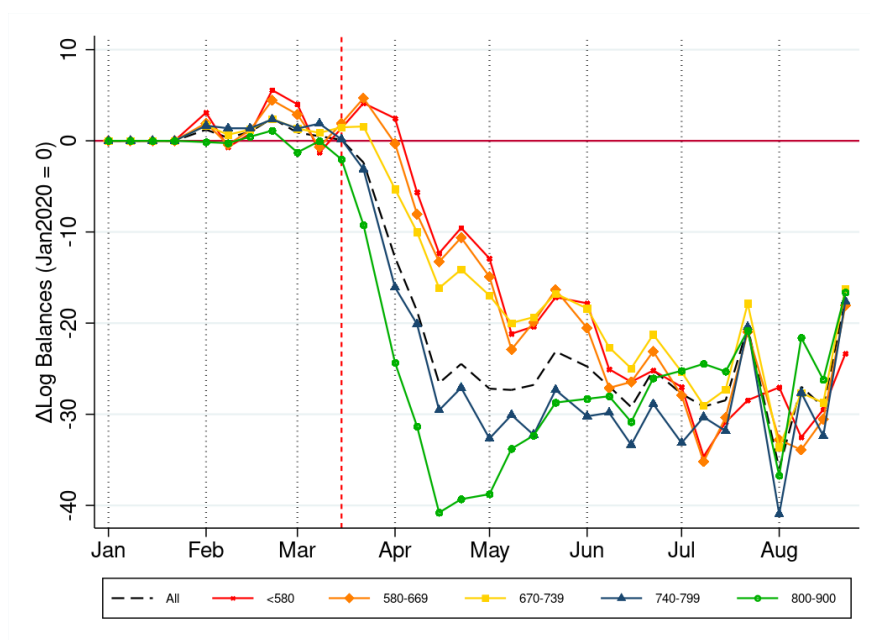
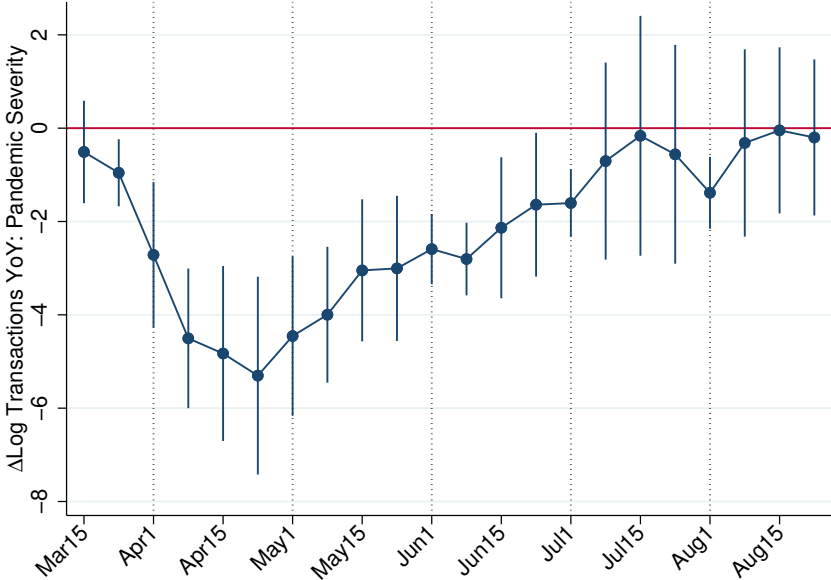


Figure 2. Changes in the Use of Credit by FICO Classes over Time. This figure illustrates the mean year-over-year change in credit card transactions (Panel A) and outstanding credit card balances (Panel B) relative to January 2020 across five different FICO classes: Less than 580 (red), 580–669 (orange), 670–739 (yellow), 740–799 (blue), 800–900 (green), and across all borrowers (black, dashed). The red, dashed, vertical line marks March 15, the date in our dataset closest to the national emergency declaration on March 13, 2020. All observations are weighted by the number of credit cards as of January 2020.

(A) The Impact of Local Pandemic Severity on Credit Card Transactions over Time



(B) The Impact of Local Pandemic Severity on Credit Card Balances over Time

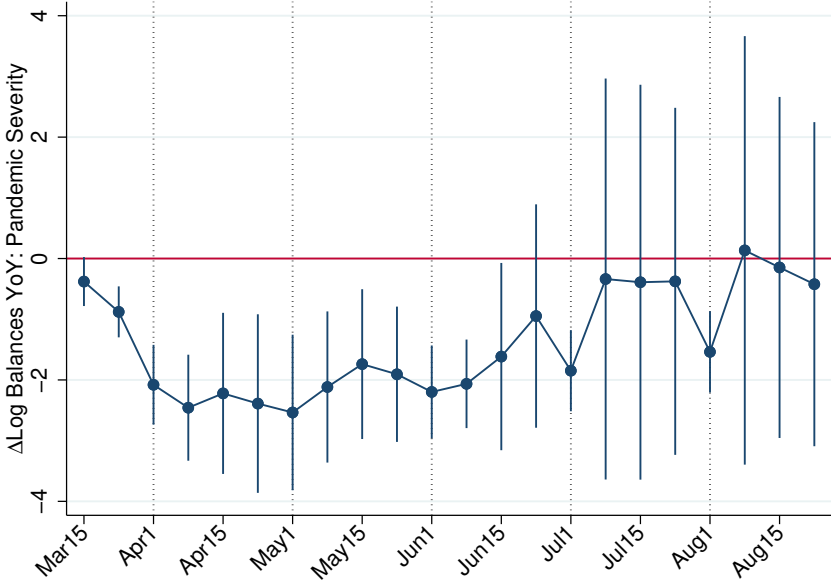
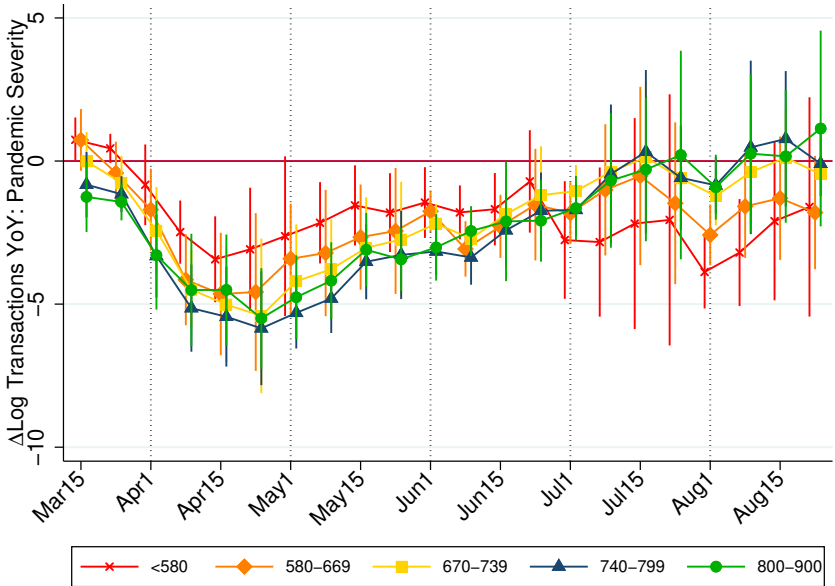


Figure 3. Local Pandemic Severity and the Use of Consumer Credit over Time. This figure illustrates the estimation results for the effect of local pandemic severity on credit card transactions (Panel A) and outstanding credit card balances (Panel B) over time. The blue line plots the regression coefficients γ^t from Equation (3) in Section III.A along with the 95 percent confidence intervals. All regressions are weighted by the number of credit cards as of January 2020 per observational unit.

(A) Local Pandemic Severity and Changes in Credit Card Transactions by FICO Class over Time



(B) Local Pandemic Severity and Changes in Credit Card Balances by FICO Class over Time

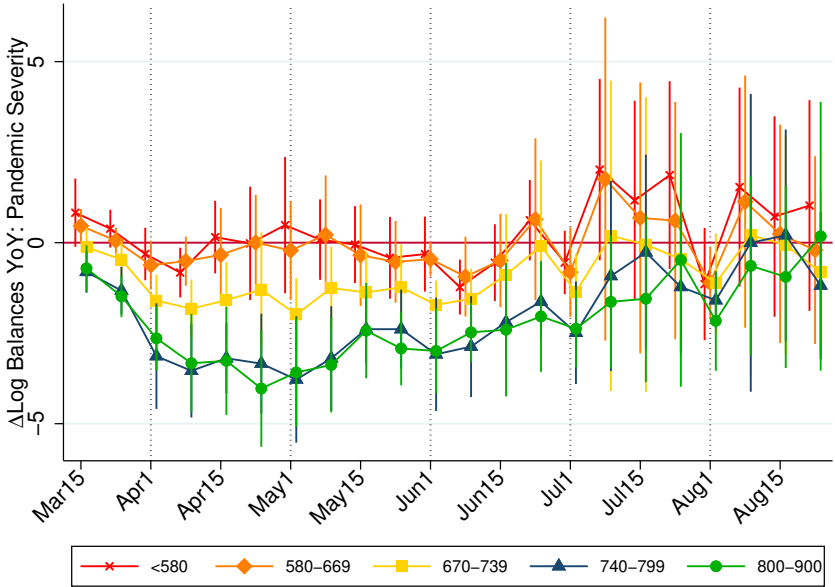
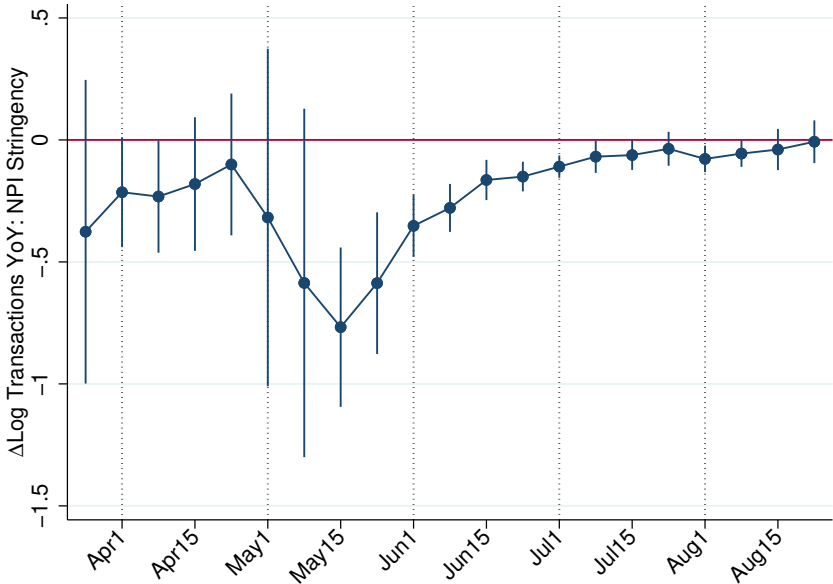


Figure 4. Local Pandemic Severity and the Use of Consumer Credit by FICO Class over Time. This figure illustrates the estimation results for the effect of local pandemic severity on credit card transactions (Panel A) and balances (Panel B) over time. The lines plot the regression coefficients $\gamma^{\tau,f}$ from Equation (4) in Section III.A for five different FICO classes: Less than 580 (red), 580-669 (orange), 670-739 (yellow), 740-799 (blue), 800-900 (green), with the 95 percent confidence intervals. All regressions are weighted by the number of credit cards as of January 2020 per observational unit.

(A) The Impact of Local NPI Stringency on Credit Card Transactions over Time



(B) The Impact of Local NPI Stringency on Credit Card Balances over Time

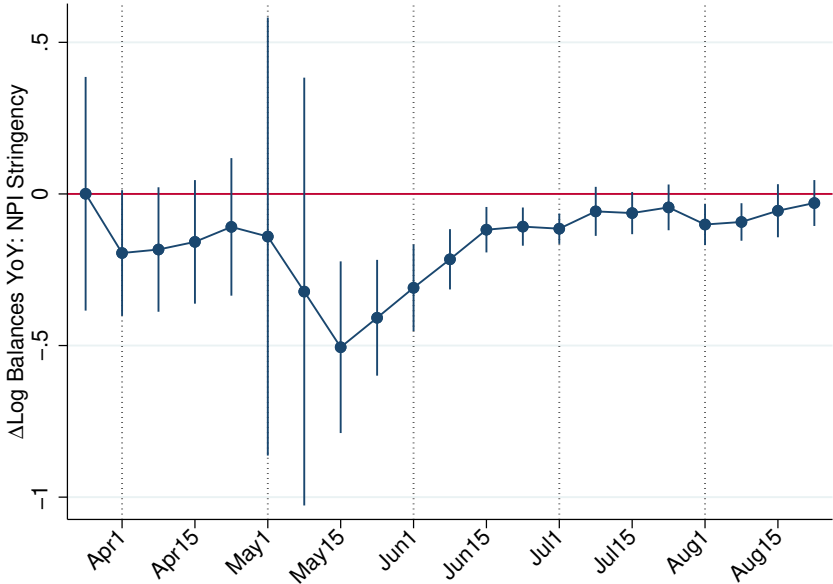
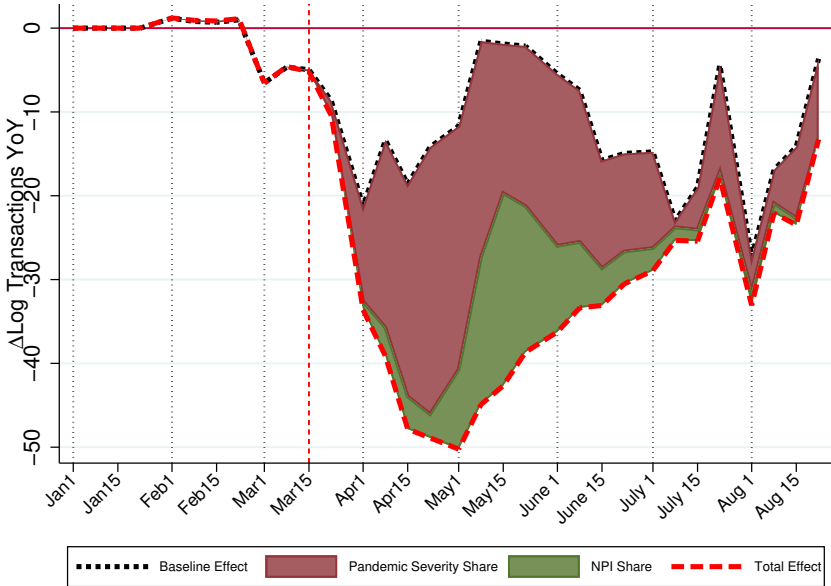


Figure 5. Local NPI Stringency and the Use of Consumer Credit. This figure illustrates the estimation results for the effect of non-pharmaceutical interventions (NPIs) on credit card transactions (Panel A) and outstanding credit card balances (Panel B) over time. The blue line plots the regression coefficients θ^t from Equation (5) in Section III.B along with the 95 percent confidence intervals. All regressions are weighted by the number of credit cards as of January 2020 per observational unit.

(A) Changes in Transactions: Local Pandemic Severity and Local NPI Decomposition



(B) Changes in Balances: Local Pandemic Severity and Local NPI Decomposition

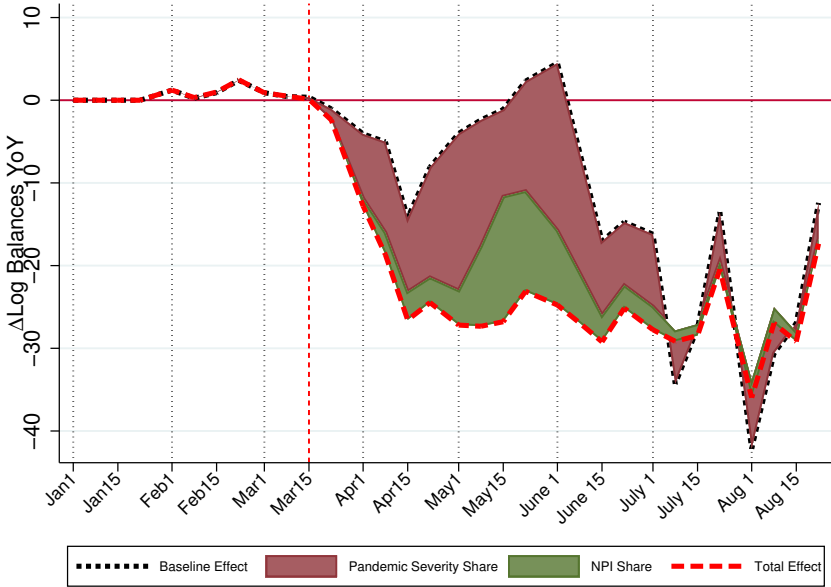


Figure 6. Local Pandemic Severity and Local NPI Stringency: Mean Decomposition. This figure illustrates the decomposition of the total reduction in credit market outcomes (dashed red line) into the model-based margins explained by (time) fixed effects (dashed black lines), average time-varying local pandemic severity (red shaded areas), and average time-varying local non-pharmaceutical intervention (NPI) stringency (green shaded areas), based on the mean decomposition in Equation (6a) - (6c). The red, dashed, vertical lines mark March 15, the date in our dataset closest to the national emergency declaration on March 13, 2020.

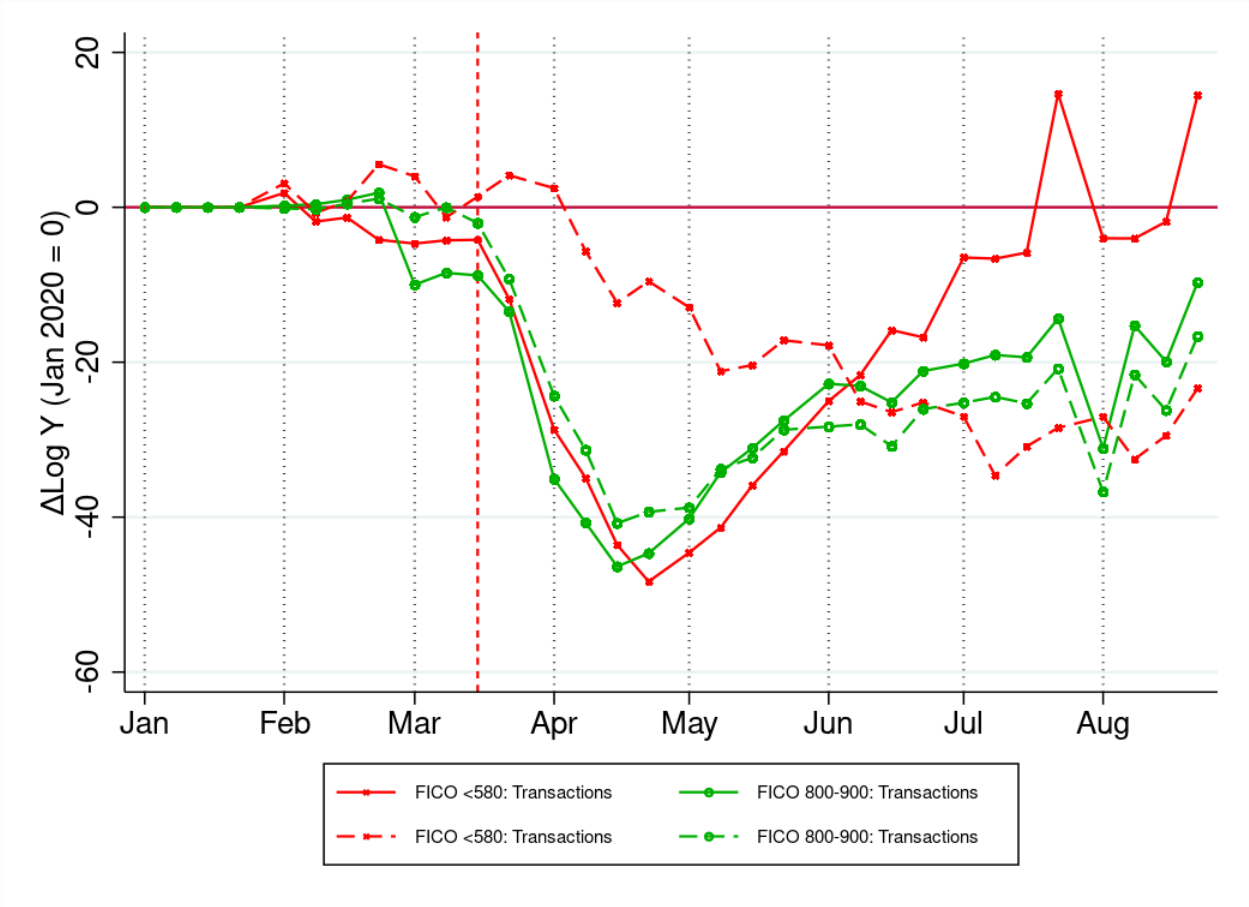
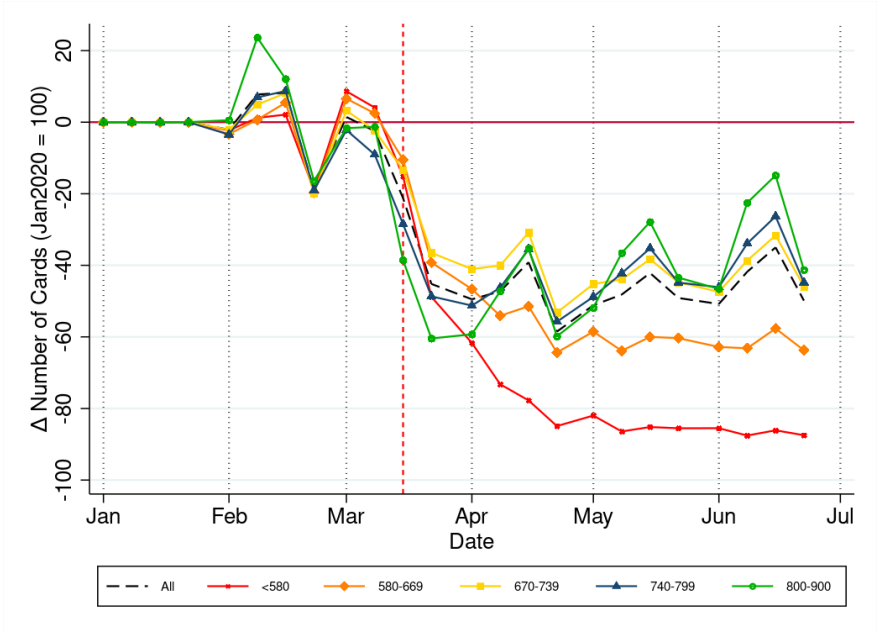
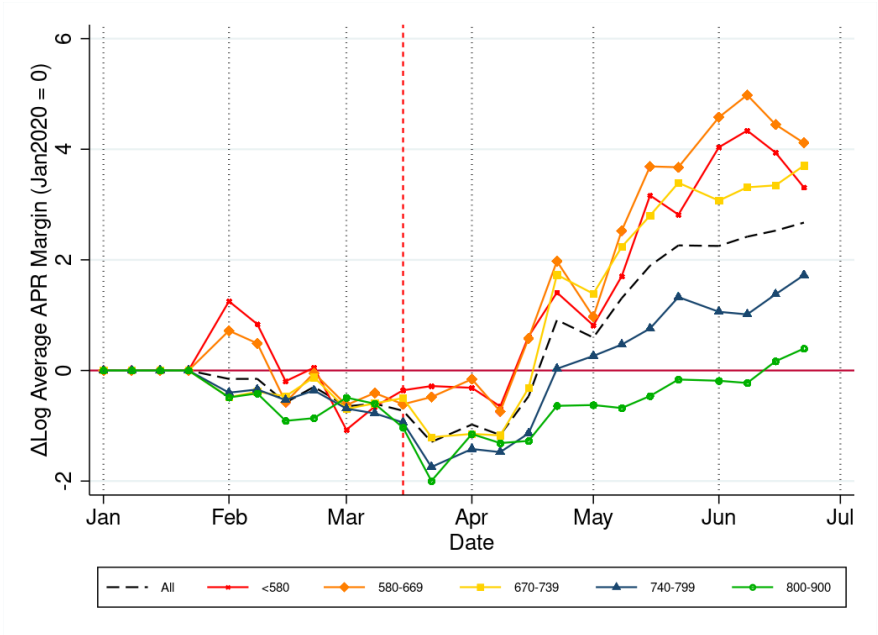


Figure 7. Transactions versus Balances for High and Low FICO Borrowers. This figure illustrates the mean year-over-year change in credit card transactions (dashed lines) and outstanding credit card balances (solid lines) for borrowers in the lowest FICO class (less than 580, red lines) and in the highest FICO class (800-900, green lines) relative to January 2020. The red, dashed, vertical line marks March 15, the date in our dataset closest to the national emergency declaration on March 13, 2020. All observations are weighted by the number of credit cards as of January 2020.

(A) Number of Credit Card Originations by FICO Classes over Time



(B) Average APR Spreads by FICO Classes over Time



(C) Average Credit Limits by FICO Classes over Time

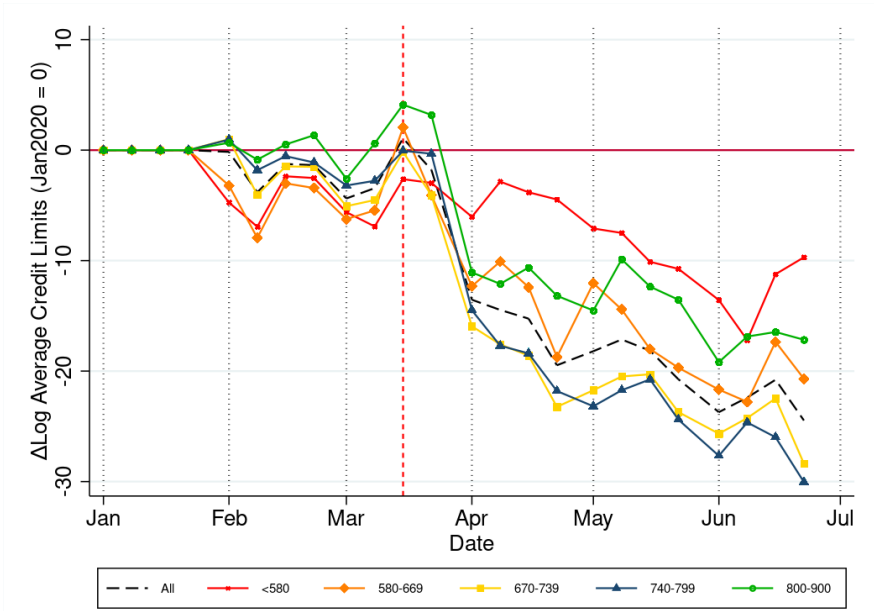
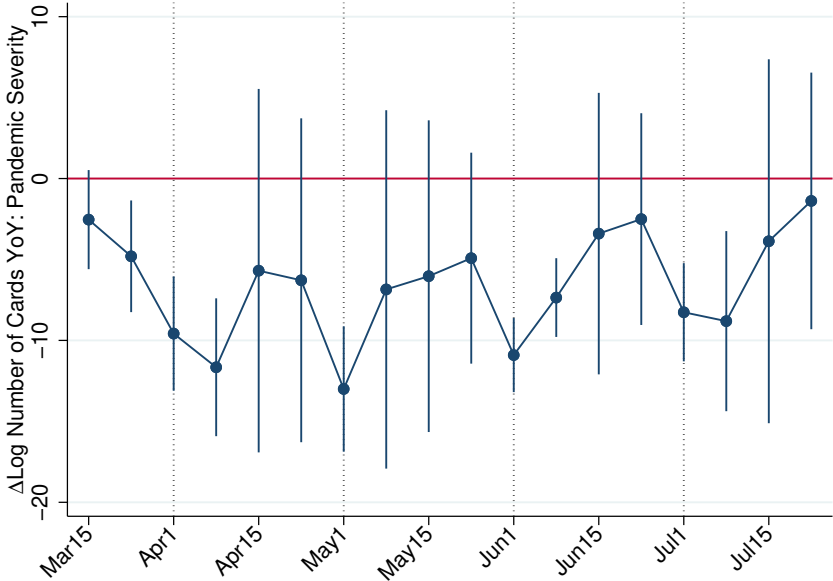
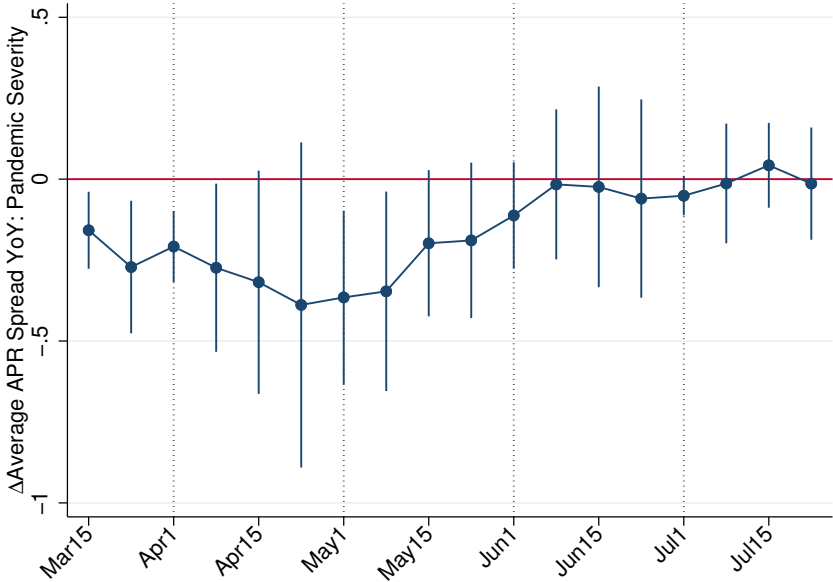


Figure 8. Availability of Credit By FICO Classes over Time. This figure illustrates the mean year-over-year change in the number of credit card originations (Panel A), the average annual percentage rate (APR) spreads (Panel B), and the average credit limits (Panel C) of newly issued credit cards relative to January 2020 across five different FICO classes: Less than 580 (red), 580-669 (orange), 670-739 (yellow), 740-799 (blue), 800-900 (green), all borrowers (black, dashed). The red, dashed, vertical line marks March 15, the date in our dataset closest to the national emergency declaration on March 13, 2020. All observations are weighted by the number of credit cards as of January 2020.

(A) Local Pandemic Severity and Changes in Credit Card Originations over Time



(B) Local Pandemic Severity and Changes in APR Spreads over Time



(C) Local Pandemic Severity and Changes in Credit Limits over Time

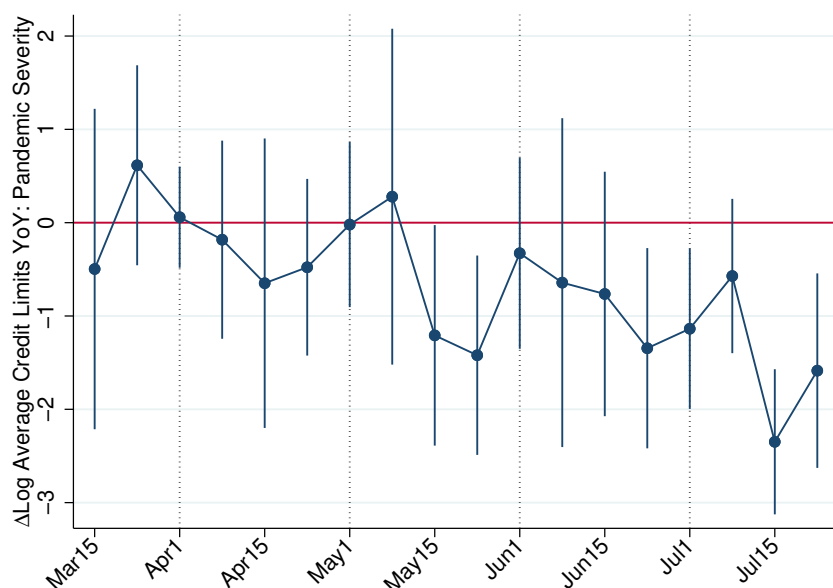
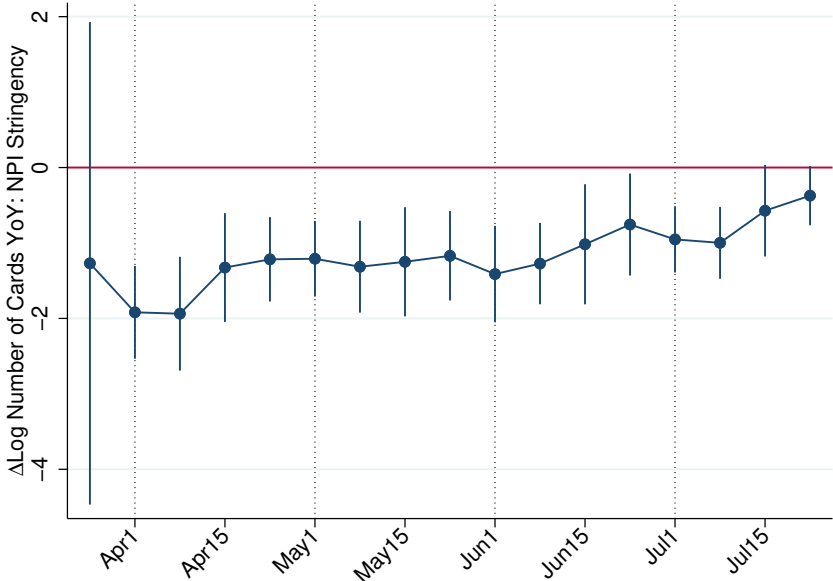
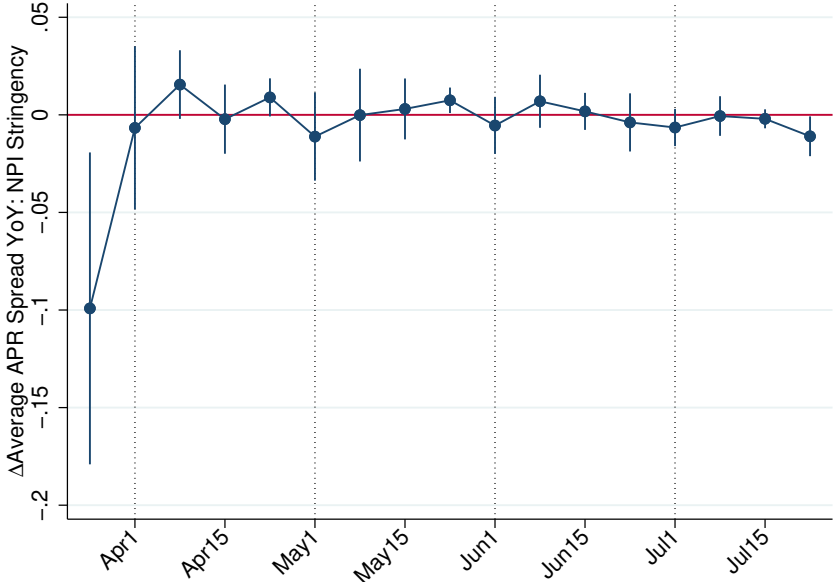


Figure 9. Local Pandemic Severity and the Availability of Consumer Credit over Time. This figure illustrates the estimation results for the effect of local pandemic severity on credit card originations (Panel A), average annual percentage rate (APR) spreads (Panel B), and average credit limits over time (Panel C). The blue line plots the regression coefficients γ^t from Equation (3) in Section III.A along with standard errors clustered at the county and bank level. All regressions are weighted by the number of credit cards as of January 2020 per observational unit.

(A) NPI Stringency and Changes in Credit Card Originations over Time



(B) NPI Stringency and Changes in APR Spreads over Time



(C) NPI Stringency and Changes in Credit Limits over Time

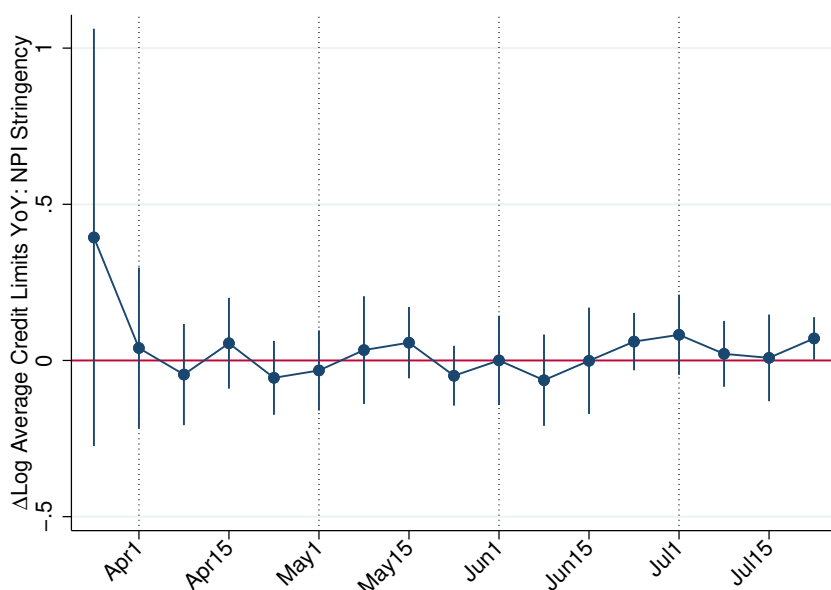
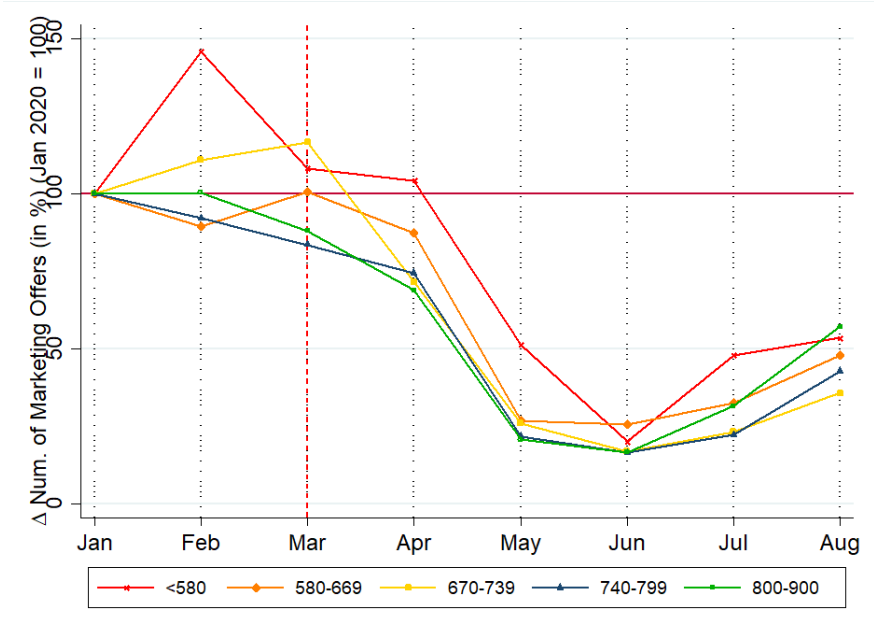


Figure 10. Local NPI Stringency and the Availability of Consumer Credit over Time. This figure illustrates the estimation results for the effect of non-pharmaceutical intervention (NPI) Stringency on credit card originations (Panel A), average average annual percentage rate (APR) spreads (Panel B), and average credit limits over time (Panel C). The blue line plots the regression coefficients θ^t from Equation (5) in Section III.B along with standard errors clustered at the county and bank level. All regressions are weighted by the number of credit cards as of January 2020 per observational unit.

(A) Number of Credit Card Marketing Offers by Vantage Score Classes over Time



(B) Average Offered APR Spreads by Vantage Score Classes over Time

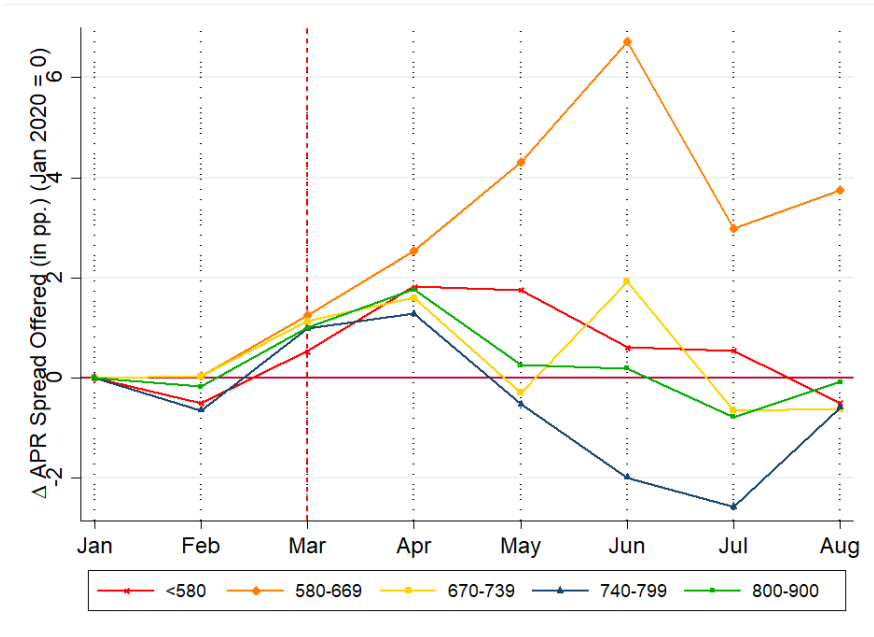
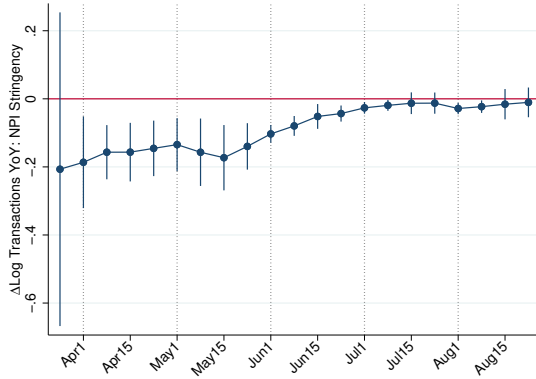
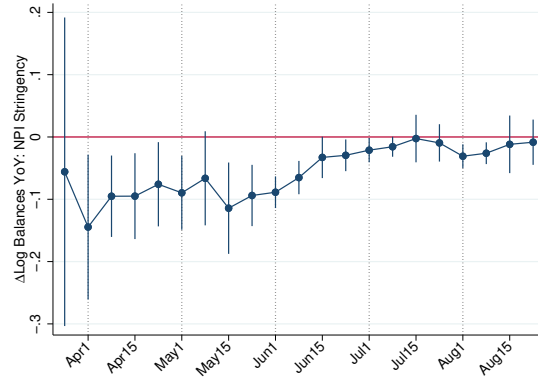


Figure 11. Credit Card Marketing By Vantage Score Classes over Time. This figure illustrates the mean change in the number of credit card marketing offers (Panel A) and the average APR spread on these offers (Panel B) relative to January 2020 across five different Vantage Score classes: Less than 580 (red), 580-669 (orange), 670-739 (yellow), 740-799 (blue), 800-900 (green), all borrowers (black, dashed).

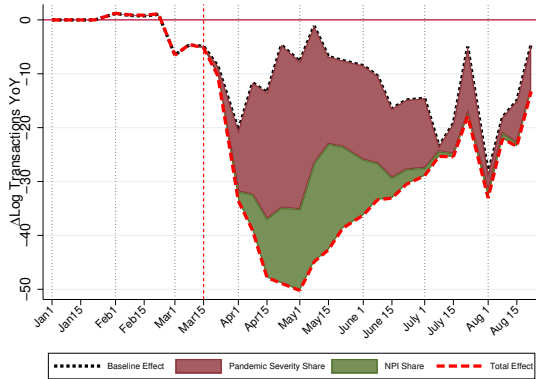
(A) Effect on Credit Card Transactions



(B) Effect on Credit Card Balances



(C) Mean Decomposition: Credit Card Transactions



(D) Mean Decomposition: Credit Card Balances

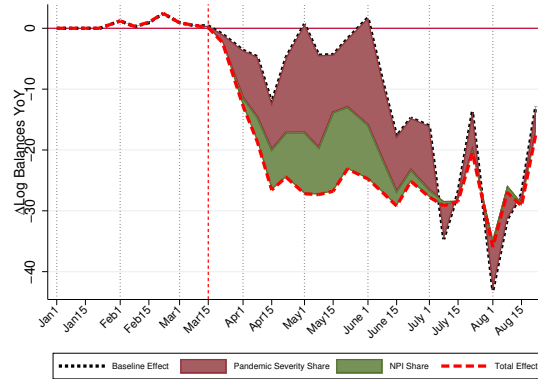
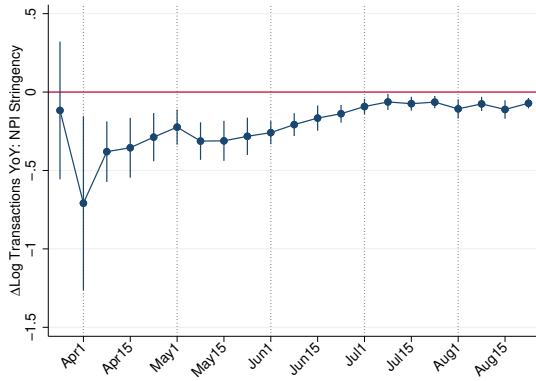


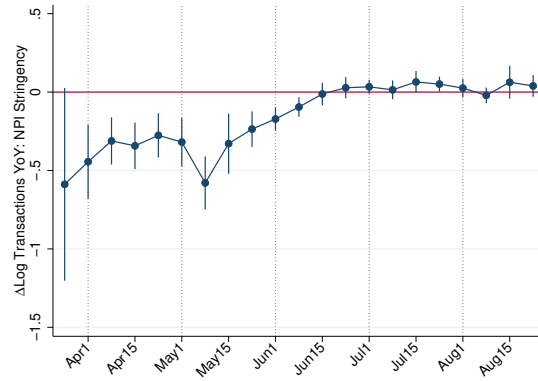
Figure 12. Robustness Check: Local NPI Stringency and the Use of Consumer Credit.

This figure illustrates the estimation results for the effect of non-pharmaceutical interventions (NPIs) on credit card transactions (Panel A) and outstanding credit card balances (Panel B) over time, using the alternative NPI stringency measure as defined in Equation (7) in Section VI.A. The blue line plots the regression coefficients θ^t from Equation (5) in Section III.B along with the 95 percent confidence intervals. All regressions are weighted by the number of credit cards as of January 2020 per observational unit. Panel C and Panel D illustrate the decomposition of the total reduction in credit market outcomes (dashed red line) into the model-based margins explained by (time) fixed effects (dashed black lines), average time-varying local pandemic severity (red shaded areas), and average time-varying local NPI stringency (green shaded areas), based on the mean decomposition in Equation (6a) - (6c). The red, dashed, vertical lines mark March 15, the date in our dataset closest to the national emergency declaration on March 13, 2020.

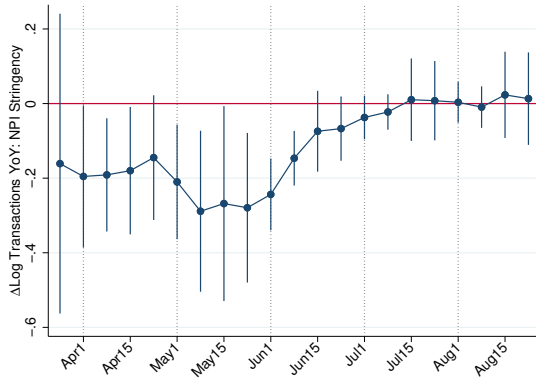
(A) Shelter-in-Place



(B) Nonessential Business Closure



(C) Public Venue Closure



(D) Gathering Size Limitation

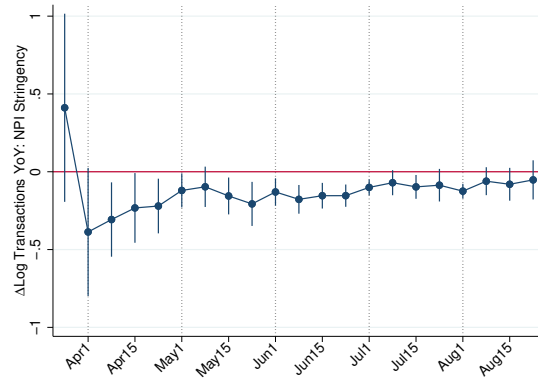


Figure 13. Individual NPIs and Credit Card Transactions. This figure illustrates the estimation results for the effect of four individual non-pharmaceutical interventions (NPIs) on credit card transactions: shelter-in-place orders (Panel A), non-essential business closures (Panel B), public venue closures (Panel C), and gathering size limitations of 10 people or less (Panel D). The blue lines in each panel plot the regression coefficients $\theta^{\tau, SIP}$, $\theta^{\tau, NEBC}$, $\theta^{\tau, PVC}$, and $\theta^{\tau, GSL}$ from Equation (8) in Section VI.B, respectively, along with the 95 percent confidence intervals. All regressions are weighted by the number of credit cards as of January 2020 per observational unit.

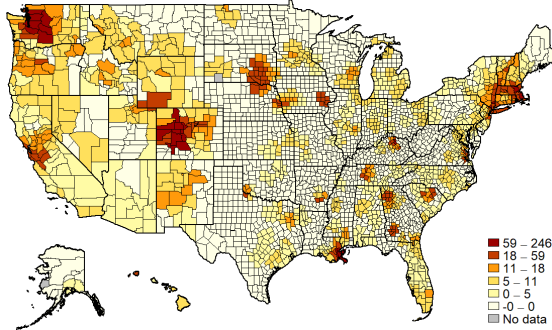
Online Appendix

“The COVID-19 Shock and Consumer Credit: Evidence from Credit Card Data”

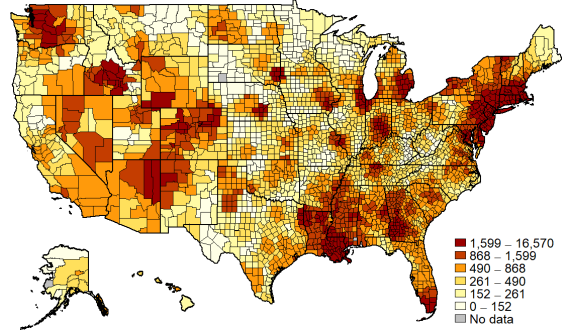
December 2020

A1. The Geographic Spread of Local Pandemic Severity

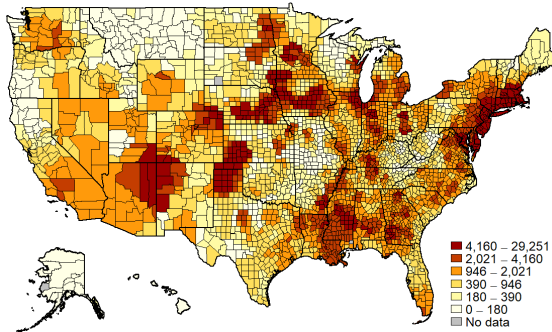
(A) March 15



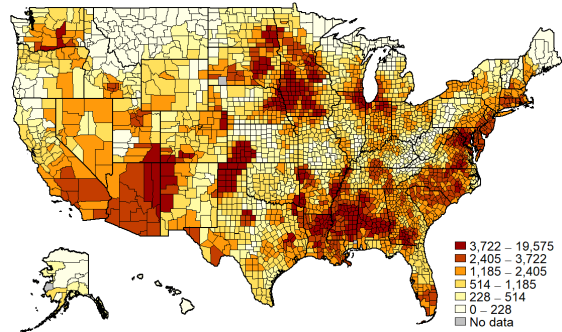
(B) April 15



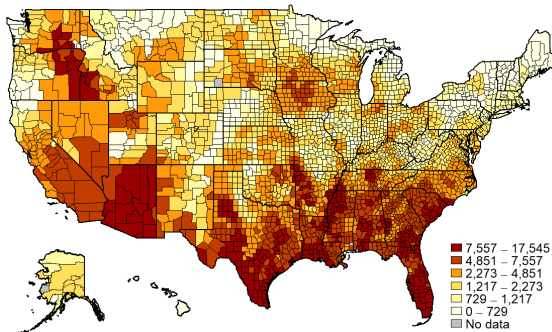
(C) May 15



(D) June 15



(E) July 15



(F) August 15

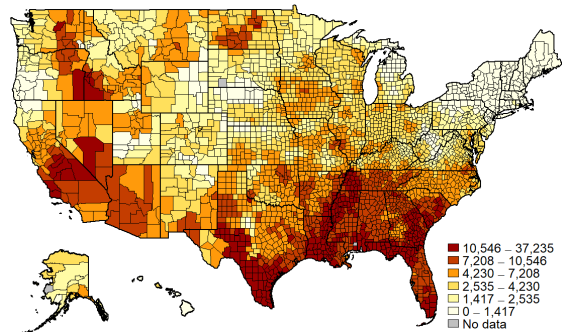


Figure A1. New Area Cases per 1 Million Population. This figure illustrates the geographic spread of the number of new area cases over the past four weeks per 1 million population as of March 15 (Panel A), April 15 (Panel B), May 15 (Panel C), June 15 (Panel D), July 15 (Panel E), and August 15 (Panel F). Cut-off values for the different colors were chosen to match the 10, 25, 50, 75, and 90, percentile of new area cases per 1 million population in the data, respectively.

A2. Individual NPIs Over Time

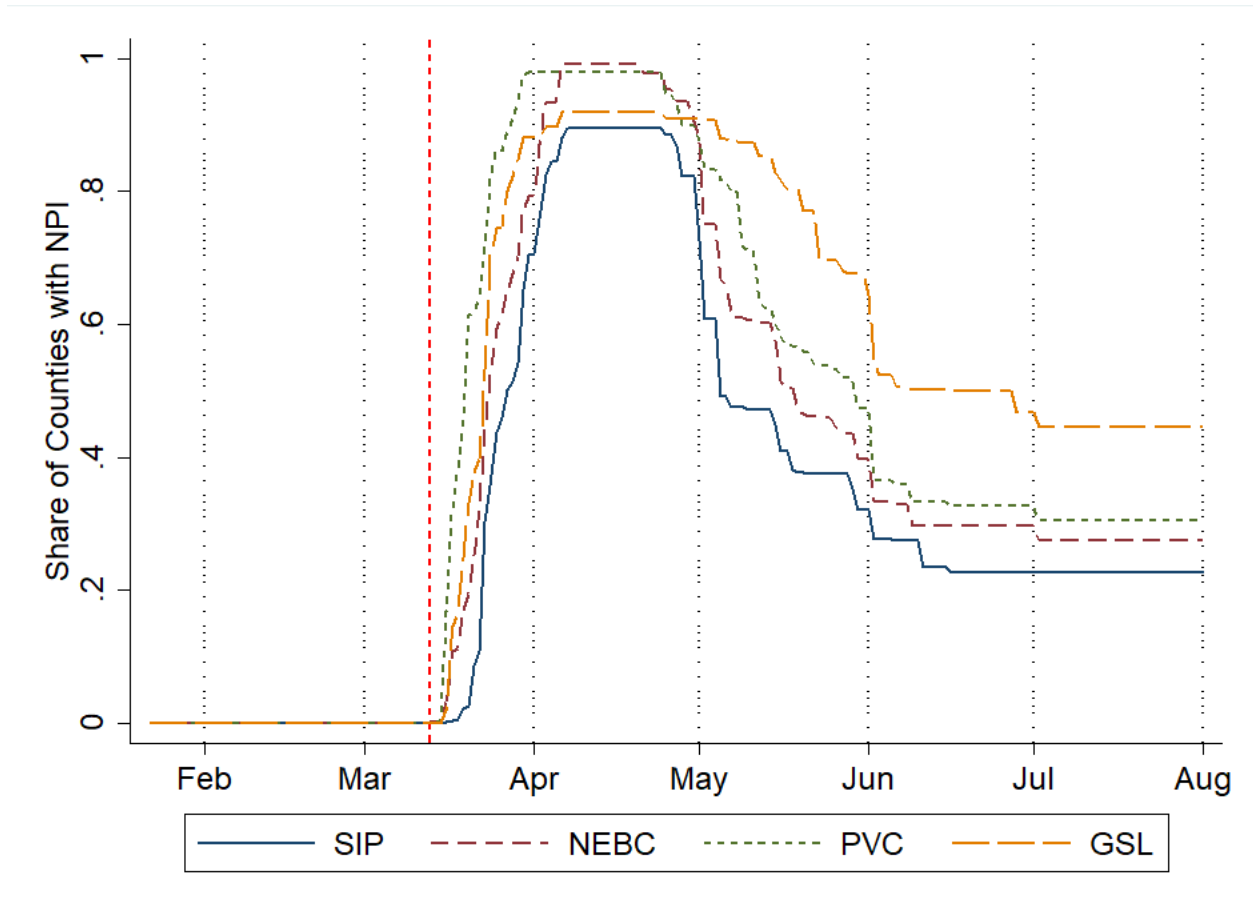
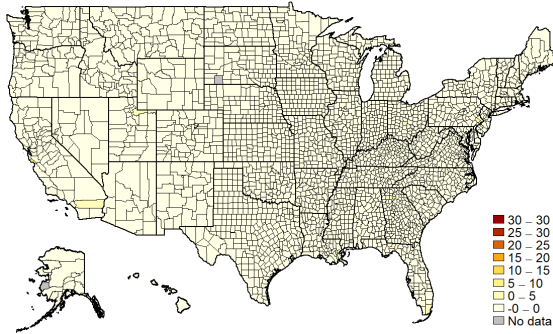


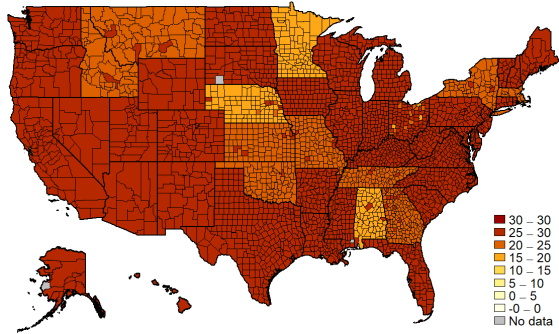
Figure A2. Individual NPIs over Time. This figure illustrates the enactment of the following four individual non-pharmaceutical interventions (NPIs) over time: shelter-in-place orders (SIP), non-essential business closures (NEBC), public venue closures (PVC), and gathering size limitations of 10 people or less (GSL). Each line indicates the share of counties that had enacted the respective NPI at any point in time. The red, dashed, vertical line marks March 13, the date of the national emergency declaration.

A3. The Geographic Spread of NPI Stringency

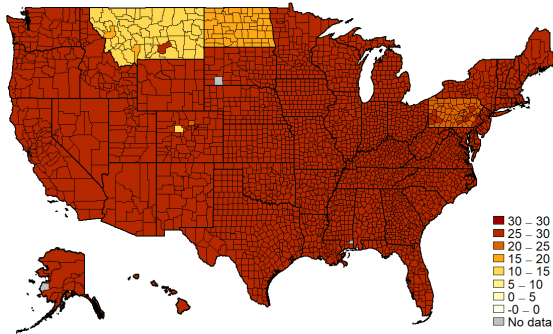
(A) March 15



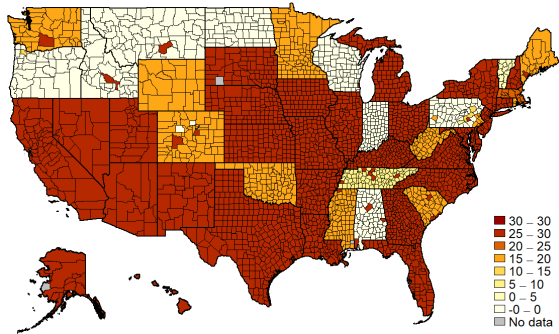
(B) April 15



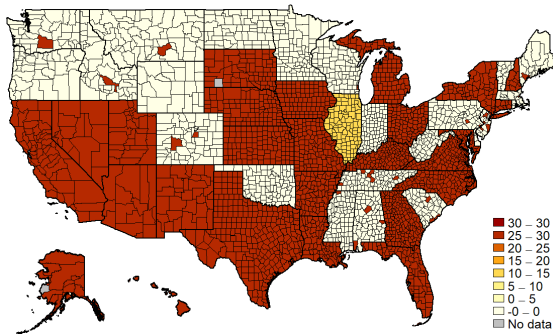
(C) May 15



(D) June 15



(E) July 15



(F) August 15

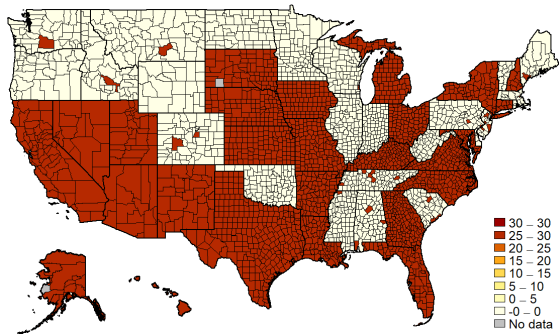


Figure A3. NPI Stringency. This figure illustrates the geographic spread of NPI stringency as defined in Equation (2) in Section II.B.2 as of March 15 (Panel A), April 15 (Panel B), May 15 (Panel C), June 15 (Panel D), July 15 (Panel E), and August 15 (Panel F). Cut-off values for the different colors were chosen to match 0, 5, 10, 15, 20, 25, and 30 days, respectively.

A4. Mobility Response

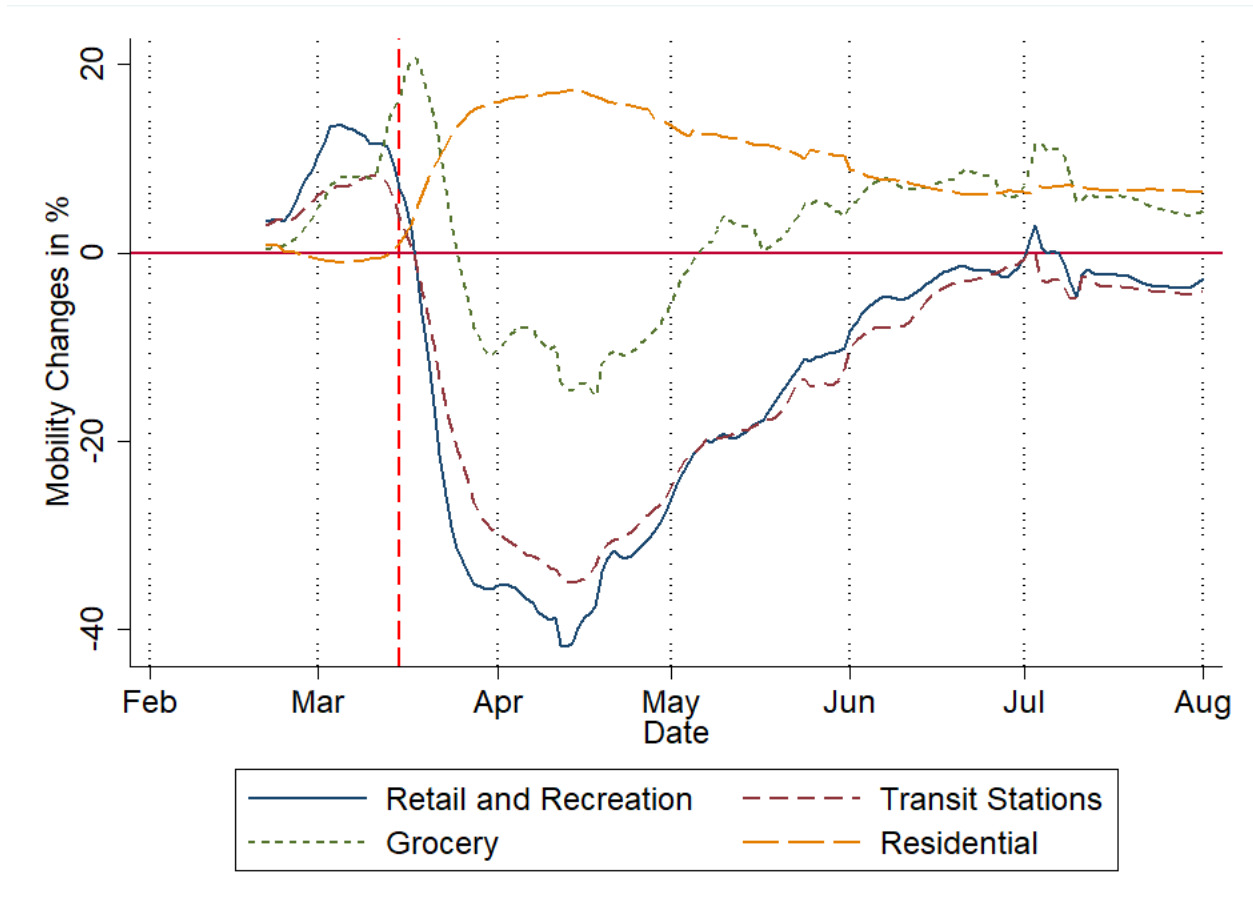
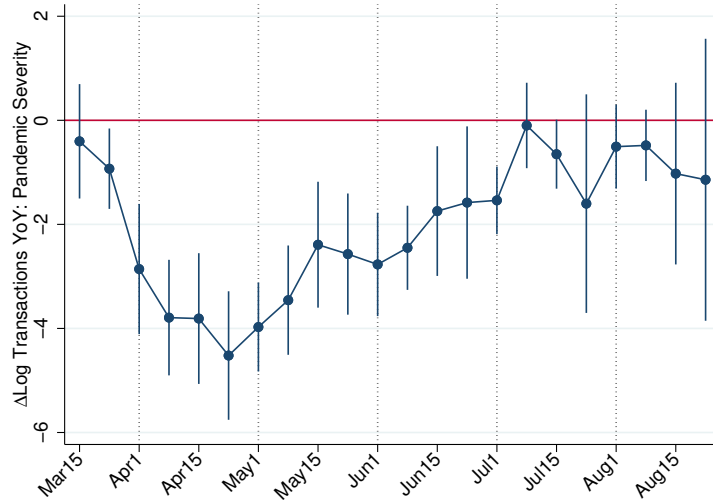


Figure A4. Mobility Response. This figure illustrates the mobility response of individuals during the COVID-19 pandemic based on Google’s COVID-19 Community Mobility Reports (Google LLC, 2020) for the categories *Retail and Recreation* (blue line), *Transit Stations* (red line), *Grocery* (green line), and *Residential* (yellow line). The lines indicate the mean percent change in visits to places across counties. The red, dashed, vertical line marks March 13, the date of the national emergency declaration.

A5. Local Pandemic Severity and Credit Use: Robustness

(A) Local Pandemic Severity and Changes in Credit Card Transactions



(B) Local Pandemic Severity and Changes in Credit Card Balances

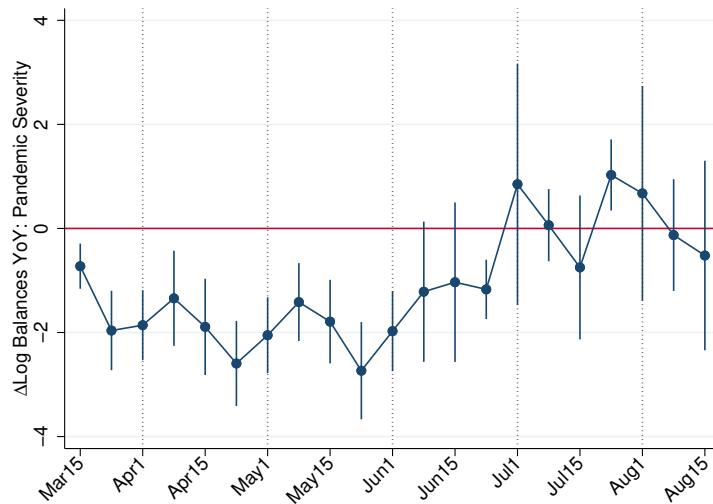


Figure A5. Robustness Check: Local Pandemic Severity and the Use of Consumer Credit. This figure illustrates the estimation results for the effect of local pandemic severity on credit card transactions (Panel A) and balances (Panel B) over time. The blue line plots the regression coefficients γ^t from Equation (5) in Section III.B along with standard errors clustered at the county and bank level. All regressions are weighted by the number of credit cards as of January 2020 per observational unit.